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ORIGINAL ARTICLE

Fast, stable, or credible? Mobile experience outcomes in certified luxury retail

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Abstract
Mobile interactions increasingly shape how consumers judge luxury brands, yet it remains unclear whether sustainable-certified brands deliver mobile experiences consistent with the elevated execution expectations implied by ethical signaling. Drawing on a signaling theory and expectation-based perspectives, this paper conceptualizes mobile UX performance as an execution-level signal through which certification credibility is reinforced or undermined. Using real-user PageSpeed Insights field data for 133 Butterfly Mark certified luxury brands, the analysis benchmarks Core Web Vitals and models Google's "Fast" mobile classification as a function of loading speed and visual stability. The findings reveal an asymmetric structure of digital performance signals: visual stability operates primarily as a baseline hygiene condition, with most brands meeting recommended thresholds and no robust sector-level differences, whereas loading speed, measured by Largest Contentful Paint, emerges as the dominant predictor of platform-defined mobile experience quality. Even modest reductions in loading time substantially increase the probability of achieving a "Fast" classification, while additional gains in stability yield diminishing returns once baseline standards are satisfied. The study advances marketing analytics research by demonstrating how platform-generated technical metrics can be modeled by showing that sustainability certification functions as an expectation amplifier.

Keywords Customer experience analytics · Luxury e-commerce · Sustainability certification · Mobile performance

Introduction

Sustainability has become a central dimension of luxury brand equity, shaping how high-end brands differentiate themselves and justify premium positioning (Rolling and Sadachar 2018; Priyadarshini and Prasad 2023). High-net-worth consumers increasingly expect luxury brands to demonstrate verifiable environmental and social responsibility, and third-party certifications such as the Butterfly Mark serve as prominent signals of such commitments (Athwal et al. 2019; Positive Luxury 2025). These certifications communicate ethical standards and organizational rigor, contributing to elevated expectations of brand execution across all consumer touchpoints.

While prior research has extensively examined sustainability in luxury product sourcing and corporate governance (Kapferer and Michaut-Denizeau 2017; Hepner et al. 2020), far less attention has been paid to how sustainability commitments are reflected in digital execution, particularly in mobile environments. This omission is notable given the increasing dominance of mobile channels in luxury retail and the heightened sensitivity of luxury consumers to friction, inconsistency, and perceived imperfections in brand encounters (Achugbu 2016; Al-Zuabi et al. 2019; Simanjuntak 2023). Thus, the quality of mobile experiences has emerged as a decisive factor in shaping customer perceptions and behaviors (Boustani and Zielinski 2023; Massi et al. 2025).

The signaling perspective shows that in luxury markets, the expectations extend beyond ethics to execution quality, making mobile UX performance a critical test of signal credibility. Moreover, in mobile-first contexts, luxury brands operate under heightened performance expectations

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(Dryl 2023). Mobile interfaces are not merely functional access points but experiential environments through which perceptions of quality, fluency, refinement, or seamless journeys are formed rapidly during page loading and interaction (Klaus 2021). Even brief delays or unstable rendering can disrupt the sense of effortlessness that defines luxury experiences, making mobile technical performance a consequential component of brand execution (Holdener et al. 2020; Ramtohul and Khedo 2023; Bansal 2024).

In luxury contexts, sustainability certifications function as ex ante indicators of organizational quality, elevating expectations of execution consistency across digital touchpoints (Song and Kim 2022; Wu and Tang 2022). Mobile UX performance also has well-documented business implications. Previous research and industry evidence consistently link mobile loading speed and interface stability to outcomes such as bounce rates, session depth or duration, and conversion likelihood (Qualid et al. 2024). In luxury retail, where customer acquisition costs are high and brand interactions are expected to be seamless, even small performance frictions can have disproportionate commercial consequences (Chevalier et al., 2020). Moreover, despite growing research on luxury sustainability and digital customer experience, three gaps remain. First, sustainability research focuses primarily on messaging and governance, while largely overlooking execution-level digital performance as a credibility test. Secondly, UX research typically treats technical performance dimensions symmetrically, without examining whether different dimensions carry asymmetric informational weight under high-expectation brand contexts. Thirdly, marketing analytics research rarely conceptualizes platform-defined technical classifications as probabilistic experience signals embedded within evaluation ecosystems. This study addresses these gaps by modeling mobile technical performance as an execution-level signal within sustainability-certified luxury brands.

In this context, the researcher examines mobile UX performance among Butterfly Mark-certified luxury brands using real-user field data from Google PageSpeed Insights. Specifically, it uses widely adopted mobile performance indicators to evaluate how execution quality aligns with certification-based expectations (Web Dev 2025). The study pursues three objectives, namely, (O1) to benchmark mobile performance across luxury sectors, (O2) to assess which technical metrics are most predictive of a fast mobile experience, and (O3) to translate performance metrics into interpretable managerial thresholds.

By reframing mobile performance metrics as execution-level signals within sustainability-certified luxury contexts, this research contributes to marketing analytics by providing a reproducible audit framework for evaluating digital execution quality. It also offers actionable insights for luxury managers seeking to align sustainability signaling with mobile experience delivery in high-expectation environments.

Empirically, the analysis shows a clear asymmetry between mobile UX dimensions. Loading speed, captured by Largest Contentful Paint (hereinafter LCP), emerges as the dominant driver of Google's "Fast" mobile classification, whereas visual stability, measured by Cumulative Layout Shift (CLS), primarily functions as a baseline hygiene factor once minimum thresholds are met. This distinction clarifies how execution-level performance signals operate in sustainability-certified luxury contexts and motivates the study's focus on translating technical metrics into actionable analytics insights.

From a marketing analytics perspective, this study contributes by reframing mobile UX performance metrics as execution-level signals rather than as purely technical indicators. While analytics research often treats performance metrics as background inputs or operational constraints, the present findings show that platform-defined outcomes such as Google's "Fast" classification can be modeled probabilistically and interpreted as meaningful experience signals within digital brand evaluation systems. This extends marketing analytics research by demonstrating how real-user technical metrics can be integrated into customer experience analytics as interpretable, decision-relevant signals and not as opaque engineering outputs.

Literature review

LCX and digital touchpoints

Luxury customer experience (LCX) has emerged as a distinct domain within customer experience research, reflecting heightened expectations, symbolic consumption, and non-utilitarian value creation. LCX integrates functional quality, emotional resonance, symbolic meaning, and personalization into a seamless brand journey (Mossberg 2008; Saunila et al. 2019; Kusal et al. 2022). Unlike standard customer experiences, luxury emphasizes aesthetics, storytelling, exclusivity, and emotional immersion as core value drivers.

Digital touchpoints have become central to delivering LCX as luxury brands increasingly adopt omnichannel strategies (Baxendale et al. 2015; Ieva and Ziliani 2018; Fu and Ren 2023). Moreover, they form the scaffolding of the modern LCX, their impact is increasingly determined by the medium through which consumers access them (Ieva and Ziliani 2018; Vannucci and Pantano 2019; Fu and Ren 2023). In luxury contexts, digital performance is not a neutral technical background but an experiential attribute of

the customer journey. Because luxury value is grounded in effortlessness, aesthetic coherence, and emotional immersion, disruptions such as slow loading or unstable layouts directly interfere with the experiential quality of the brand encounter (Mossberg 2008; Klaus 2021). Accordingly, mobile performance characteristics such as speed and visual stability should be understood as constitutive elements of luxury customer experience, not technical conditions. Thus, digital interfaces function as transactional platforms but also, as experiential environments, in which brand meaning and identity are continuously constructed. In this context, visually unstable or slow-loading interfaces can disrupt experiential continuity and generate brand dissonance (Bansal 2024). Thus, from a relational perspective, such breakdowns can be interpreted as violations of implicit psychological expectations between brand and consumer, leading to perceived brand incongruity (Berry 2000; Chen et al. 2010).

Moreover, from a human–computer interaction (HCI) perspective, digital luxury encounters are cognitive and affective experiences shaped by interface fluency, perceptual continuity, and trustworthiness. As such, technical execution becomes a necessary condition for sustaining the symbolic and emotional of LCX. However, despite this rich conceptualization of luxury customer experience, research largely treats digital execution quality as a background condition, not only as an empirically observable component of LCX, leaving open how technical performance contributes to experience formation in mobile environments.

Mobile-first strategy in luxury contexts

Building on the centrality of digital touchpoints in luxury customer experience, mobile-first strategies have emerged as a defining feature of contemporary luxury engagement.

The growing dominance of mobile devices has fundamentally reshaped luxury brand engagement (Chung et al. 2018; Jain et al. 2022). Mobile-first strategies require designing interaction, content, and performance with mobile users as the primary reference point, which represents more than adapting desktop experiences ex post (AbouElgheit 2024).

In luxury contexts, mobile experiences are especially consequential because consumers form rapid judgments about brand quality and credibility during early stages of mobile interaction (Hepner et al. 2020). Technical imperfections such as loading delays or unstable layouts are therefore interpreted not merely as usability flaws but as violations of the luxury brand promise. From an HCI standpoint, mobile-first luxury design reflects the need to optimize perceptual fluency, minimize cognitive load, and maintain emotional continuity across digital interactions (Al-Zuabi et al. 2019; Akkaya et al. 2024). Given the importance of mobile channels in luxury engagement, the effectiveness of a mobile-first strategy ultimately depends on the technical performance of the interface, which shapes how seamlessly and credibly the experience is delivered. Although mobile-first strategies are widely advocated in luxury research, empirical evidence linking such strategies to specific performance indicators remains limited, particularly in high-expectation luxury settings.

For sustainability-certified luxury brands, mobile execution may carry additional symbolic weight, as certification can amplify expectations across touchpoints. In this context, mobile performance becomes more than a usability concern; it operates as an execution-level signal through which the credibility of sustainability claims is indirectly assessed. In this sense, inconsistencies in mobile execution may weaken the coherence between ethical positioning and operational delivery. While mobile-first strategies are widely advocated in luxury research, empirical work rarely specifies which aspects of mobile execution drive experience outcomes, particularly under the heightened expectations characteristic of luxury contexts.

Technical performance and mobile luxury UX

From an expectations-based and signaling perspective, not all technical performance dimensions carry equal informational weight in shaping early experience judgments. Research in HCI shows that loading speed directly influences perceptual fluency and cognitive ease during the earliest moments of interaction, when users form rapid assessments of competence and quality (Duric et al. 2002; Erdman et al. 2025; Lang et al. 2025; Vázquez-Martínez, et al. 2025). By contrast, visual stability primarily prevents negative disruption. than generating positive differentiation once minimum standards are met. This asymmetry suggests that speed functions as a primary execution-level signal, while stability operates closer to a baseline condition whose absence is penalized but whose presence is taken for granted, particularly in high-expectation luxury contexts. Responding to this dependency, research has increasingly focused on technical performance indicators that shape how mobile experiences are rendered and perceived. Technical performance has long been recognized as a core determinant of digital UX (Shao and Chang 2020; Balcombe and Leo 2022; Seale et al., 2022), yet its emotional and symbolic implications in luxury contexts remain underexplored. Metrics such as LCP and CLS introduced within Google's Core Web Vitals framework, capture key aspects of mobile speed and visual stability that shape users' early interaction experiences (Król and Sroka 2023; Wibagso 2023; Romero and Torres 2024).

Although other studies document the general importance of speed and visual stability for user experience, most treat these dimensions symmetrically or as interchangeable indicators of "good UX," offering limited insight into their potentially asymmetric roles in shaping early judgments, particularly in luxury entities.

Unexpected layout shifts and slow rendering can disrupt attentional flow, increase cognitive load, and elicit negative affective responses (Wang and Rodriguez 2024). By contrast, once minimum standards of visual stability are met, the absence of disruption becomes expected rather than diagnostic, implying diminishing value for differentiation-consistent with a "hygiene factor" role. These effects are amplified in luxury settings, where users are particularly sensitive to aesthetic coherence and experiential disruptions (Berry 2000). Empirical evidence further suggests that perceptions of experiential quality and emotional engagement are shaped early in the mobile page-loading process (Bakar et al., 2024). Again, from an expectations-based signaling perspective, loading speed functions as a primary execution cue through which users rapidly assess whether operational performance aligns with the quality expectations implied by brand positioning.

Certifications function as trust signals intended to convey ethical leadership, yet their effectiveness depends on consistent and high-quality execution across digital touchpoints. For sustainability-oriented luxury brands, technical execution acquires additional significance, as disruptions in mobile performance can directly undermine perceptions of fluency, refinement, and experiential coherence. Several studies document the general importance of speed and visual stability for UX, yet few examine their implications in luxury contexts or assess these effects using real-user field data.

While these technical indicators are essential for delivering seamless mobile experiences, their role becomes especially consequential when brands engage in sustainability-based signaling. Importantly, signaling theory implies not that certification guarantees superior performance, but that it amplifies expectations regarding execution quality. In luxury contexts, third-party sustainability certifications elevate assumptions about organizational rigor and operational competence, increasing the likelihood that execution-level deviations will be noticed and negatively evaluated.

Sustainability certification as a digital execution signal

While the previous section focuses on the experiential consequences of technical performance, this section conceptualizes sustainability certification as a signaling mechanism whose credibility depends on consistent execution across digital touchpoints.

In parallel with the digital transformation of luxury, sustainability has become a defining axis of differentiation and consumer engagement (Piligrimienė et al. 2020; Judijanto et al. 2024). Certifications such as the Butterfly Mark have been developed to communicate verified environmental and social commitments across luxury sectors. These third-party endorsements enhance transparency in markets increasingly attentive to greenwashing and ESG rhetoric (Kapferer and Michaut-Denizeau 2017). The Butterfly Mark, in particular, functions as a communication mechanism that signals ethical excellence positioning and organizational rigor in complex, information-rich marketplace.

Research suggests that the effectiveness of such signals depends on the coherence with broader brand execution and experiential consistency (Chen et al. 2010; Andriyani and Yudhistira 2023). In digital contexts, especially when interfaces fail to meet baseline expectations of technical performance and visual fluidity, misalignment may emerge between ethical signaling and experiential delivery. In luxury settings, where perceived authenticity and brand harmony are especially salient, such inconsistencies can weaken the alignment between sustainability messaging and the lived brand experience.

Importantly, signaling theory implies not that certification guarantees superior performance, but that it amplifies expectations regarding execution quality. In luxury contexts, third-party sustainability certifications elevate assumptions about organizational rigor and operational competence, increasing the likelihood that execution-level deviations will be noticed and negatively evaluated. Mobile UX performance thus becomes a salient arena in which the credibility of sustainability signaling is tested, as inconsistencies between ethical positioning and observable execution can weaken perceived authenticity. Sustainability certifications have become key quality signals in markets where consumers and stakeholders cannot directly observe underlying organizational performance. Signaling theory suggests that such cues reduce information asymmetry and allow observers to infer competence and commitment from external markers. Certifications such as Butterfly Mark, therefore, communicate ethical achievement and also, shape expectations of executional excellence, as consumers increasingly interpret sustainability signals through the lens of brand competence and overall quality perception. Research shows that sustainability signaling influences how consumers define brand value, trust, and authenticity and that third-party certifications enhance perceived credibility when aligned with coherent performance signals (Theocharis and Tsekouropoulos 2025).

From a HCI perspective, sustainability signaling can therefore be viewed as interacting with the integrity of the UX. In mobile environments, where interactions are frequent and time-constrained, technical UX performance constitutes a salient execution-level signal through which sustainability claims are enacted. For such certifications to function effectively as signals, they must be supported by mobile experiences whose performance characteristics are consistent with the expectations implied by ethical positioning.

Despite the prominence of sustainability certifications as quality signals, little empirical research examines how their credibility depends on alignment with observable digital execution quality, particularly in mobile-first luxury environments. In this sense, sustainability certification is better understood as an expectation-amplifying signal, increasing the likelihood that execution-level deviations in mobile UX will be noticed and penalized. This perspective positions mobile UX performance as an outcome of and as an execution-level signal through which certification credibility is reinforced or undermined in practice.

Methodology

Research design

This study adopts a quantitative, descriptive–predictive research design grounded in marketing analytics. A formal a priori power analysis was not conducted because the study relies on a fixed population of sustainability-certified luxury brands with available real-user field data, not on a sample designed for hypothesis testing. The objective is to assess whether sustainability-certified luxury brands deliver mobile user experiences that are technically consistent with the execution-quality expectations implied by certification. Rather than evaluating consumer perceptions directly, the analysis focuses on observable, execution-level performance signals captured through real-user mobile performance data.

Mobile user experience quality is operationalized using Google's Core Web Vitals, which provide standardized, field-based indicators of how users experience loading speed and visual stability on mobile devices. Two metrics are central to the analysis. LCP captures loading speed by measuring how quickly the main content becomes visible, while CLS captures visual stability by measuring unexpected layout shifts during page rendering. These metrics are particularly relevant in luxury contexts, where technical disruptions can undermine perceived fluency, refinement, and brand credibility.

The empirical strategy combines three analytical components. Firstly, the study benchmarks mobile performance across luxury sectors to describe the distribution of loading speed and visual stability among certified brands. Secondly, it estimates the probability that a website is classified by Google as delivering a "Fast" mobile experience as a function of Core Web Vitals. Thirdly, the analysis translates model estimates into interpretable performance thresholds that indicate where incremental technical improvements are associated with meaningful changes in mobile experience classification.

To enhance robustness, First Contentful Paint (FCP) is included in an alternative specification as an additional speed-related metric. All analyses rely on real-user field data obtained via the Google PageSpeed Insights API and are designed to provide an execution-focused audit of mobile UX performance within sustainability-certified luxury brands.

Data collection

The sample comprises 133 luxury brand websites certified with the Butterfly Mark by Positive Luxury. Brand URLs were sourced from the public "Real Changers" listing to ensure transparency and replicability. Sectors include Fashion & Accessories, Interiors & Living, Beauty & Fragrance, Jewelry & Watches, Premium Drinks, and Travel & Leisure. Field data were unavailable for some certified brands due to insufficient real-user Chrome data at the time of collection, consistent with PageSpeed Insights reporting thresholds. At the time of data collection, several certified brand websites did not return field-level Core Web Vitals due to insufficient traffic volume, restricted data availability, or incomplete reporting by the API. As a result, only sites with valid CLS and LCP field data were retained for analysis. Thus, out of the 133 Butterfly Mark certified brand websites initially identified, only sites with valid PageSpeed Insights field data for the relevant Core Web Vitals were retained, resulting in a final analytic sample of 64 websites after listwise deletion for missing metrics. Given the relatively small final sample size, the author acknowledges that the statistical power of the regression model may be limited, particularly with multiple sector dummy variables. While no formal power analysis was conducted, robustness checks were performed with FCP as an additional speed metric, and sector-level comparisons were included to provide additional validation. All descriptive and inferential analyses reported in the Results section are based on this final sample unless otherwise specified. Therefore, mobile performance was collected via the Google PSI API (v5) using the strategy = mobile parameter. Custom Python 3.11.9 scripts (requests or JSON) handled API calls with a 1-s rate limit to conform to usage policies. All raw JSON responses were saved one-per-site to preserve traceability and enable replication. All PageSpeed Insights

API requests were executed within a single, continuous data-collection window in April 2025, ensuring temporal consistency across observations despite the rolling nature of field data.

Variables and measurement

The dependent variable is mobile experience quality, operationalized as a binary indicator (as FastUX) derived from PageSpeed's page-level field data: sites classified as FAST are coded 1, and those classified as AVERAGE or SLOW are coded 0. The core predictors are Google's Core Web Vitals from field data. CLS captures visual stability and is used in its fractional form (0–1), with values ≤ 0.10 interpreted as "good." LCP captures loading speed and is obtained in milliseconds; for modeling the researcher analyzes it in seconds. FCP also in milliseconds (analyzed in seconds), is included in a robustness specification to assess overlapping speed information with LCP. Interaction to Next Paint was not returned by the PageSpeed API for this sample and is therefore not analyzed; this fact is labelled by the researcher as a limitation. For the multidimensional radar visualization only, Lighthouse's Total Blocking Time (or TBT) was added as a lab proxy for responsiveness; TBT is clearly labeled as lab data and is not used for inference in the main field-data models.

Control variables include sector (treated as a categorical factor with Fashion & Accessories as the reference category) and available brand descriptors (region, founding year, and employee count, where recorded). All metrics are extracted from the PageSpeed Insights response's loading experience. CLS requires no unit conversion beyond confirming fractional scale; LCP and FCP were converted from milliseconds to seconds for interpretability and comparability in regression. Website URLs are normalized (scheme and trailing-slash harmonization) and merged to the brand list; observations with missing values for a given analysis are removed by listwise deletion. The dataset presents valid field coverage for CLS: 65 sites, LCP: 64 sites, FCP: 65 sites, and INP (Interaction to Next Paint (noted as INP): 0 sites. The predictive sample used for the main logistic regression (complete cases for FastUX, CLS, and LCP) was $N = 64$. FastUX is operationalized using Google PageSpeed Insights' field-based classification, where pages labeled "FAST" are coded as 1 and "AVERAGE" or "SLOW" as 0.

Metric selection and justification

Metric choice followed both theoretical relevance for mobile CX and data availability in PageSpeed Insights field responses. CLS was selected as the primary indicator of visual stability, a perceptual quality central to luxury UX. LCP was included as the primary speed metric used by Google to summarize real-user loading experience. FCP was added in a robustness specification to capture earlier render timing and to assess overlap with LCP. INP which shows responsiveness was not returned by the API for this sample and is therefore excluded from inference; for visualization only, TBT from Lighthouse lab audits is used as a clearly labelled proxy.

All raw PageSpeed Insights JSON files were batch-processed in Python 3.11.9 using pandas. The author extracted the reported percentile/p75 values for CLS, LCP, and FCP. CLS values were verified to be on a fractional scale; where a value exceeded 1.0, it was divided by 100 to normalize to 0.00–1.00. LCP and FCP were obtained in milliseconds and converted to seconds for modeling. Variance inflation factors were examined to assess multicollinearity; all VIF values were below commonly accepted thresholds, indicating that collinearity between LCP and FCP does not materially affect model estimation.

Statistical analysis and visualization techniques

The analysis is descriptive and predictive in nature; no causal relationships are inferred and proceeded in three stages. Firstly, descriptive benchmarks for the field metrics were produced, reporting means, medians, and 95% confidence intervals for CLS and LCP (with FCP included in a robustness summary). The researcher also reported the share of sites in Google's threshold bands (*good, needs improvement, poor*) and visualized distributions with histograms and box plots. Secondly, to assess sectoral differences, the Kruskal–Wallis test was applied to non-normally distributed metrics and conducted Holm-adjusted post-hoc pairwise comparisons. Thirdly, a binary logistic regression was estimated for the probability of a fast classification ($\text{FastUX} = 1$) as a function of CLS and LCP with sector controls; a robustness model added FCP to gauge overlap in speed information. The author reports coefficients, odds ratios, 95% confidence intervals, and model discrimination by using the area under ROC curve. From the fitted models were computed marginal effects and predicted probabilities, translating metric changes into percentage-point shifts useful as managerial thresholds. Interaction terms, such as CLS crossed by sector, were explored to benchmark mobile UX performance across luxury sectors.

Visualizations were created in Python using matplotlib and seaborn. To highlight relationships among metrics, a CLS–LCP convergence plot and a radar chart were used to show normalized performance profiles for top sites. The radar chart combines CLS, LCP, FCP and, for visualization only, TBT.

To mitigate estimation instability arising from low cell counts, sector categories with fewer than other sector, such as 'Interiors & Living' observations, were collapsed into a broader 'Other luxury categories' group for regression analyses.

Ethical considerations

All data were obtained from public sources (Positive Luxury listings and Google PageSpeed Insights API). The dataset contains no human subjects or personal data and involves no intervention; therefore, ethics committee approval was not required. API requests complied with Google's Terms of Service and were rate-limited to avoid undue load. Brand names and website URLs are publicly available identifiers; only site-level performance metrics were collected. Raw JSON files were stored securely and processed into aggregated analysis tables for reproducibility.

Results

The histogram (Fig. 1) shows a strongly right-skewed (positively skewed) distribution, with most websites clustered in the *good* category. Among the 65 sites with valid CLS, 48 (73.8%) meet Google's *good* threshold (CLS≤0.10), 7 (10.8%) require improvement (0.10–0.25), and 10 (15.4%) are *poor* (>0.25). This pattern suggests broad adoption of layout-stability practices, alongside a non-trivial tail of underperformance that may undermine perceived polish. A few outliers exhibit very high CLS values, which merits brand-level diagnostics such as late-injected content, deferred media without reserved space, or font reflow.

Sector-level comparisons are presented for descriptive benchmarking purposes and should be interpreted as exploratory, given the limited number of observations in some categories. Descriptively, Fashion & Accessories tends to cluster at very low CLS, Jewelry & Watches appears higher on average, and Interiors & Living lies in between, with Beauty & Fragrance and Travel & Leisure mostly within the *good* category (Fig. 2). However, formal testing finds no statistically significant sectoral differences in CLS (Kruskal–Wallis H=6.078, p=0.299; Holm-adjusted pairwise contrasts non-significant). Accordingly, sector patterns are reported as descriptive benchmarks rather than evidence of systematic sector differences in this sample. Thus, sector patterns should be treated as indicative, not robust once variability and sample sizes are considered.

To examine the joint behavior of stability and speed, Fig. 3 presents a CLS–LCP convergence matrix crossing CLS bands (≤0.10; 0.10–0.25; >0.25) with LCP bands (≤2.5 s; 2.5–4.0 s; >4.0 s). Nearly half of the sample sits in the good–good cell (29/64, 45.3%). A further 28.1% achieve good CLS but slower LCP (2.5–4.0 s or >4.0 s), indicating that loading speed is the more prevalent constraint. The mirror trade-off fast LCP with unstable CLS accounts for 14.1% of cases, and only 3.1% fall into the poor–poor cell. Overall, the matrix shows broad success on visual stability with meaningful room to improve loading speed; prioritizing LCP optimization would shift many sites from mixed quadrants into the good–good cell (top-left of the matrix).

The researcher modelled the probability that a site is classified as Fast on mobile (FastUX=1) using a binary logistic regression with CLS and LCP as predictors and sector dummies (Fashion & Accessories as the reference). Model discrimination is outstanding (AUC=0.919) on N=64 complete cases and results (Table 1) show that LCP is the dominant driver; each additional second reduces the odds of a Fast label by about 96% (β=−3.204, OR=0.041, p=0.003). Equivalently, cutting LCP by one second multiplies the odds by roughly 24×; even a 0.1-s improvement raises the odds by about 38%. To see how changes in LCP

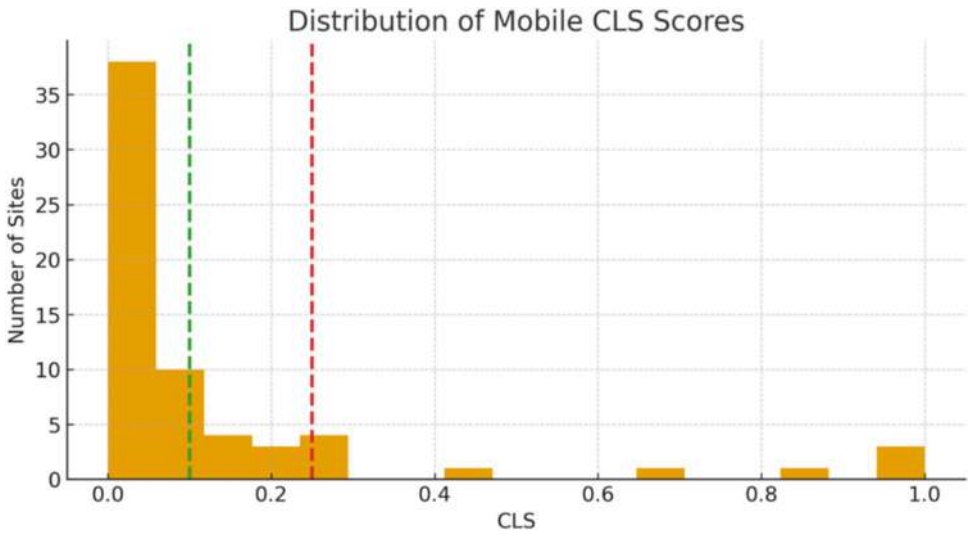

Fig. 1 Distribution of Mobile CLS Scores. Vertical dashed lines mark Google's thresholds at 0.10 (*good*) and 0.25 (*poor*)

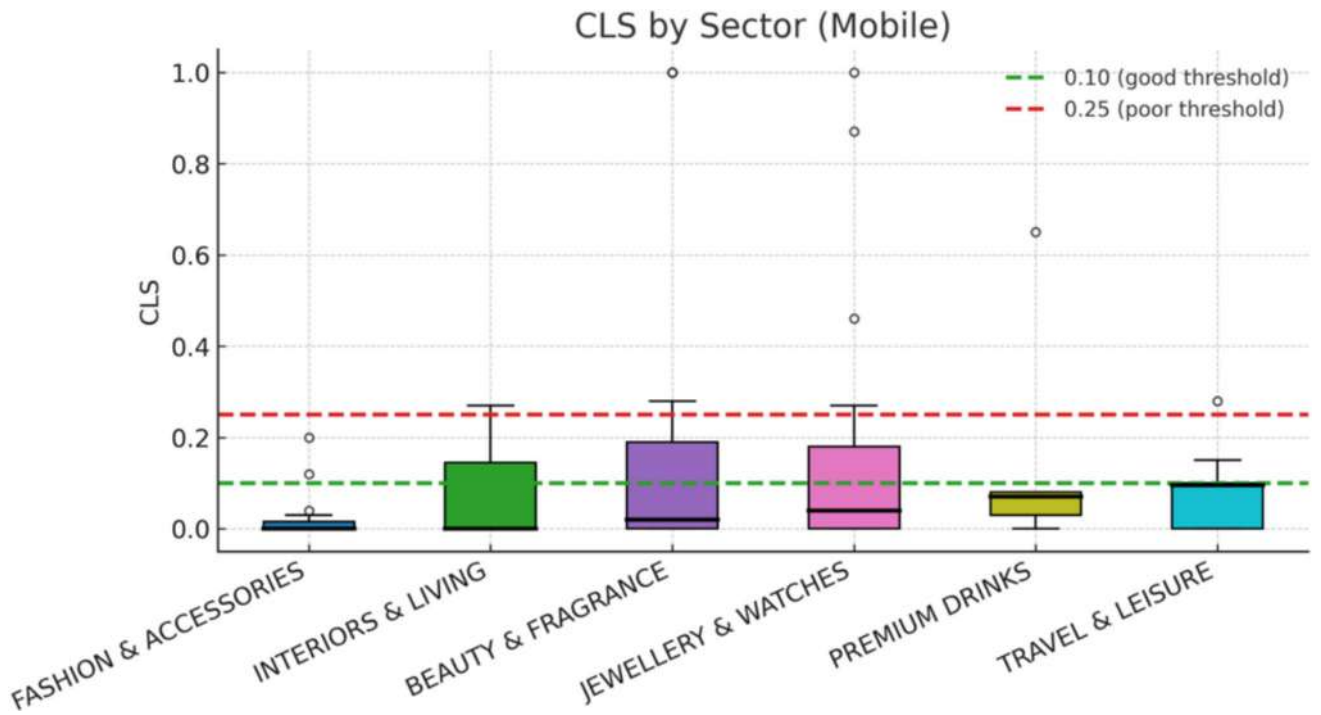

Fig. 2 CLS by sector. *Note*: Kruskal–Wallis H = 6.078, $p = 0.299$ (no significant sector differences)

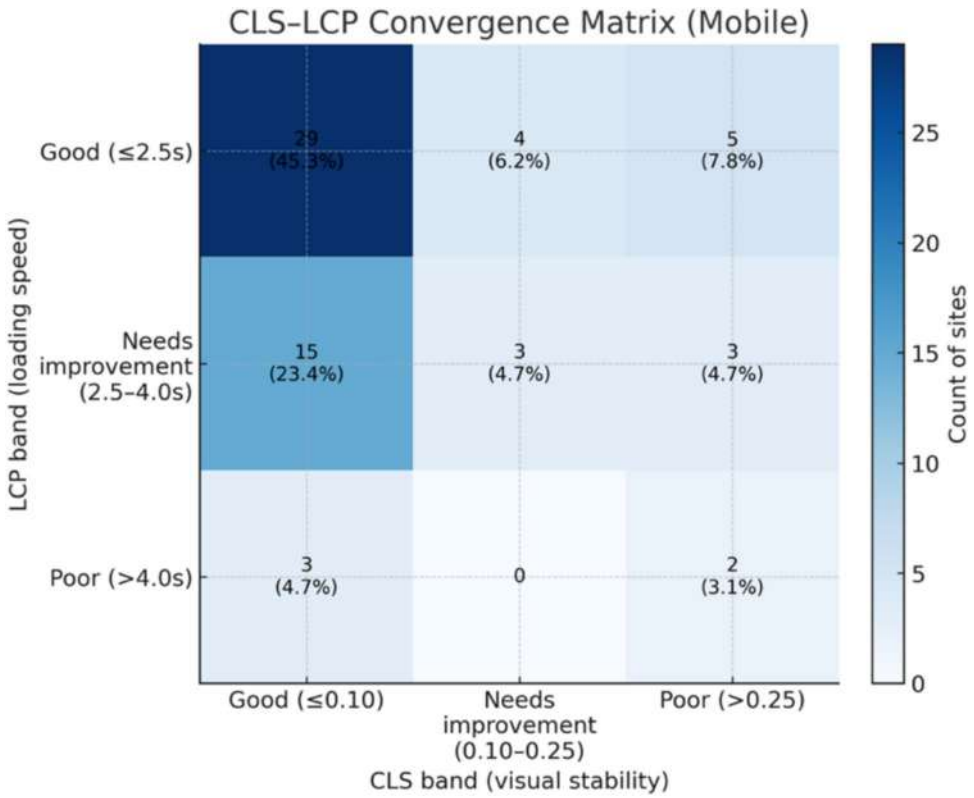

Fig. 3 CLS–LCP convergence matrix (quadrant markers indicate good/good, good/slow, etc.). *Note*: Cell entries show absolute counts, with percentages relative to the full sample (N = 64) reported in parentheses

translate into the likelihood of achieving a "Fast" mobile classification, the visualization presented in Appendix B strengthens interpretability by making the nonlinear impact of loading speed immediately visible.

By contrast, CLS is not a meaningful predictor here ($\beta = -0.557$, OR = 0.573, $p = 0.657$); within the observed range, a 0.10 increase changes the odds by only 5%, and the confidence interval is wide. After controlling for metrics,

Table 1 Predictors of Google "Fast" Mobile Classification

Variable	Coef (β)	Odds ratio (OR)	OR 95% CI low	OR 95% CI high	*p*-value
Intercept	7.981	2925.050	20.173	424,120.674	0.002
CLS	−0.557	0.573	0.049	6.686	0.657
LCP	−3.204	0.041	0.005	0.345	0.003
Beauty & Fragrance (vs Fashion & Accessories)	−2.430	0.088	0.009	0.864	0.037
Interiors & Living (vs Fashion & Accessories)	−13.495	0.000	0.000	∞	0.944
Jewellery & Watches (vs Fashion & Accessories)	−1.366	0.255	0.035	1.870	0.179
Premium Drinks (vs Fashion & Accessories)	−1.680	0.186	0.012	2.867	0.228
Travel & Leisure (vs Fashion & Accessories)	−2.605	0.074	0.005	1.193	0.066

Dependent variable FastUX (*1* = *Fast*). Reference sector = Fashion & Accessories. N = 64; AUC = 0.919

Beauty & Fragrance sites have significantly lower odds of being Fast than Fashion & Accessories (β = −2.430, OR = 0.088, p = 0.037). Travel & Leisure shows a borderline penalty (p = 0.066). Jewelry & Watches and Premium Drinks are not statistically different. Interiors & Living shows an extreme negative coefficient with an unbounded confidence interval. Due to quasi-separation caused by sparse observations in certain sectors, coefficient estimates for individual sector dummies are reported descriptively and are not interpreted inferentially. Sector-level coefficients, particularly for categories with low observation counts such as Interiors & Living, should be interpreted descriptively rather than inferentially due to estimation instability.

To translate coefficients into practical guidance, the researcher computed marginal effects holding each sector's median LCP constant. Holding other variables constant, increases in LCP are associated with a monotonic decline in the probability that a site is classified as delivering a "Fast" mobile experience. The magnitude of this decline accelerates as LCP moves beyond commonly used performance benchmarks, underscoring the practical importance of loading speed for mobile experience outcomes. Marginal effects are reported numerically to maintain interpretive caution given the limited sample size and the exploratory nature of the field data.

Therefore, improving CLS from 0.18 to 0.08 yields small gains in the predicted probability of a Fast classification: + 1.4 pp in Jewelry & Watches (0.55 to 0.56), + 1.1 pp in Premium Drinks (0.28–0.29), + 1.0 pp in Fashion & Accessories (0.75–0.76), and + 0.9 pp in Beauty & Fragrance (0.19–0.20). For Interiors & Living and Travel & Leisure, effects are approximately zero at current median LCP levels. Managerially, this points to a clear priority: reduce LCP through asset optimization, critical-path CSS/JS, server/TTFB improvements, and caching/CDN, while treating CLS hardening as hygiene that protects perceived polish.

As a robustness check, adding FCP as an additional speed indicator raises discrimination to AUC = 0.931. In this specification, FCP absorbs much of the speed signal (β = −5.214, OR = 0.005, p = 0.055), and LCP remains negative but is no longer significant (β = −1.810, p = 0.131). This pattern is consistent with overlapping information between the two-timing metrics and the modest sample size; the substantive conclusion is unchanged: speed drives Fast. The robustness specification including FCP highlights the conceptual overlap among speed-related performance metrics. That FCP absorbs some of LCP's predictive power is theoretically consistent with both metrics capturing different phases of the same underlying construct: perceived loading speed. Rather than contradicting the main findings, this convergence reinforces the conclusion that speed, irrespective of the specific metric, is the dominant driver of Fast classification. By contrast, CLS appears closer to a baseline hygiene factor, critical for preserving experiential coherence but offering limited incremental explanatory power once speed is accounted for.

For completeness, a radar chart illustrating normalized performance profiles for selected sites is provided in Appendix A. It shows top five sites with the lowest CLS, combining CLS, LCP, FCP and, for visual context only, TBT from Lighthouse. Axes are min–max normalized so values closer to the center indicate better performance. FAST sites remain near the center across axes, while several AVERAGE sites show low CLS but higher LCP/FCP (and sometimes higher TBT), revealing loading and main-thread bottlenecks despite stable layouts. *Note:* Fig. 4 is presented for descriptive and illustrative purposes only, combining field-based and lab-based metrics to provide a broad overview of mobile performance dimensions; no statistical inference or direct comparison across measurement contexts is implied. The robustness model including FCP is intended to assess sensitivity to alternative speed metrics and should be interpreted as a supplementary analysis.

The figure plots the top five sites with the lowest CLS. Each axis is min–max normalized within the sample to 0–1, so values closer to the center indicate more favorable performance across metrics. Sites labelled FAST tend to remain near the center on all axes, indicating balanced strength in stability and speed. Several AVERAGE sites exhibit low CLS yet higher LCP and/or FCP (and sometimes higher TBT), revealing bottlenecks in loading and main thread blocking despite stable layouts. This pattern underscores the need to evaluate Web Vitals holistically: strength in visual stability does not compensate for weaknesses in speed or responsiveness.

Discussion

This study advances marketing theory by demonstrating that execution-level digital performance metrics operate as asymmetric signals within sustainability-certified luxury contexts. While research conceptualizes sustainability certification as a quality signal (Kauppi et al. 2025), it has not examined how observable technical execution interacts with elevated expectations in mobile-first environments. The findings show that loading speed functions as a dominant execution signal (result aligned with other outcomes in the literature such as Kim et al. (2009), whereas visual stability operates as a hygiene condition once baseline standards are met. This also confirms the Deloitte's (2018) insight which states for 0.1 s improvement in mobile speed which increases conversion rates and engagement. Therefore, this asymmetric structure extends signaling theory by specifying that not all execution cues are equally diagnostic under high-expectation brand positioning. Certification amplifies expectations of operational competence, rendering execution-level deviations more consequential in evaluative judgments. This pattern aligns with work on service brand equity (Berry 2000) and luxury experience formation (Klaus 2021), which emphasize that violations of expected fluency are disproportionately penalized in high-value brand contexts. Loading delays interrupt perceptual continuity and cognitive ease, reinforcing the salience of speed as an execution-level signal.

Thus, the paper presents the advance analytics theory by distinguishing between dominant and hygiene performance dimensions within platform-mediated evaluation environments. Loading speed emerges as a dominant metric that strongly shapes classification outcomes, whereas visual stability functions as a hygiene condition whose primary role is to prevent negative disconfirmation once baseline thresholds are met. From a marketing analytics perspective, this study demonstrates how platform-generated technical metrics can be reverse-engineered into interpretable probabilistic experience signals. Rather than treating Google's 'Fast' classification as a black-box output, the analysis models its underlying execution drivers and translates metric changes into probability shifts, thereby transforming engineering indicators into decision-relevant analytics insights. Thus, this distinction contributes to marketing analytics research by showing that not all UX metrics carry equal explanatory or managerial value, and that performance analytics should account for asymmetric metric roles. This study connects two strands that are rarely examined together in luxury research, namely, performance based UX metrics and sustainability signaling. Using field data from Butterfly Mark–certified brands, it shows that the credibility of ethical claims in digital contexts is intertwined with the technical quality of mobile experiences. In short, the sustainability story is only as persuasive as the interface that carries it.

It is important to note that the "Fast" classification used as the dependent outcome in this study is a platform-defined label assigned by Google, reflecting how mobile performance is evaluated and operationalized within a dominant digital ecosystem. As such, the findings are directly relevant for managers seeking to optimize performance within platform-mediated environments where external classification systems shape visibility, ranking, and user experience judgments.

The logistic model achieves outstanding discrimination and indicates that LCP dominates the probability of being classified as Fast, whereas CLS adds little incremental predictive power at the levels observed in this sample. The asymmetric roles of LCP and CLS can be interpreted through established principles in human–computer interaction and luxury customer-experience research. Loading speed directly shapes users' earliest perceptual and cognitive evaluations during the critical initial moments of mobile interaction, when judgments of fluency, responsiveness, and competence are formed. Delays in content rendering interrupt attentional flow and increase perceived effort, making speed a highly salient execution signal in mobile-first contexts. By contrast, visual stability appears to function as a hygiene factor: disruptive layout shifts are noticeable and damaging when present, but once a minimum threshold of stability is achieved, further improvements yield diminishing experiential returns. In luxury contexts, where baseline expectations of polish are high, stability is therefore necessary to avoid negative disconfirmation but insufficient to differentiate experience quality or platform-level performance classifications. This interpretation aligns with the observed distribution of CLS in the sample, where most certified brands already meet "good" stability thresholds, leaving loading speed as the primary remaining source of variation in mobile experience outcomes. This finding complements HCI theory on interface fluency and trust:

moment-to-moment load performance shapes users' cognitive ease and, by extension, perceptions of quality and credibility.

At the same time, visual stability is not irrelevant. The CLS distribution is encouraging, nearly three-quarters of sites meet the ≤0.10 "good" threshold, suggesting that layout hygiene is largely institutionalized among certified brands. The convergence matrix clarifies where progress is still needed; almost half of sites are good on both stability and speed, yet over a quarter combine good stability with slow loading, revealing LCP as the more common bottleneck. The mirror trade-off, fast but unstable, is smaller but non-trivial, reinforcing the need to manage both dimensions.

The lack of statistically significant sector differences in CLS suggests that, within sustainability-certified luxury brands, visual stability may be closer to a standardized "hygiene" requirement than a sector-specific differentiator. One explanation is that Core Web Vitals benchmark logic and mobile UX conventions impose similar minimum expectations across categories, so brands converge on layout-stability practices regardless of sector. A second explanation is shared technological infrastructure: luxury sites often rely on similar stacks (CMS platforms, tag managers, consent tools, third-party scripts), which can homogenize stability outcomes across verticals even when creative content differs. Finally, sector-level variation may exist but remain difficult to detect in field-based samples with uneven cell sizes; in that setting, the absence of statistical significance is consistent with effects that are smaller than the dominant, cross-sector role of loading performance. Overall, the results imply that sector comparisons are most informative as benchmarks, while the primary actionable leverage point remains reducing loading delays. Sector patterns should be interpreted cautiously. Descriptively, some verticals populate the "good–good" cell more often, but formal tests show no significant sector differences in CLS ($p = 0.299$). In the regression, only Beauty & Fragrance retains a residual penalty after controlling for CLS and LCP, which likely reflects unmeasured content or infrastructure factors, such as asset strategies, personalization scripts, and hosting architecture.

The residual performance penalty observed for Beauty & Fragrance sites after controlling for loading speed and visual stability likely reflects category-specific execution choices. Beauty and fragrance brands tend to rely heavily on rich visual assets, high-resolution imagery, video backgrounds, personalization layers, and third-party integrations (such as recommendation engines, analytics, consent tools), all of which can increase critical-path load and main-thread activity. In mobile contexts, these design and marketing features may be strategically justified to convey sensorial richness and brand storytelling, yet they introduce performance trade-offs that disproportionately affect loading speed. From a signaling perspective, this suggests that Beauty & Fragrance brands may face a sharper tension between experiential richness and executional efficiency, making speed optimization particularly consequential in this category. Importantly, this interpretation is descriptive and exploratory; it highlights where performance governance efforts may be most impactful.

Managerially, the implication is clear, by highlighting to prioritize LCP improvement, optimize image and font pipelines, trim or defer non-critical CSS/JS on the critical path, reduce TTFB via server and CDN tuning, and cache aggressively. CLS hardening remains essential hygiene (reserved space for media, predictable font loading, controlled late-injected content) because it protects perceived polish and trust, but it does not materially shift the *Fast* classification once speed is addressed. The marginal-effects analysis underscores the asymmetry, tightening CLS from 0.18 to 0.08 yields small probability gains, whereas shaving even fractions of a second from LCP can move sites across the *fast* threshold.

By situating these analytics insights within sustainability-certified luxury contexts, the study also extends research on ethical signaling by showing how analytics-based execution signals interact with expectation formation. Sustainability certification amplifies expectations of operational quality, increasing the diagnostic value of execution-level analytics signals such as mobile performance. From an analytics standpoint, this highlights how performance metrics gain contextual meaning depending on brand positioning and certification status, reinforcing the need for context-aware analytics frameworks.

Methodologically, the paper demonstrates how Core Web Vitals can be operationalized as marketing-analytics signals for LCX dashboards. Convergence matrices reveal where portfolios sit relative to benchmarks; regression and marginal effects translate technical changes into managerial probabilities. These tools are replicable for ongoing performance governance and for auditing alignment between sustainability narratives and mobile UX delivery.

Finally, the results foreground an important boundary condition for sustainability communication in luxury. Certification may earn initial trust, but ongoing trust is mediated by experience quality in the high-expectation, mobile-first contexts where brand meaning is negotiated. Investing in fast, stable interfaces is more than a technical exercise; it is a strategic requirement for preserving the authenticity and premium positioning that sustainability is intended to support.

The findings translate into clear and prioritized guidance for luxury brand managers responsible for digital execution. Firstly, loading speed should be treated as the primary performance lever. Actions with the highest expected impact include

optimizing and resizing hero images and video thumbnails, preloading and sub-setting brand fonts, reducing render-blocking CSS and JavaScript on the critical path, improving server response time through CDN configuration, and caching non-critical assets. Even small reductions in LCP can materially increase the likelihood of delivering a "Fast" mobile experience. Secondly, visual stability should be managed as a non-negotiable hygiene requirement. Brands should ensure reserved space for images and embedded media, avoid late-injected content above the fold, implement predictable font-loading strategies, and audit third-party scripts that introduce layout shifts. While these measures may not substantially increase Fast classification probabilities on their own, they protect perceived polish, trust, and experiential coherence. Thirdly, resource prioritization matters. When budgets or development capacity are constrained, the evidence suggests that investments in speed optimization yield higher returns than marginal improvements in already-acceptable stability. For categories such as Beauty & Fragrance, where rich media and personalization are central to storytelling, performance governance should focus on balancing experiential richness with disciplined asset and script management to prevent speed degradation. Together, these recommendations enable luxury brands to align sustainability signaling with credible, high-quality mobile execution.

In practice, luxury brands often face trade-offs between competing digital investments, particularly when development resources, budgets, or release cycles are constrained. The findings suggest that not all UX improvements deliver equal returns. When baseline visual stability is already acceptable, further refinements in CLS may protect experiential polish but generate limited incremental gains in mobile performance classification. By contrast, investments that reduce loading delays, such as optimizing media assets, streamlining scripts, or improving server response times, offer disproportionately higher returns by materially increasing the probability of delivering a fast mobile experience. For resource-constrained teams, this implies a sequencing logic: first secure layout stability to avoid negative disconfirmation, then allocate incremental resources to speed optimization, which functions as the primary driver of performance outcomes. Framing mobile UX optimization in this way enables managers to make defensible, data-informed trade-offs rather than pursuing uniformly "perfect" experiences that may not be economically feasible.

The findings should also be interpreted considering the specific context examined. The analysis focuses on sustainability-certified luxury brands, which operate under unusually high expectations of quality, polish, and execution consistency. In such contexts, baseline visual stability may already be institutionalized, rendering CLS closer to a hygiene condition. In mass-market or low-involvement categories, where expectations and tolerance for friction differ, the relative roles of speed and stability may not follow the same asymmetric pattern observed here. Accordingly, the dominance of loading speed over visual stability should not be assumed to generalize beyond luxury or similarly high-expectation brand environments.

This study contributes to business analytics research by demonstrating how platform-defined technical classifications can be reverse-engineered into interpretable, probability-based performance insights. Rather than treating Google's "Fast" label as a black-box outcome, the analysis shows how underlying execution metrics can be modeled to quantify the marginal impact of technical improvements on experience classifications. This approach advances analytics research by illustrating how operational data generated by digital platforms can be transformed into actionable decision metrics, bridging the gap between technical measurement systems and managerial analytics.

From a business analytics practice perspective, the findings provide a clear framework for prioritizing digital optimization efforts. The results show that not all UX metrics contribute equally to platform-level outcomes: loading speed functions as a high-leverage variable with large marginal effects, while visual stability operates primarily as a risk-mitigation metric once baseline standards are met. For analytics teams, this implies that dashboards, KPIs, and optimization roadmaps should differentiate between dominant and hygiene metrics.

Based on these insights, several analytics-oriented recommendations follow. Firstly, organizations should integrate Core Web Vitals into customer experience analytics as probabilistic performance indicators rather than binary pass–fail checks. Secondly, analytics governance should focus on monitoring and optimizing loading speed as the primary driver of platform-defined experience outcomes, using marginal-effects analyses to guide resource allocation. Thirdly, stability metrics should be treated as hygiene thresholds that protect experience quality but offer limited incremental returns once minimum standards are achieved. Together, these recommendations provide a structured analytics approach for aligning sustainability signaling, mobile execution, and performance governance in high-expectation digital environments.

Conclusions

This study makes two primary theoretical contributions. Firstly, to marketing analytics, it demonstrates how platform-level technical metrics, specifically Google's Core Web Vitals, can be operationalized as execution-quality signals within customer experience analytics. The analysis reframes them as probabilistic predictors of platform-mediated experience classifications, translating engineering metrics into interpretable managerial thresholds. This extends marketing analytics research by showing how real-user performance data can be integrated into experience governance

and diagnostic dashboards in high-expectation categories. Secondly, to HCI, the findings provide field-based evidence for an asymmetric role of mobile UX dimensions in luxury contexts. Loading speed emerges as a dominant signal shaping early experience judgment, while visual stability operates as a hygiene condition that prevents negative disconfirmation but offers limited differentiation once baseline expectations are met. By situating this distinction within sustainability-certified luxury environments, the study advances HCI research on how performance signals interact with contextual expectations and symbolic brand meaning under real-world mobile conditions.

Managerial implications

This study offers both theoretical and managerial implications by linking sustainability signaling, luxury customer experience, and mobile performance analytics within a unified execution-level framework. The findings yield several actionable implications for luxury brand managers and digital leaders. Firstly, mobile loading speed should be treated as the primary performance lever in mobile optimization efforts. Even small improvements in loading time materially increase the likelihood that a site is classified as delivering a fast experience, suggesting high returns from investments in image optimization, critical-path CSS and JavaScript reduction, server response time improvements, and content delivery networks.

Secondly, visual stability should be managed as a baseline hygiene factor and not a differentiator. While most certified brands already meet recommended CLS thresholds, lapses in layout stability can quickly erode perceptions of polish and trust. Managers should therefore enforce strict layout-discipline practices, including reserving space for dynamic content, controlling late content injection, and stabilizing font loading.

Thirdly, sustainability-certified luxury brands should recognize that ethical signaling elevates expectations of execution quality across digital touchpoints. Certification alone does not insulate brands from negative experience judgments if mobile performance falls short. Accordingly, mobile UX metrics should be integrated into brand governance and sustainability oversight processes, ensuring that technical execution aligns with the values communicated through certification.

Finally, the convergence-matrix and marginal-effects approach demonstrated in this study provides a practical diagnostic framework that managers can use to prioritize optimization efforts, benchmark portfolios, and translate technical metrics into clear probability-based performance targets.

Managerial implications are direct. Firstly, treat LCP reduction as the priority lever by optimizing images and fonts, minimize critical-path CSS/JS, reduce TTFB through server/CDN tuning, and use caching and lazy-loading for non-critical assets. Secondly, maintain CLS hardening (reserved space, predictable font loading, disciplined late-injection) as hygiene that protects perceived polish and trust, even if it does not, on its own, shift the Fast classification. Thirdly, use convergence matrices and marginal-effects dashboards to track portfolios and translate technical changes into clear probability gains for decision-making.

In sustainability-certified luxury contexts, mobile performance carries symbolic weight: interface delays or instability can undermine the perceived authenticity of ethical positioning by signaling executional inconsistency.

Limitations

In terms of limits, the author is aware that cohort is restricted to Butterfly Mark, certified brands, which may limit generalizability. It is important to note that the sample size for this study (N = 64) remains a limitation, particularly with respect to the inclusion of several sector dummies in the logistic regression model. Although the findings provide useful insights, they should be interpreted with caution, and future research should aim for larger, more representative samples to validate these results. Moreover, sector-level coefficients should be interpreted descriptively, not inferentially, as the analysis is not powered to estimate precise effects for low-frequency categories. The study relies on Core Web Vitals field data available in the PageSpeed API; INP was not returned for this sample and could not be modeled, and FCP was used only as a robustness check. Core Web Vitals are commonly interpreted using benchmark thresholds such as "good" vs. "needs improvement". In this study, thresholds are used primarily to support interpretability and managerial translation and then to claim universal cutoffs. Alternative threshold choices such as stricter targets for high-end luxury experiences, or more lenient cutoffs reflecting heterogeneous mobile conditions would change the proportion of sites classified as meeting benchmarks, but they would not change the conceptual interpretation of the models: loading performance metrics capture the dominant source of variation in "Fast" classification in this dataset, whereas visual stability appears closer to a baseline hygiene condition among certified luxury brands. Accordingly, threshold-based statements should be interpreted as decision aids more than immutable standards. The design is observational, so causal claims are not warranted; coefficients and AUC are in-sample and may be optimistic. Given the limited number of observations in some sectors, sector effects are included primarily to control for broad category differences. Additionally, within this sample of sustainability-certified luxury brands, technical mobile performance varies, indicating that certification alone does not imply uniformly high execution quality. Finally, the researcher does not model back-end architecture or front-end framework choices that undoubtedly shape performance. Nevertheless, the study's strengths, such as, ecologically valid field data,

objective industry-standard metrics, a transparent and reproducible pipeline, triangulation across descriptive benchmarks, non-parametric tests, predictive modeling, and robustness checks, which support credible inferences and deliver actionable guidance for luxury managers while providing a replicable analytics template for future research.

Future research

Several targeted research directions emerge from this study. Firstly, comparative designs that include both sustainability-certified and non-certified luxury brands would allow researchers to test whether certification is associated with systematically different levels of mobile UX performance or whether the observed variation reflects broader industry practices. Secondly, future work should incorporate responsiveness metrics such as INP as field data coverage improves, enabling a more complete assessment of how speed, stability, and interactivity jointly shape luxury mobile experiences. Thirdly, linking Core Web Vitals to downstream behavioral and commercial outcomes, such as bounce rates, conversion probability, dwell time, or repeat visits, would clarify how technical performance translates into economic value in luxury contexts. Finally, mixed-method approaches combining field metrics with qualitative interviews of UX and digital teams could surface organizational constraints, design trade-offs, and governance practices that explain why some sustainability-certified brands achieve superior mobile execution while others do not.

More broadly, the findings underscore that in contemporary luxury markets, digital marketing strategy cannot be separated from technical execution. Mobile interfaces are not neutral delivery channels but active sites where brand meaning, trust, and credibility are negotiated in real time. Sustainability certifications and ethical narratives may attract attention and shape expectations, but their persuasive power ultimately depends on whether the mobile experience performs in ways consistent with luxury's promise of effortlessness and refinement. From a strategic perspective, this implies that luxury brands must integrate mobile performance governance into their core brand management and sustainability strategies and not treating it as a downstream technical concern. Investments in speed, stability, and performance monitoring should be understood as brand-protective actions that sustain premium positioning in mobile-first environments. As digital touchpoints increasingly dominate luxury consumption journeys, technical excellence becomes a central component of how luxury value is created, communicated, and maintained.

Appendix A. The radar chart

See Fig. 4.

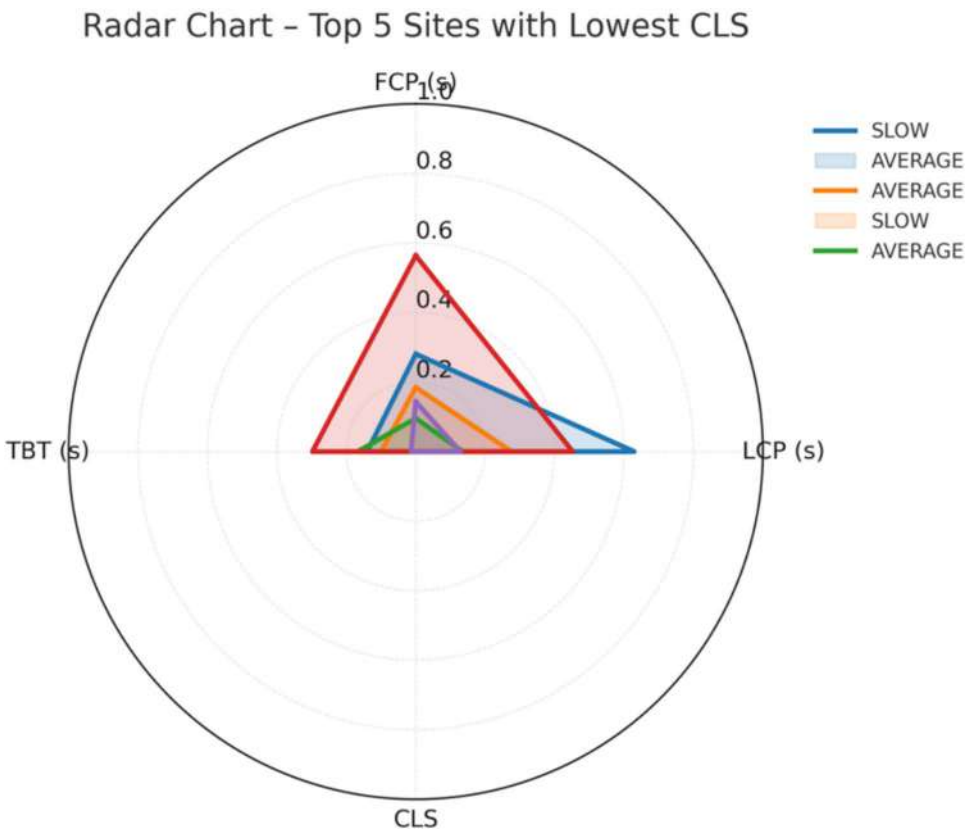

Fig. 4 Radar chart for top sites, combining field metrics (CLS, LCP, FCP) and TBT as a lab proxy. *Note*: CLS, LCP, and FCP are field-based metrics, while TBT is a lab-based metric. Metrics are displayed jointly for illustrative context only and are not directly comparable. Moreover, TBT is included for illustrative purposes only and is not used in statistical inference

Appendix B. Predicted probabilities and marginal effects

This appendix reports the predicted probabilities underlying Fig. 5 and documents how these values were derived from the estimated logistic regression model. The results are provided to support transparency and interpretability and are not intended for out-of-sample prediction (Tables 2 and 3).

Calculation details

Predicted probabilities are computed using the estimated logistic regression model:

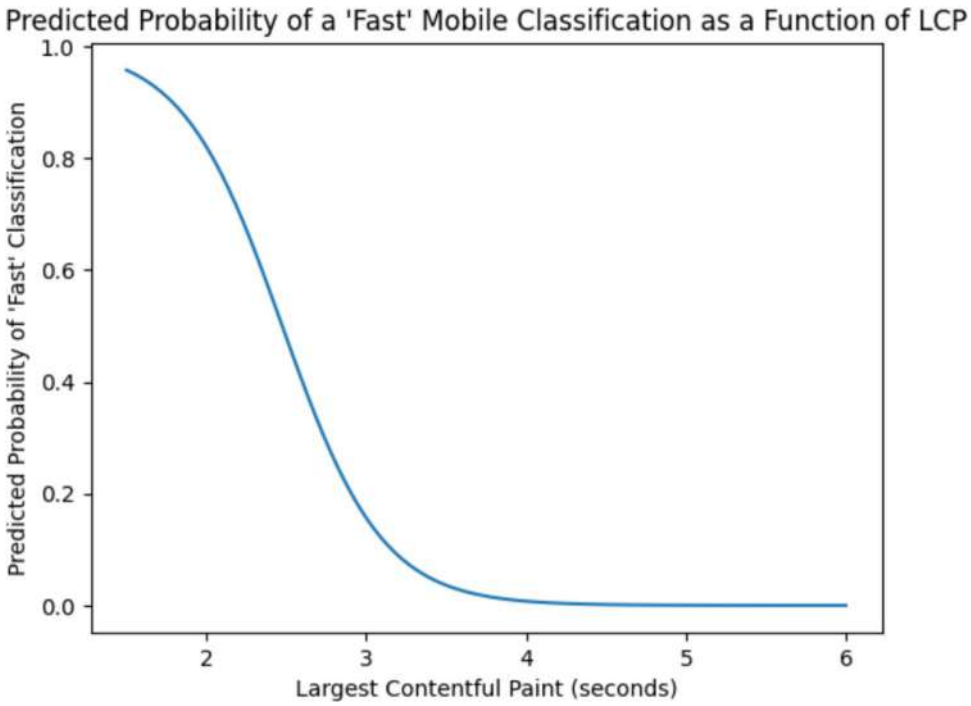

Fig. 5 Predicted Probability of a "Fast" Mobile Classification as a Function of Loading Speed LCP. *Note:* Predicted probabilities are derived from the main logistic regression model reported in Table 1. Largest Contentful Paint varies across the range shown, while Cumulative Layout Shift is held constant at 0.10 (the "good" threshold). All other covariates are held at their reference levels

Table 2 Predicted probability of a "Fast" mobile classification by LCP (CLS fixed at 0.10)

LCP (seconds)	CLS (fixed)	Predicted probability of fast
1.50	0.10	0.9577
1.75	0.10	0.9104
2.00	0.10	0.8201
2.25	0.10	0.6718
2.50	0.10	0.4788
2.75	0.10	0.2920
3.00	0.10	0.1562
3.25	0.10	0.0767
3.50	0.10	0.0360
3.75	0.10	0.0165
4.00	0.10	0.0075
4.25	0.10	0.0034
4.50	0.10	0.0015
4.75	0.10	0.0007
5.00	0.10	0.0003
5.25	0.10	0.0001
5.50	0.10	0.0001
5.75	0.10	0.0000
6.00	0.10	0.0000

The predicted probabilities are post-estimation quantities derived directly from the coefficients reported in Table 1 and are included solely to aid interpretation

Table 3 Logistic regression coefficients used for predicted probabilities

Variable	Coeficient
Intercept	7.981
LCP	−3.204
CLS	−0.557

$$\text{logit}\left(\text{P}\left(\text{Fast}=1\right)\right) = \beta 0 + \beta_{\text{LCP}}\text{LCP} + \beta_{\text{CLS}}\text{CLS}$$

$$P\left(fast\right) = \frac{1}{1+e^{-logit}}$$

Data availability Available data on request.

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Getting users out of the loop: Key factors to surpass the messy middle point

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ABSTRACT

In a world dominated by technology, the consumer journey should not be a priority only for those who have the skills to understand the search engine optimisation factors or online stores' technological performances. It must be a priority for entrepreneurs, retailers, and marketing specialists, too. The customers might be won or lost depending on their experience, and the space between their choices is named the messy middle point. Considering this issue, the authors highlight the key factors necessary to exit the loop in the light of four dimensions, i) technology, ii) experience, iii) accessibility, and iv) marketing, aiming to identify and promote specific actions to create and maintain a non-interrupted experience. Based on data from 210 certified trusted online stores, the results generated 13 specific actions incorporated in the conceptualized TEAM model. Appealingly, unexpected outcomes were identified, highlighting the interconnected activities that online stores perform nowadays.

1. Introduction

In the last two decades, e-commerce transactions have skyrocketed around the world due to the development of Internet Technology, and research in this area is a *sine qua non* for academics and professionals. In this context, some key factors must be addressed. Generation Z lives in an inseparable world between online and offline, spending eight hours a day online. With a growing income set to reach a combined $33 trillion over the next decade, the earning potential of Gen Z by 2031 (THG, 2022) cannot be ignored when it comes to the future of electronic commerce. In 2020, over two billion people purchased goods and services online, and e-retail sales exceeded 4.2 trillion U.S. dollars worldwide. Forecast e-commerce share of total global retail sales by 2025 is estimated at 24.5% (STATISTA, 2022). Lately, the development of 4th generation mobile telecommunication technologies has stimulated the expansion of mobile commerce (m-commerce) worldwide, as an extension of e-commerce in which business activities took place in a wireless environment via mobile devices (Chimborazo et al., 2021; Puiu et al., 2022; Sharma and Madan, 2022; Vărzaru and Bocean, 2021; Vinerean et al., 2022). According to (Kleisiari et al., 2021; Sardjono et al., 2021; Schaefer and Figliozzi, 2021; Vărzaru and Bocean, 2021), the COVID-19 pandemic played a significant role in the growth of e-commerce websites; consumer habits shifted from physical stores to online, as the global confinement led to the closure of many businesses, increasing the number and the volume of activity of e-commerce websites.

Under such circumstances, consumers expect a successful journey (Rodrigues and Coelho, 2021), and plenty of factors influence it. A review regarding the consumer decision journey (Santos and Gonçalves, 2021) systemizes both classic and flexible decision models. As highlighted by the literature, a special interest was given to the consumer decision journey models, highly influenced by digital touchpoints expected to function excellently and not interrupt the purchase flow.

The existing factors for a purchasing-driven journey are countless in a world full of technology. With the possibility of conducting commercial transactions using wireless devices (Kumbhakar, 2021) and crossing borders through its features and facilities, e-commerce has accelerated the integration of the global economy (Chen et al., 2021; Murthy et al., 2021) with high-performant digital assets. For electronic commerce, the website is one of these assets and it has been named *the critical digital touchpoint* for the consumers' decision-making process. In a context where the purchase journey is defined by the messy middle point, it becomes increasingly complicated to manage users who can endlessly wander through unsatisfactory touchpoints along the journey until the moment they buy under the conditions that are expected.

This gap determined the authors to analyse the website performance considering digital touchpoints, as part of the messy middle point decisive elements. In this regard, the critical research question was "***How might a retailer get users out of the loop?"***. The loop is the

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representation of the non-linear journey users can have between the choice of searching for a product (the trigger) and the choice of purchasing it. Time spent for the evaluation (pre-purchase phase) can last until the customers are either won or lost, depending on the touchpoints they have met and whether they found what they were looking for. Through this paper, the authors draw attention to the online store's website, aiming to find the key factors that determine users to get out of the loop and move forward from evaluation to purchase stage, surpassing the messy middle point (Fig. 1). By using 15 Search Engine Optimisation factors, the authors intended to discover which of them contribute to accessibility, experience, marketing, and technology, as relevant touchpoints for a high-quality user experience during the consumer journey.

For this purpose, the authors have set objectives to (O_1) analyse the level of the online store's accessibility, (O_2) understand how well the online store guides the users between pages, and (O_3) determine the influence of the images' quality on the marketing dimension performance. The research was based on a case study, which allows investigating some complex, contemporary situations from real world (Patnaik and Pandey, 2019; Rashid et al., 2019).

The findings highlight the importance of researching new perspectives and opportunities for the ever-changing field of electronic commerce and contribute to the research knowledge field with an universally available framework for researchers from all over the scientific world. It is grounded in proposing 13 actions to improve the digital touchpoints related to the websites of retailers. Also, the study revealed that incoming links, headings, printability, meta tags, and page titles contribute to the expected user experience and to surpassing the messy middle point from the pre-purchase (evaluation) to the purchase stage.

After the introduction of the context, the paper presents the theoretical background, highly needed for the solid foundation of the study performed. It describes the current knowledge stage about touchpoints and consumer decision making, the messy middle point of the consumer journey, and the search engine optimisation and the messy middle point connection.

The next section presents the research design and hypothesis development, followed by analysis methods. The results are discussed according to the proposed combined model and the arguments for theoretical lens contribution, compared with previous research. The final part is allocated to conclusions section that highlight the managerial and theoretical implications, the limitations of the study, and future research.

2. Theoretical background

To understand the approach developed by the authors, three subsections of the theoretical background were designed. First, the literature on touchpoints and consumer decision-making was revised, followed by explaining the concept of messy middle point within the consumer journey. Finally, knowledge was linked to search engine optimisation.

2.1. Touchpoints and consumer decision-making

Lately, the importance of touchpoints has grown considerably, and not mentioning them in current studies would be a significant mistake (Chylinski and Heller, 2022; Hollebeek et al., 2022). The concept was introduced among the terms for modern contemporary communication from the new world (Seebacher, 2022) with applicability in many areas (Foya and Garikayi, 2022; Gao et al., 2021; Hassan et al., 2022) or at different stages of the consumer journey (Pham, 2022). A recent study demonstrates this fact through the use of touchpoints for funnel analysis using the knowledge space theory (Lin et al., 2022), and the examples can continue by easily searching for this keyword in prestigious databases.

A touchpoint has been defined as the place or the situation through which a consumer interacts with a business (Oxford Learner's Dictionaries, 2022) with a significant influence on the consumer journey (Koch and Hartmann, 2022). On this basis, several types of touchpoints (brand owned, outside the control touchpoints, third-party, etc.) and three decision-making process stages were unveiled (pre-purchase, purchase, post-purchase) (Towers and Towers, 2022). Because not all touchpoints are under the control of organisations, they must control well at least the ones they own. Many studies focused on search engine optimisation and websites performance as digital touchpoints (Bolton et al., 2022; Dominique-Ferreira et al., 2021; Koch and Hartmann, 2022; Maechler et al., 2016), that can be employed to control and optimise moments in the consumer decision-making process. The scientists highlighted the importance of website touchpoints and the influence of a positive perceived quality during the customer experience, especially for electronic commerce, an area where users expect an excellent experience (Darboe, 2022).

2.2. The messy middle point of the consumer journey

The path to purchase is littered with complicated touchpoints that can stop the consumers to move forward in case of dissatisfaction. The

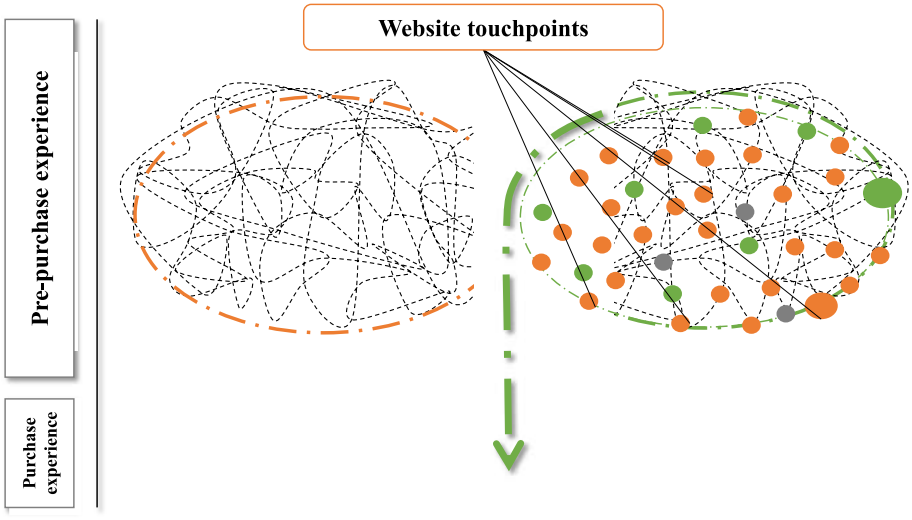

Fig. 1. The messy middle point and website touchpoints. Source: authors' conceptualisation based on the aim of the study.

increasingly complicated shapes of sales funnels provoke academics and the managerial environment in finding the most relevant solutions for meeting the high-demanding expectations of consumers.

Despite its worldwide application, electronic commerce is directly impacted by the *modus operandi* of consumers. Moreover, the use of Internet for purchasing disturbs, even more, the way they make decisions. The unlimited options and opportunities set by the technology advancements determine a sudden behavioural change. In this context, they are comparing everything, not only prices or products, causing emotional changes that remain unveiled by professionals. Therefore, the need to decode consumer behaviour is more pressing than ever. The full report "Decoding Decisions", published by Google (2022) (Rennie et al., 2020), presents the brief history of marketing models, from AIDA (1898) to ZMOT (2011), emphasizing the way of thinking and consumer perspective have changed. In the same sense, postgraduate research was performed to observe shopping behaviour for 310 different purchasing journeys across 31 categories. The results of the study introduced in the literature the most noteworthy concept that describes the mental mode of decision-making. It places the "messy middle point" in the centre of the purchase journey between two poles, namely, the triggers and purchase phase (Edwards, 2022; Gkikas and Theodoridis, 2022). Within the loop shape, the way out of the middle point leads the consumer to the product only if the consumer's journey is not affected by other factors.

2.3. The search engine optimisation and the messy middle point

The literature presents several web marketing methods that should be considered when making a website effective online, such as Search Engine Optimisation (SEO), Pay-per-click (PPC), Online Advertising, Email Marketing, Blog Marketing, Social Media Marketing, Online Public Relations, Multimedia Marketing, Mobile Marketing (Miller, 2010). Each one of these marketing tools plays a key role in business website marketing. Among the main two methods to achieve high rankings: SEO and PPC, SEO is the preferable marketing system for e-commerce-based websites (Kritzinger and Weideman, 2017).

Search Engine Optimisation (SEO) is the process of improving a site to increase its visibility when people search for products or services related to their business in search engines (Search Engine Land, 2022). The better visibility a page has in search results, the better the chances to garner attention and transform online visitors into effective customers. In marketing, the way a consumer takes note of a brand and interacts with it during the purchase process, measured as the totality of the touchpoints the customer has with a company, is called "the customer journey" (Search Engine Journal, 2022). The SEO strategy contributes to a productive customer journey. Through the study, the authors assumed that the way out can be stopped if some website particularities do not meet the expectations of the consumer. The hypotheses explained in the next section expose this assumption and show the context of the research.

Considering the increase in the number and expertise of consumers regarding the use of the Internet, they tend to have higher demands from websites, both in terms of their performance and content (Król and Zdonek, 2020). Consequently, the structure of websites is constantly changing which leads to a need of measuring these changes in terms of performance (Saverimoutou et al., 2019) and identify their strengths and weaknesses (Saeidnia et al., 2022). The quality of a website greatly influences e-loyalty and trust in that website (Aslam et al., 2020; Garcia-Madariaga et al., 2019).

Measuring website performance (influenced by a wide variety of factors and criteria) is extremely important for business development in a very competitive market (Ulutaş, 2019), the decrease in performance leads to a decrease in demand and a lower probability of website traffic conversion in firm orders (Gallino et al., 2018). The first access to a website is of particular importance in creating the consumer's impression, loading speed being crucial in this regard. The websites with a low loading speed have a clear competitive disadvantage (Muriyatmoko and Musthafa, 2022; Stringam and Gerdes, 2019).

However, a study conducted in the USA on apparel mobile commerce shows that "website information quality, website visual appeal, apparel visual appeal, and website security" have a greater impact on ensuring consumer satisfaction and less "response time and brand trust" (Chi, 2018).

During the process of creating a website, the principles of graphic design, the logic of its structure, and interactivity must be taken into account because they will outline the customer journey and will condition the time spent by them on that site (Lopriore, 2022), thus the quality of the website influencing "online impulse buying behavior" (Akram et al., 2018; Rita et al., 2019). Users must not detect any anomaly in the operation of a website because this can lead to losses for merchants or even fraud, identity theft, damage to brand image, and loss of consumers. Any technical inefficiency can irritate the user and make him leave the website (Dahiya and Duggal, 2018).

The factors that influence the performance of a website are "conversion rate, average session duration, and bounce rate" (Domazet and Simović, 2020), "high performance, better accessibility and usability" but also "mobile-friendliness", connection with social media and security (Kumar et al., 2021; Kwangsawad et al., 2019). Specialists consider that another key performance for website effectiveness is the bounce rate, which in turn is directly influenced by "unique pageviews, average time on page, entrance, and percent exit" (Idemudia et al., 2021).

The use of loyalty programs by an increasing number of companies makes their size influence website traffic (Sundjaja et al., 2022), strongly correlated to the degree of customer satisfaction with these programs (O'Connor, 2021). Studies show that the determining factors in the use of loyalty programs are "playfulness, affective commitment, and attitude toward them" (Sundjaja et al., 2022).

To maintain customers and give them an advantage and, at the same time, to increase the attractiveness of the products, online stores use gamification techniques even in loyalty programs (Sundjaja et al., 2022), studies showing that they lead to repeated purchases. The use of these techniques fosters an increased consumer engagement and profitability, the elements most used in gamification being "rewards, badges, and leader boards" (Azmi et al., 2021). To increase the level of perceived customer satisfaction when accessing websites, online retailers must adopt "specific semantic web technologies" which stand for more detailed product descriptions and information related to the importance of product features (Necula et al., 2018). In the current context marked by the continuous growth of the online market, it is very important for merchants to practice digital marketing through SEO and SEM, to make information more easily accessible (Sipayung et al., 2021), and to create a favourable positioning in search engines (Mendez Lobato, 2021; Verma et al., 2020).

3. Research design and hypothesis development

To accomplish the aim of the study, the research design (Fig. 2) was substantiated by the key concepts presented in the first part of the article.

The gap regarding how the purchase journey is managed and positively influenced by satisfactory touchpoints led the authors to address the complicated model of messy middle point, to find key factors that determine users to get out of the loop, and move forward from the evaluation stage, surpassing the point where it was possible to return and explore another solution (another retailer), in case of dissatisfaction.

The validity and reliability of choosing the website as a relevant factor for digital touchpoints are based on the Brand Touchpoint Wheel tool, that place the website as an asset for the pre-purchase experience, being used and mentioned in various studies over time (Hong and Hardy, 2022; Jevons, 2005; Lee et al., 2013). A literature review was carried out to select the most relevant research variables for the website analysis, which eventually revealed the most important priorities for e-

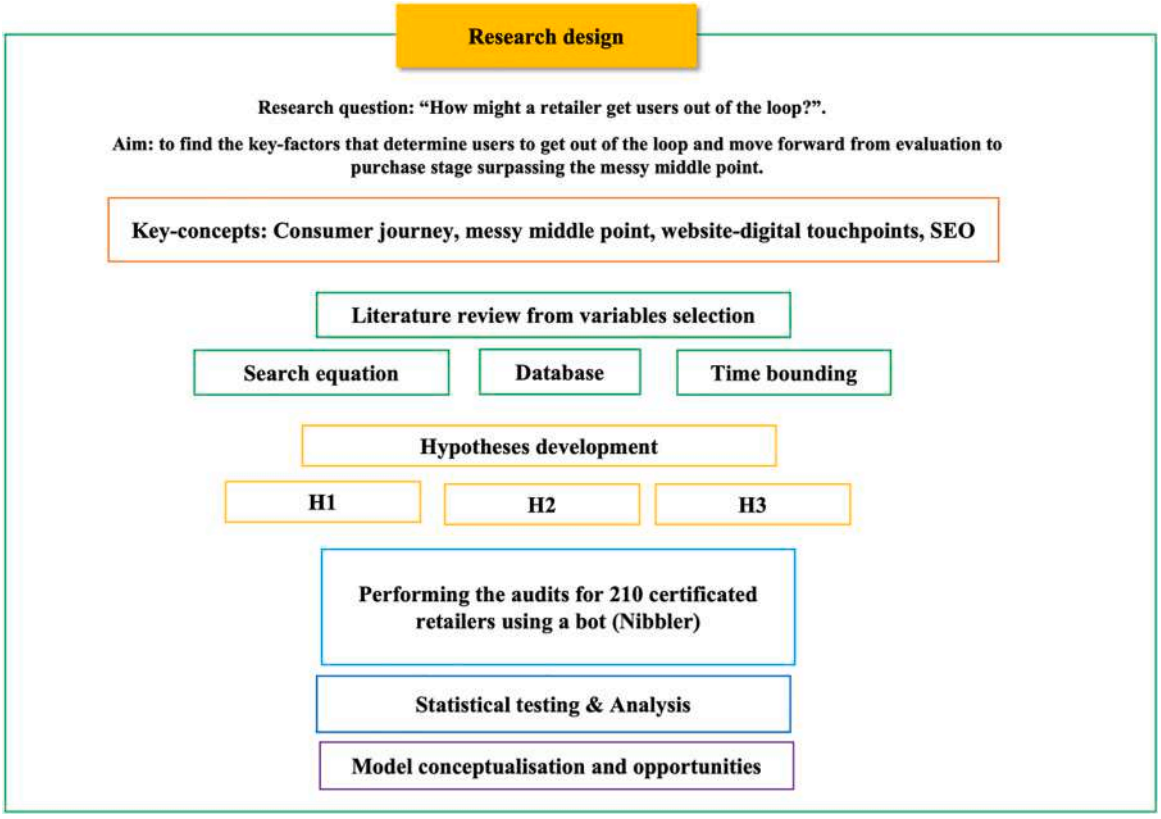

Fig. 2. Research design from aim to model conceptualisation and opportunities. Source: authors' conceptualisation.

commerce websites development: *accessibility* (how accessible the website is to mobile and disabled users), *experience* (how satisfying the website is likely to be for users), *marketing* (how well marketed and popular is the website) and *technology* (how well designed and built is the website). The literature review process was based on a combined approach based on practices in the field and studies published in internationally recognized databases. The authors created a document list with the keywords around the research question, and around the relevant elements of Brand Touchpoint Element Wheel for research. Among these are "pre-purchase experience", "purchase experience", "website performance", "messy middle point", "search engine optimisation", and "consumer journey". The databases consulted were Web of Science, Google Scholar, ScienceDirect and Springer. The authors' searches can be described as a process of a snowball, because from the initially found articles, information and concepts were discovered that led to the identification of other important scientific resources for the research topic (e.g., "digital touchpoints"). The search period for the documents lasted several weeks from June 2022 to August 2022, but the process was continued during the writing of the paper because supporting references were needed to compare the results of the study with previous similar research. After the process of identifying valuable documents for research, the literature review was written based on solid information for the formulation of four hypotheses. Each one is based on the specialized literature and practicing methods in the field, considering accessibility, user experience and visual components of online stores.

Web accessibility refers to the properties of the websites that allow people with incapacities to use the web. Accessibility is an essential characteristic in determining the success or failure of a digital business (Acosta-Vargas et al., 2022). Web accessibility has a direct effect on the e-loyalty, satisfaction, and trust of the consumers (Paștiu et al., 2020). Web Content Accessibility Guidelines (WCAG) cover a wide range of recommendations for making Web content more accessible (particularly for people with diverse types of disabilities or cognitive limitations).

The main principles that provide the foundation for web accessibility are the following: *perceivable* (content and user interface components should be presentable to users in ways they can perceive), *operable* (a website should be as intuitive as possible), *understandable* (the site should include legible elements, predictable in navigation), and *robust* (compatible with all browsers, operating systems, and devices) (Alsaeedi, 2020; Fernández-Díaz et al., 2020; Nietzio et al., 2014; Spyridonis and Daylamani-Zad, 2019; W3C, 2018). If any of these principles is not fulfilled, users with disabilities will not be able to use the web (Pelzetter, 2021). Vulnerable populations are those that are the most susceptible to being affected by crises, and the COVID-19 pandemic exacerbated the inequalities (Figliozzi and Unnikrishnan, 2021; Gartland et al., 2022; Jankowska, 2021; Sanchez-Diaz et al., 2021). Considering all these aspects, the researchers identified research opportunities. Thus, a first hypothesis of the study has arisen:

H_1: The accessibility of online stores is high, favouring the consumer experience.

In addition to accessibility features, e-commerce platforms are strongly aiming to enhance the overall user experience (Mantha et al., 2020), considering the widespread use of mobile devices and large connections to social media. Different facets of customer interactions in the online shopping process generate the online customer experience, such as the easiness to locate the website/app (Rennick, 2019), ease of use (Anaya-Aguilar et al., 2021; Lindh et al., 2020; Stafford et al., 2021) perceived usefulness (Grange and Barki, 2020; McLean and Wilson, 2019), hedonic and utilitarian features (Karampournioti and Wiedmann, 2021; McLean et al., 2018; Riegger et al., 2021; Tyrväinen et al., 2020), perceived enjoyment (Kim, 2021), personalization (Karimi Mansoub et al., 2020; Raufi et al., 2019), social interactions and multi-device compatibility (Bilgihan et al., 2016). Therefore, in addition to accessibility, user experience was considered for formulating the second hypothesis:

H_2: The online stores' pages guide the users properly for a good shopping experience.

As the perceived utility, ease-of-use, visual attractiveness, and interactivity of the website/app, the perceived enjoyment, and satisfaction of the user increase, having a positive impact on buying behaviour and on website loyalty (Bilgihan et al., 2014; Do et al., 2020; Rauwers et al., 2020; Soares et al., 2022). People's shopping experience can also be optimized by improving the usability and efficiency of websites in interface design (Cheng, 2019). Positive attitudes and shopping experiences among online customers can be attracted by perceived value and trust in online shopping, which proved to be the result of well-designed websites, information design, navigation design, and visual design (Ijaz and Rhee, 2018).

Customised and personalised offerings and influential visual designs on the online platforms contribute to a greater extent to the customer experience than purchasing experience itself, and the amount of time a person spends on the online platform critically matters for customer satisfaction and loyalty (Ertemel et al., 2021). Based on the information provided by the literature review on this topic, the authors underlined the third premise:

H_3: The quality of the images influences the marketing performance of online stores.

The research design was created based on the case study method substantiated following the stages proposed by Yin (2009). The first phase was to "define and select the cases for study" when 225 websites were identified. The second one consisted in "using multiples cases as part of the case study". At this point 210 eligible websites were selected. Finally, "strengthening the evidence used in the case study and analysing the case study evidence" was performed and widely described in the section of analysis methods. The selection of the cases included in the research is motivated by the certified high trust that online stores have at the time of the study. At the level of online stores, trust and credibility are factors of utmost importance (Guerrero et al., 2023), their lack causing barriers and affecting purchases (Dogra and Kaushal, 2023). Thus, users' trust was a selection criterion for the sample of the study, a criterion that is found in recent studies to research electronic commerce (Dang et al., 2023; Özdemir, 2022; Yang and Ngo, 2023). Of course, sample could be used if they did not compound websites without trademark, but the existence of other papers where mentions of certified online stores with the trusted mark (Burlea-Schiopoiu et al., 2022) offered the authors a strong precedent for reliable effectiveness of the selection method. In addition, the standards that online stores must meet to obtain certification are aligned with the aim of the study. In total, websites must comply with a total of 35 requirements to be marked as trustworthy (TRUSTED.RO, 2023). This fact ensure that all aspects related to legality, commercial transparency and good practices are respected before addressing the research question regarding the exiting the loop after technological issues are surpassed.

The initial sample (Fig. 3) was represented by 225 websites through which Romanian retailers operate and which obtained the Mark of Trust certification through the National Program for the Certification of Online Stores (TRUSTED.RO, 2022).

After a preliminary analysis, 210 of them were considered eligible for the study due to their compatibility with the Nibbler platform (Nibbler, 2022), the software used to perform the audits. Nibbler is a bot, a free tool for website analysis providing fifteen key areas for the four priorities for electronic commerce. By using the domain of each retailer included in the study, it was possible to evaluate up to five pages for each and collect the scores (Fig. 4).

Besides the scores, the authors collected the issues for every contributing test, creating a large database, which favoured the performance analysis for fifteen areas and main priorities for website improvement, issues, to improve, awarding, and adiaphorous (neither good nor bad).

4. Analysis methods

To analyse data, five methods were applied, namely, descriptive analysis, reliability of the model analysis, factor analysis, analysis of covariances, compared mean analysis, and bivariate analysis.

However, the first step was to establish the structure of the model and clearly understand the technological factors (touchpoints) that

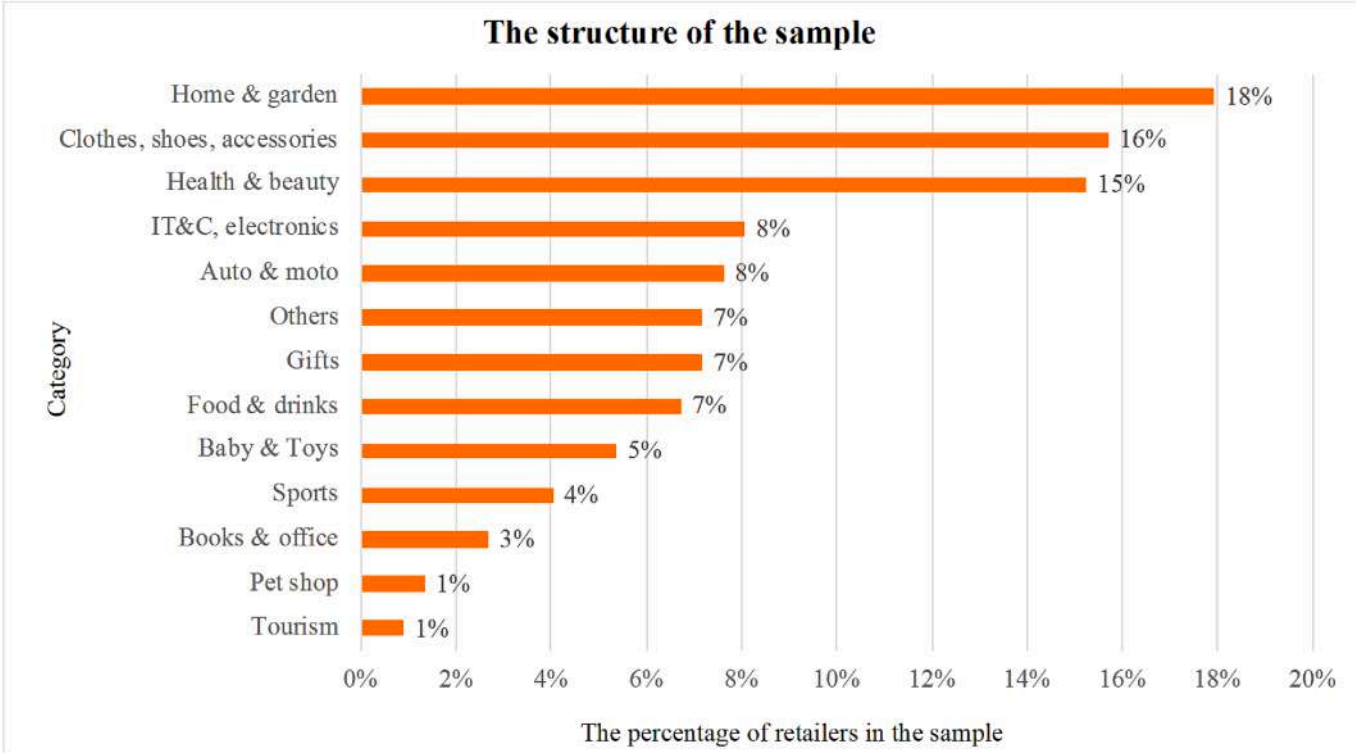

Fig. 3. The structure of the sample. Source: author's conceptualisation based on collected data.

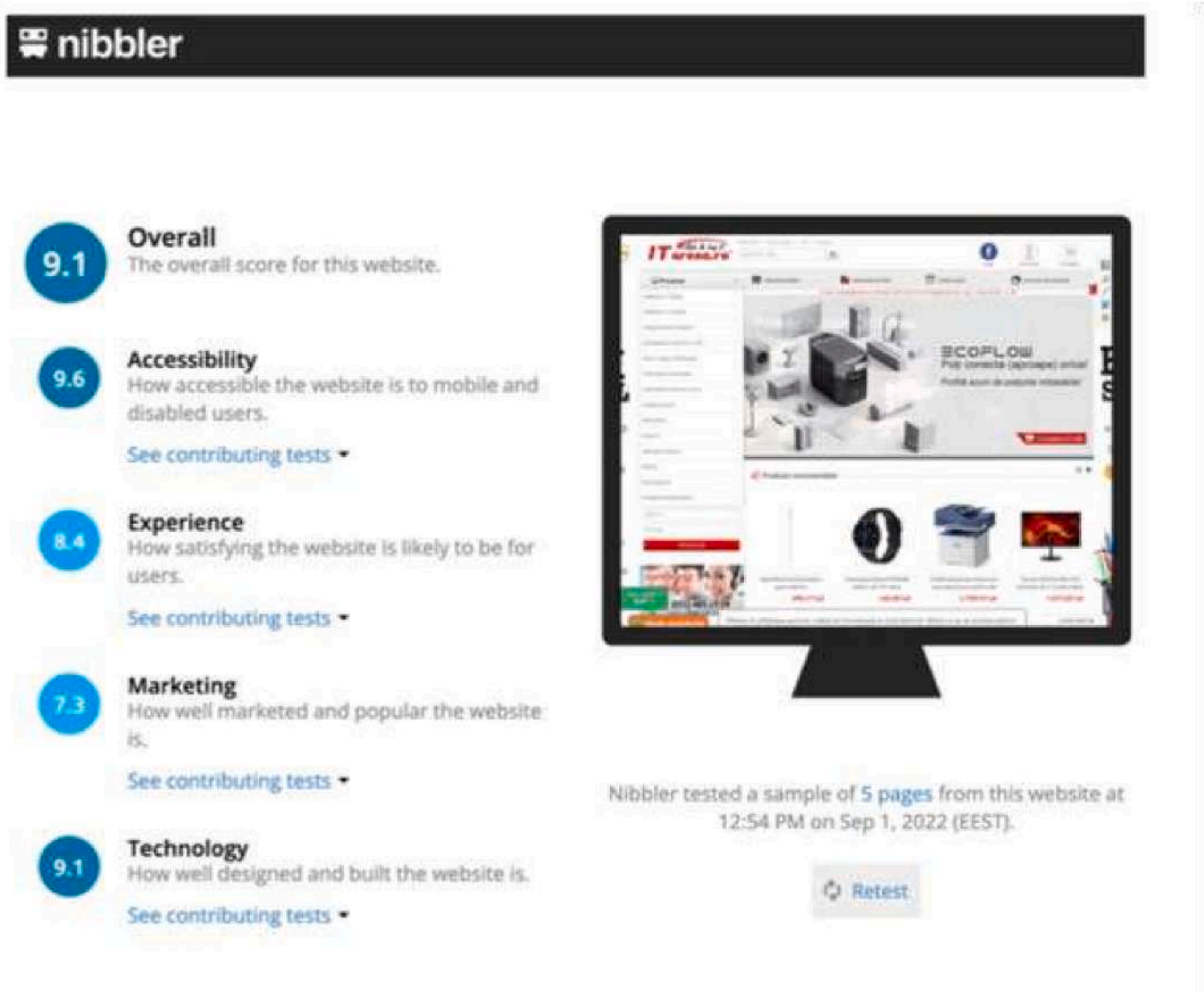

Fig. 4. Test demo for one of the retailers. Source: screenshot from Nibbler running software.

influence the overall score of the websites. Because the fifteen technological elements are common for more than two main components (Fig. 5) and they cannot be easily measured directly with high reliability, the researchers appealed to a data reduction technique, thus enabling the investigation process.

After the descriptive analysis, the factor analysis was applied. Using this method, 210 certified online stores with the trusted mark were analysed from the perspective of the four main components, for the overall performance of the websites (accessibility, experience, marketing, and technology), each one being analysed with fifteen different contributing tests.

Although the Nibbler platform highlights contributing tests for all the four components, factor analysis facilitates discovering the latent elements hidden behind the raw data, due to the possible variables related to one another and associated with the same factor. The authors used the principal component analysis, to identify the underlying factors and reduce the set of variables to a smaller one, more meaningful, by looking for clusters of variables that share variance. For such purpose, the size of the dataset was reduced with the factor function from SPSS 20.

5. Results

The results allowed the authors to discuss the key factors identified, but not until the reliability of the model was assessed. Therefore, based on the factor analysis results, multiple linear regression was used to test if the high loading technological element significantly predicted the overall performance (OP). In the final, compared mean analysis was performed, to test if there are significant differences between online store categories.

5.1. Reliability of the model

First, to ensure the relevance of the approached model, the reliability test run shows internal consistency (Cochran's alpha: 0.765). Thus, the model can be approached furthermore.

5.2. Factor analysis

After processing the model reliability, the exploratory factor analysis was run. In this regard, fifteen technological elements were used to analyse the relationship between the variables and to identify the structural latent factors with varimax rotation. The null hypothesis

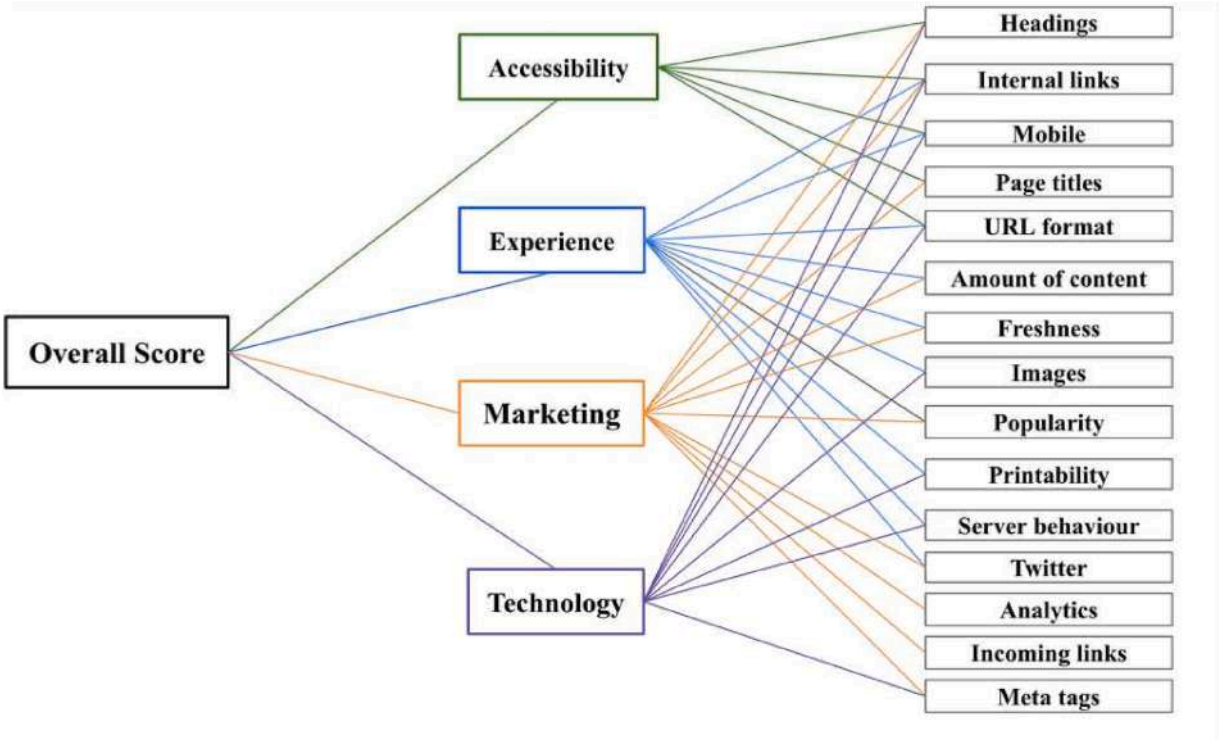

Fig. 5. Technological elements proposed in the model. Source: authors' conceptualisation.

stated that four numbers of factors (one for each principal component for OP) are enough to capture the full dimensionality of the dataset. The Kaiser-Meyer-Olkin test of sampling showed that the sample size is adequate for analysis and Barlett's test of sphericity demonstrated the relevance of correlations for factor analysis (KMO: 0.5, $\chi^2 = 188{,}994$, df $= 105$, $p < 0.001$). Using both the scree plot and the eigenvalues > 1, the extraction sums of squared loadings after rotation show six factors (a significant amount of variance in the dataset with maximized loading of each of the chosen variables) explaining 56.54 percent of the variance. Due to the mathematical grouping of the variables, it was easier to

	COMPONENT					
	1	2	3	4	5	6
Incoming links	0.696					
Popularity	0.692					
Mobile	-0.521					
Freshness	0.471					
Headings		0.652				
URL format		0.645				
Twitter		0.457				
Printability			0.747			
Images			0.638			
Meta tags				0.852		
Amount of content				0.681		
Server behaviour					0.765	
Analytics					0.723	
Page titles						0.721
Internal links						0.676

Fig. 6. Rotated component matrix. Source: authors' conceptualisation.

present the categories (Fig. 6).

Factor 1 was labelled IPMF (according to its components) because of the high loadings of the popular technological element. The first factor explained 11.66 percent of the variance after rotation. The justifications for labelling the other factors are exhibited in Table 1.

The overall regression was statistically significant ($R^2 = 0.74$, $R^2_{adjusted}$ F (6, 203) = 40.922, $p < 0.000$). It was found that incoming links (IL) ($\beta = 0.369$, t(208) = 7.499, $p < 0.000$), headings (H) ($\beta = 0.103$, t(208) = 7.342,$p < 0.000$), printability (PRINT) ($\beta = 0.041$, t (208) = 6.337, $p < 0.000$), meta tags (MT) ($\beta = 0.082$, t(208) = 7.201p < 0.000), and server behaviour (SB) ($\beta = 0.118$, t(208) = 4.762, $p < 0.000$) significantly predicted overall score. Otherwise, it was found that page titles (PT) did not significantly predict overall score ($\beta = 0.78$, t (208) = 1.627, not significant (ns)).

To show the effect of the independent variables without covariates, ANCOVA was applied to analyse the OP, by removing the effect of page titles independent variable. Levene's test and normality show the assumption of the equal variances as $p > 0.05$ and the residuals are normally distributed. By adjusting the PT variable, there was a significant difference in mean OP between the high loading technological elements (SB:F(31,29) = 3.492, p = 0.001; MT:F(5,29) = 19.701, p = 0.000; PRINT:F(6,29) = 12.502, p = 0.000; IL:F(28,29) = 6.981, p = 0.000; H:F(33,29) = 7.181, p = 0.000).

The partial Eta squared value shows the effect size. Comparing it according to Cohen's values, one may say that for IL, MT, and SB, the effect size is moderate (0.33, 0.586, 0.690 respectively). The smallest effect is for PRINT (0.18) and the largest is for H (0.740). The values describe how much of the variance is explained in overall performance by the independent variables.

By controlling the covariate "PT", it was possible to interpret the estimated marginal means for each important technological element. Thus, it was easier to understand the online stores' OP.

Server behaviour (SB): For the group evaluated with 10 (maximum score), the mean overall score is 8.46. The situation of the groups with OP having lower scores than 8.98 is even more worrisome due to lower scores than 7.8. For very few cases, a high OP score also means high scores for SB. Concluding, many OP means above eight are for the online stores with low performance in terms of SB.

Meta Tags (MT): the highest OP means showing the maximum score for MT is 8.698. MT scores are included in the range [2–10], for the OP given by the scores between [7.850–8.690].

Printability (PRINT): unfortunately, the group of online stores with the fourth average OP = 8.247 presents a score of 0 for printability. The scores of PRINT are included in the interval [0–10], and the maximum OP score for 10 is the group of the mean OP = 8.557.

Incoming links (IL): The scores for IL are included in the range [1.20–10]. None of the OP scores of 10 is included in the range, which denotes the poor performance of online stores with a score above 8.580 in the case of this technological element.

Headings (H): The range of scores for H is [1–10], and no score above 8.50 is included in this range.

To understand the issues and the improvements necessary for the most significant factors, descriptive analysis outcomes are presented in Fig. 7. Also, awarding actions and adiaphorous were illustrated as touchpoints placed within the loop, for a better overview of the concept.

Table 1
Factors labelling.

Factor number	Label	High loading technological element	% of variance after rotation
1	IPMF	Incoming links – IL (0.696)	11.66
2	HUT	Headings – H (0.652)	21.05
3	PI	Printability – P (0,747)	30.01
4	MAC	Meta Tags – MT (0,852)	38.95
5	SA	Server behaviour – SB (0,765)	47.83
6	PIL	Page titles – PT (0,721)	56.54

5.3. The robustness of the multiple linear regression

The assumption of non-zero variances was tested, and the analysis of standard residuals showed that the data contained no outliers (Std. Residual Min = -3.04, Std. Residual Max = 2.02). Also, regarding the assumption of collinearity, tests indicated that multicollinearity is missing (IL: tolerance = 0.928, VIF = 1.07; H: tolerance = 0.947, VIF = 1.05; PRINT: tolerance = 0.988, VIF = 1.012; MT: tolerance = 0.989, VIF = 1.011; SB: tolerance = 0.957, VIF = 1.045). To see if the correlation between residual terms is missing, the Durbin-Watson test was run, and its value met the assumption of independent errors (DW = 1.859). Regarding homoscedasticity and linearity, the histogram and normal P-P plot of standardised residuals illustrate all the points close to the line. Along with the scatterplot, the model met the assumption of homogeneity of variance and linearity (Fig. 8).

5.4. Compared mean analysis

The online stores were analysed according to the membership in a specific category, and the authors considered it relevant to perform a test of homogeneity of variances regarding the five influential technological elements for OP. The results show homogeneous variances for IL, PRINT, and SB. Therefore, ANOVA concluded that significant differences exist between online store categories due to MT and H only (SB:F(14,195) = 1.459, ns; MT:F(14,195) = 1.852, p = 0.034; PRINT:F(14,195) = 0.993, ns; IL:F(14,195) = 0.981, ns; H:F(14,195) = 2.021, p = 0.18).

6. Discussion

The scientific contribution that the authors bring to the knowledge field entails multiple gaps centred on the consumer decision journey model and the outcomes of the study unfold the dilemma of finding solutions for the current challenges and the life span of knowledge in electronic commerce. The applicative aspect that the paper renders locate the retailers who should consider the potential of the infinite journey that a user can experience in searching process for the desired product. Electronic commerce is constantly changing, thus, understanding concepts such as *loop* or *touchpoints* will lead to providing the necessary framework for a good shopping experience, from a technical point of view. For a crystal-clear overview of the study's findings and its effectiveness for the knowledge stage, the discussion was divided into two different sub-sections. The first one has recalled the concepts used to improve the theoretical lens with TEAM model and the second part sequentially presents the arguments for the contribution to theory as a subject of discussion in the context of previous studies.

6.1. The TEAM combined model

Retailers need to assess the results of their assets evaluation performed by users, as an opportunity to adapt to the new requirements of the digital environment. The website is the medium where users meet retailers' image and resources, and the Brand Touchpoint Wheel shows it as an important element during the pre-purchase experience. Thereby, the website-based touchpoints and SEO factors should be considered to untangle the messy middle point and help users continue their journey to purchase action.

Analysing all SEO factors simultaneously is arguably impossible in one single research paper, but an evaluation of few separate components through artificial intelligence (using a bot) allowed the authors to reflect on four dimensions relevant for e-commerce website optimisation (technology, experience, accessibility, and marketing) (Fig. 9). By aiming to connect the loop and messy middle point to the four dimensions, the authors discovered which factor should be considered with priority and to which dimension it belongs to.

Extracting data and organising the outcomes, five key factors, namely, meta tags, incoming links, headings, server behaviour, and

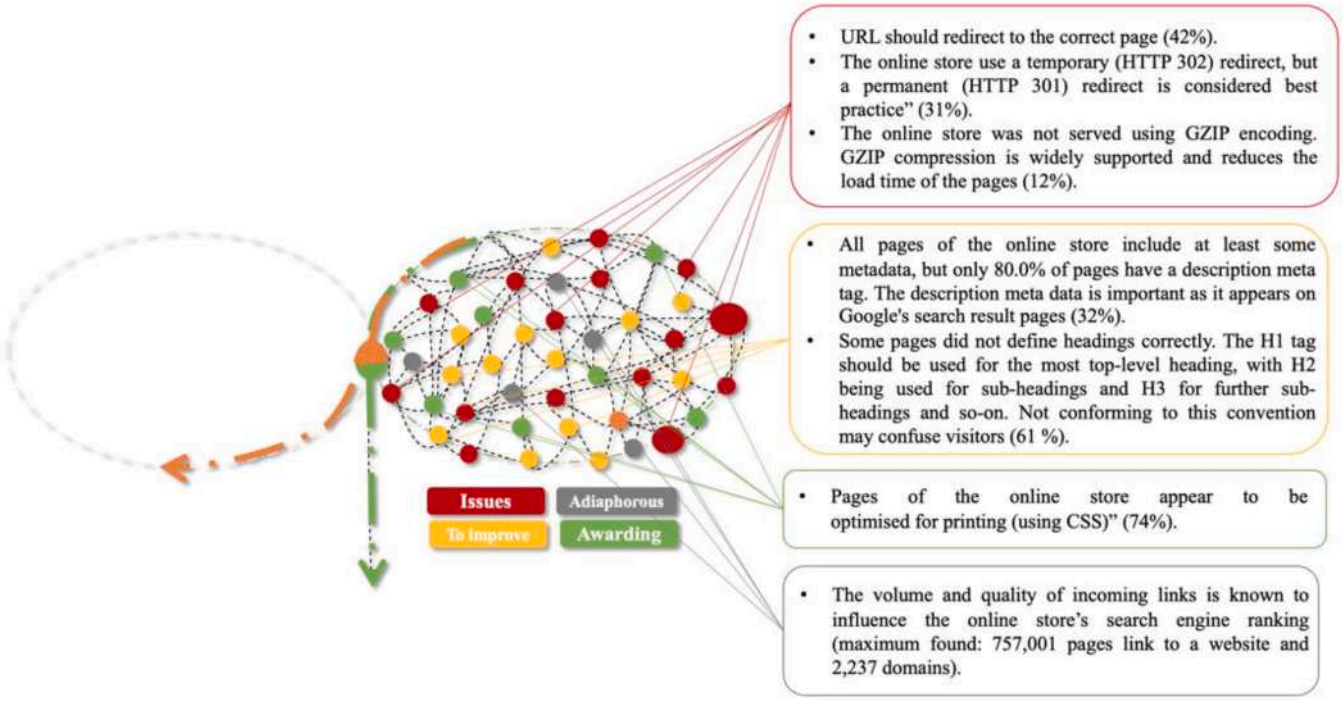

Fig. 7. Results of the analysis (issues, to improve, awarding, and adiaphorous outcomes). Source: authors' conceptualisation.

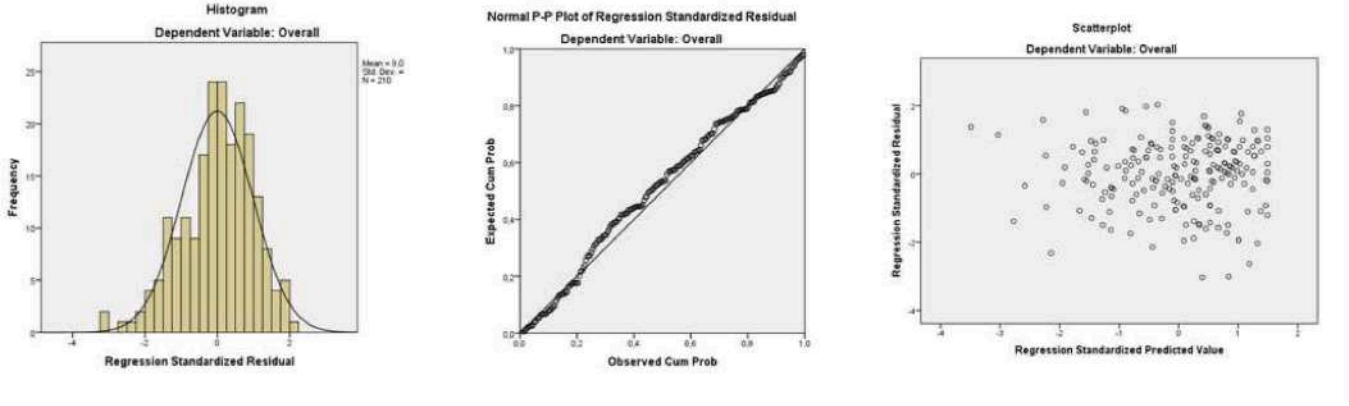

Fig. 8. The homoscedasticity and linearity of the proposed model. Source: SPSS outcomes.

printability were identified as catalysts for passing the messy middle point. Each of them exhibits several opportunities, summing up to 13 actions for the e-commerce strategy when considering a better consumer journey in the pre-purchase experience. The specific actions were presented as part of the TEAM model (acronyms of dimensions) and defined the core priorities for getting users out of the loop through the online store's website optimisation (Fig. 10).

At first impression, some results that revealed the five factors seemed totally irrelevant for achieving the balance between the current challenges and the development of e-commerce in the future. A good example is the printability factor, which in terms of consumer decision-making process, would seem very little relevant for the continuation of the consumer journey. Practically, the first thought would be that there are not many users who would print the pages with the images of the products they want, right? But studying more deeply and understanding the fact that printability technical capacity of website's pages optimisation by using CSS for screen-based stylesheets means this is a key-factor to offer users virtual mediums with good user experience conditions. Due to this type of aspects, several arguments for the applicability and the effectiveness of the TEAM model were explained further.

6.2. *Arguments*

The contribution to theory presents multiple approaches that support the answer for the research question. First, the scientific value of the paper derives precisely from the researched nexus between three concepts, as follows: i) the loop and messy middle point of the consumer journey, ii) the website (and its touchpoints), and iii) the SEO factors. Placed together, the big picture of the findings illustrates the necessity of engaging teams and managers from different departments or fields to share efforts in empowering the retailer to handle the customer experience and the demanding user requirements. Previous studies showed the necessity of creating a mixed-combined algorithm. Moreno and Martinez (Moreno and Martinez, 2013) introduced the high relevance of web accessibility, considered an indicator of high quality. As critical

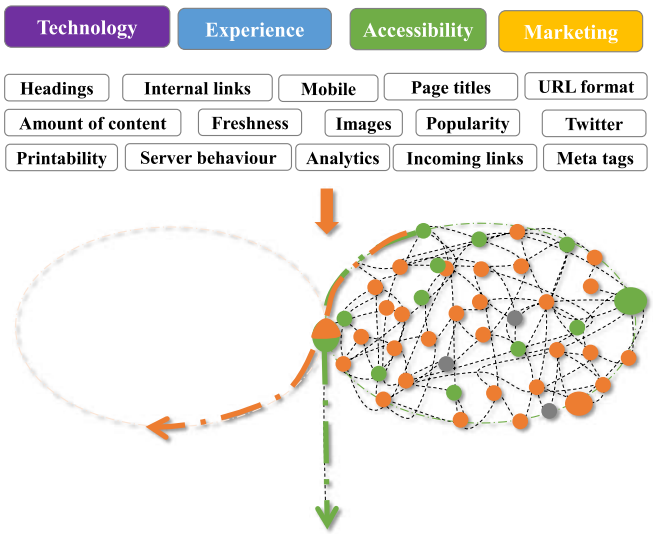

Fig. 9. The four dimensions, 15 SEO factors on the messy middle point.Source: authors' conceptualisation.

digital touchpoint for the consumers' decision-making process, the website, as part of a flexible model, needs constant optimisation and current alignment for customer journeys (Darboe, 2022) and because SEO is the preferable marketing system for e-commerce-based websites (Kritzinger and Weideman, 2017), the algorithm is founded on solid scientific arguments and comparable with existing literature. When it comes to SEO, studies show a concern with the content (Confetto and Covucci, 2021; Nagpal and Petersen, 2021) or similar schemes addressed in this study, such as redirecting pages (Wu, 2011) or trust by usability (Downing and Liu, 2011), but the results of this research expand the area of applications, conducting the managers and academics to different perspectives, presented as the second contribution to the theory. The aim of understanding how retailers might get the users out of the loop was fulfilled, by unveiling five SEO key factors and 13 technical actions that online stores' websites must attend. At first sight, the simplicity of the results may be presumed due to the accepted influence of search engine optimisations factors on the websites, but upon a closer look, new perspectives can be described as follows.

Starting from the research question, the authors intended to achieve three objectives related to the accessibility, the guidance between online stores' pages, and the influence of images used for marketing performance. For each objective, one hypothesis was formulated, and the findings highlights two unexpected results (Fig. 11).

Trying to understand if the online stores' accessibility is high, the results determined the authors to refute the first hypothesis. The findings show that optimising headings is more significant for the marketing dimension than for the accessibility. For this purpose, the authors proceeded to analyse the incoming links which conducted them to achieve the first objective. By reason of refuting the H_1, the authors highlight the alarming situation of existing more than half of retailers selling products on a website that loads empty headings or incorrectly defined. Framing this fact into the scenario where the online shops display the trademark of trustworthy, the authors can affirm that the experience customers embrace at the first time is not synchronised with their expectations and the customer journey is in danger. A decrease in demand and a lower probability of website traffic conversion might cause real challenges for retailers. This fact can affect the pre-purchase experience and might determine the user to continue searching without getting out of the loop. This consequence will lead the users to a possible endless searching journey. Worse, if shortly afterwards they find another provider who will satisfy their demands, they will remove the initial brand from the perception map when they buy again. In case they will not forget the brand, they will recall that pain produced when they did not find the correct or well-defined information on that website and will avoid it. The unexpected result obtained from this research action is that the first objective was correlated to the link building initiative. The authors expected to find the outcomes for this SEO factor close to the accessibility dimension, not to the marketing. However, the effect of this result place the link building activity as priority in marketing strategies, especially

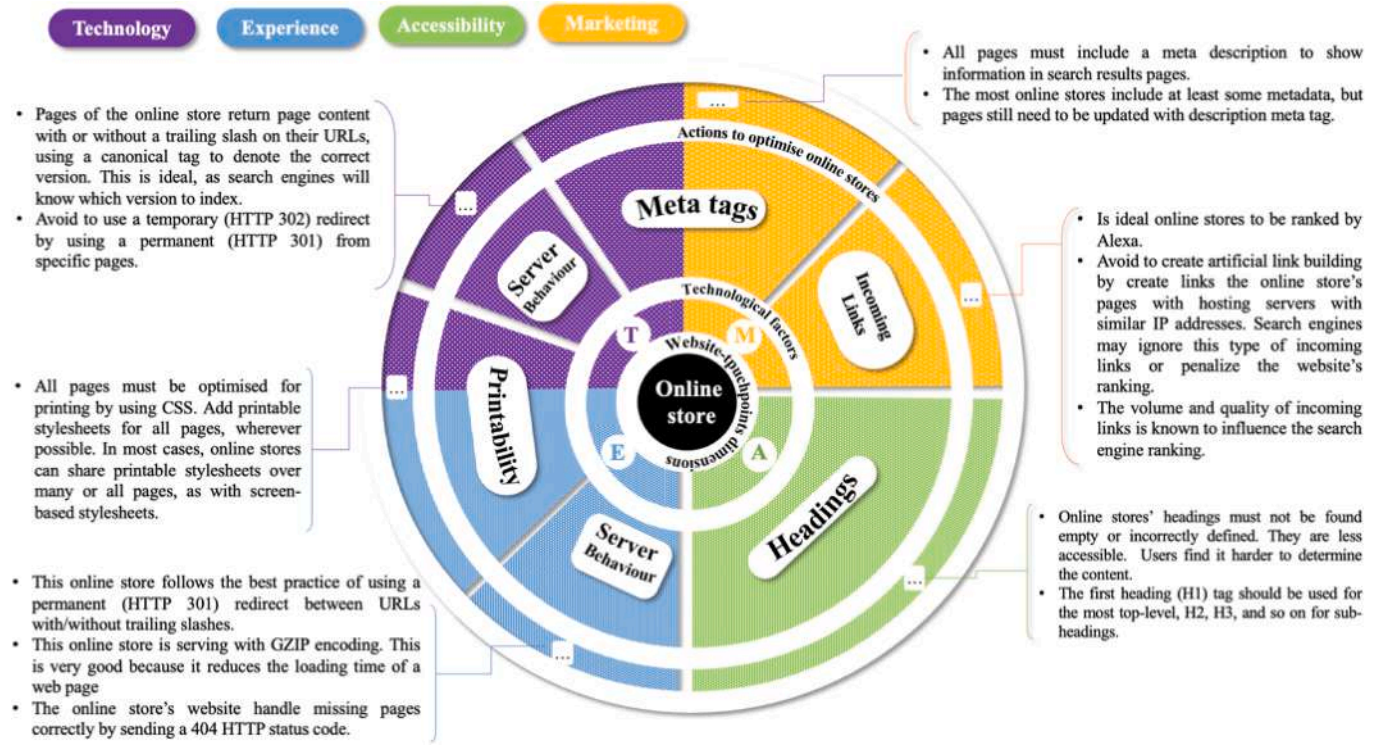

Fig. 10. The TEAM model proposal.Source: authors' conceptualisation.

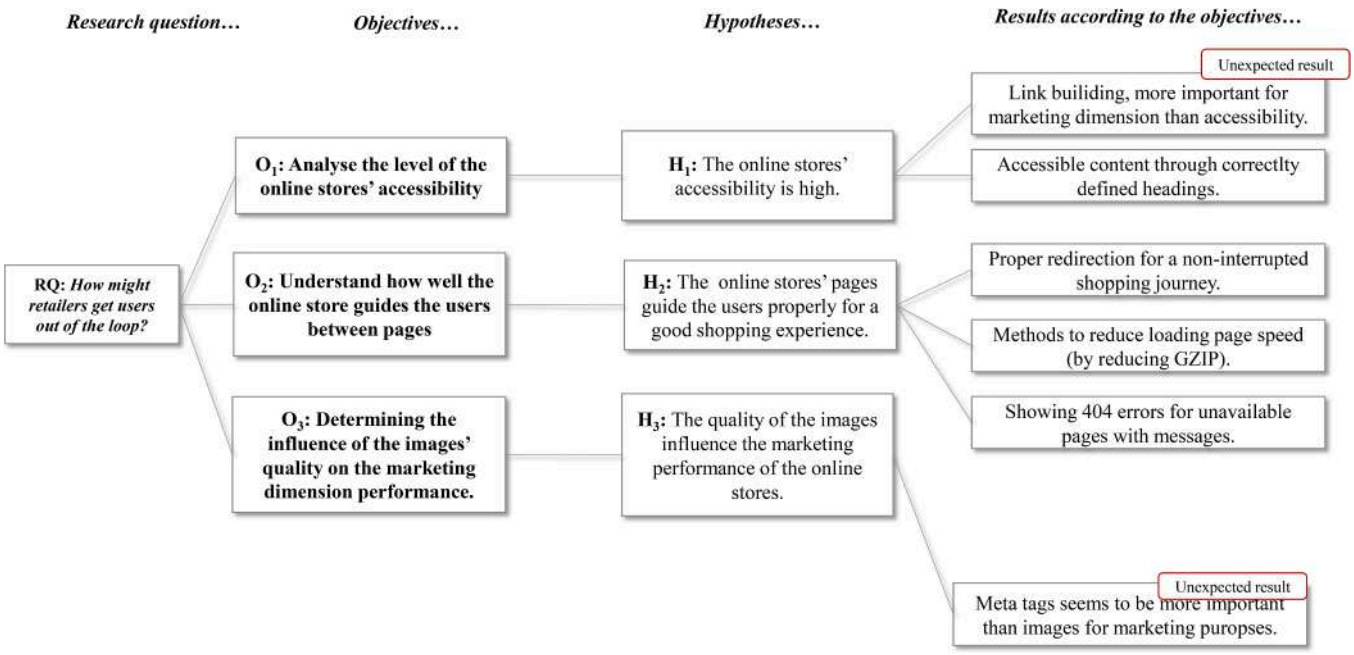

Fig. 11. The overall structure of the research in terms of objectives and results. Source: authors' conceptualisation.

when SEO is required.

The second objective of understanding how well the online store guides the users between pages determined the researchers to analyse the technical performance. The findings place the refutation of the second hypothesis and revealed that necessary improvements are to be made for guiding the user to the correct pages of the online store. In particular, in the case of certified online stores, with transparency ensured by the required standards, increased attention on right redirections is a must for a non-interrupted shopping journey. Most of them (42%) should try to lead to a requested webpage available instead of returning an error page (404), thus helping visitors interact with the desired product and move on to the purchase experience. The third hypothesis was not confirmed either, because the analysis showed that the influence of image quality on the marketing performance is not higher than the influence of meta tags and the actions on the organic link building. If this fact is known, artificial link building can be avoided, and the overall performance of the online store can be improved for a better user experience. Even so, the third objective was achieved and the connection of images on marketing performance was refuted and the influence of a different factor than images being demonstrated.

Finally, the authors intersected the technological issues and proposals for optimisation with business aims, which can be considered a major contribution to the electronic commerce knowledge field and applications because it enriches the literature with changing sales funnels. This is the first study that creates a connection between the messy middle point, the concept of the loop, the digital touchpoints and the vital collaboration between marketing professionals and information technology specialists within a single model to flourish the trust which the website influence (Aslam et al., 2020; Garcia-Madariaga et al., 2019).

7. Conclusions and implications

The authors' approach highlights several concepts that substantiate the way retailers should address user experience in relation to their online stores. By introducing the TEAM model for surpassing the messy middle point and getting users out of the loop, from pre-purchase experience to purchase, they intend to find a balance between the current state of mind of retailers, entrepreneurs, and marketing specialists, and the changing knowledge in the field of e-commerce. One top priority for the online store of the future should reflect on a highly requested need of adapting capabilities to a continuous and non-interrupted consumer experience, thus having effective touchpoints. This is highly dependable on human resources showing the openness to understand and deploy modern concepts, combined with classic principles to achieve customer satisfaction.

The managerial implications are particularly unique because the study combines basic elements of SEO with the modern model of the loop, seeking to address the user experience. The retailers who are concerned about continuous optimisation of the online store are searching for methods that bring results, and most often, implementing outdated solutions can be harmful.

The findings indicate which factors are the most significant for the online store performance and describe specific actions for optimisation. Moreover, the conceptual framework of the TEAM model sets priorities for the department responsible with managing the model components. An extremely interesting fact regarding the server behaviour factor was revealed, which involves the collaboration between the Technology dimension and Experience. The managers might consider that people responsible for optimizing the experience should not have a close relationship with those who must ensure the optimal technical conditions for online purchases. Such a fact becomes even more clear when it is spoken or written, as technology is needed for the functionality of the online store. However, the role of certain consumer experience components might have been overlooked so far. For example, the analysis revealed that the quality of the printed pages influences the customer experience, to a greater extent than images.

External factors can also share their influence. Once the mobile device displays the images correctly, it does not bother the consumer anymore. However, when there is the need to print pieces of content, the users lose interest due to the lack of functionality. This fact underlines the need for people who manage the online stores to understand and address these issues. The loop and the messy middle point are not simple concepts that can be addressed by the website admins only, as the entire team should work together to understand and respond to the user's digital demands. For this reason, the authors consider that the target audience for this paper should not be limited to the fields of Information Systems or Computer Science due to the technological components

addressed. The electronic commerce field must also be of interest considering that managers, entrepreneurs, IT and marketing specialists need to be more and more aware of their shared efforts, all off these determining high managerial implications.

The theoretical implications can be extended to several layers. Firstly, the study proposes a new conceptual framework based on four dimensions, which arguably influence the existence of the online store. Secondly, the paper generates valuable knowledge on how electronic commerce is conducted in a very dynamic and changing manner, which determines the importance of a multi-perspective approach in academic. The methods of research applied, along with the fields addressed to elaborate the research ensure the multi-perspective view of a qualitative user experience. Finally, the study contributes to the existing literature by providing a fresh perspective on topics such as consumer journey, user experience, touchpoints, and search engine optimisation, all applied in the e-commerce field.

Limitations and future research show that complementary research should be addressed. A first limit is derived from the tool used to generate the primary data, a bot that limited the extension to other SEO factors. This can generate a first research perspective for the academic environment, that is to include more factors within the TEAM model, by using other online store performance analysis software. The second limitation of the study derives from the analysis of two hundred and ten online stores certified with the trust mark, which hardly can be considered a representative sample for the researched population.

However, to ground the theoretical foundation, the results are relevant for the scaled future study based on quantitative methods. Also, the qualitative analysis might enable the TEAM model validation in practice, by performing survey-based quantitative research to understand the attitudes and necessary assets of retailers (managers, IT specialists, and marketing specialists) and to optimise the online store by relying on collaboration between all four dimensions. Finally, the TEAM model is a concept conditioned by the evolving changes that take place in terms of SEO. This fact conditions everything we know and define at this moment. That's why the TEAM model can be relevant nowadays, but without constant monitoring and updating according to the constantly changing field, its relevance would decrease. From this, the enrichment of the TEAM model with the recently appeared practices represents a future research direction. A good example for this case would be the addition of artificial intelligence, at the beginning, but undoubtedly with a resounding impact on the future regarding the way search engine optimisation would be done. As a takeaway statement, the authors affirm that more research is needed to bridge the initiatives related to technology, user experience, accessibility, and marketing, all in the current context in which the online stores operate.

CRediT authorship contribution statement

Eliza Nichifor: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Gabriel Brătucu:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Ioana Bianca Chiţu:** Conceptualization, Writing – original draft, Writing – review & editing. **Ovidiu Mircea Ţierean:** Conceptualization, Methodology, Software, Writing – review & editing. **Adriana Veronica Litră:** Conceptualization, Writing – original draft, Writing – review & editing. **Alexandra Zamfirache:** Conceptualization, Writing – original draft. **Daniela Roxana Vuţă:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Buy Now Pay Later—A Fad or a Reality? A Perspective on Electronic Commerce

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Abstract: The Millennials and Generation Z use online shopping for a holistic experience and buy more expensive or better-quality products with buy now pay later payment methods for their highly demanding needs. The authors aimed to deepen understanding of this phenomenon by finding related knowledge fields and discovering the type of economy that will represent an increasing market share for the method of domestic e-commerce payments. The methodology used combined computer-assisted review, descriptive statistics, and linear regression to explain the market share of 23 economies worldwide. Student credit card use, myopic consumer law, buying tendencies. and dark financial triangles were identified as related topics. Logistics performance, ease of doing business, and postal development were found to be significant factors. Finally, economies with medium ranks are inclined to adopt this kind of payment easily. Hence, major implications, both managerial and academic, must be addressed. High responsibility should be borne by industry associations, which should run information campaigns by collaborating with public institutions. From the point of view of theoretical implications, studying the buy now and pay later concept and its outcomes might deepen understanding of consumer behaviour, decision-making processes, risk perception mitigation, debt behaviours, and credit adoption.

Keywords: buy now pay later; e-commerce; fintech; Generation Z; bibliometric analysis

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1. Introduction

Buy-now-pay-later (hereinafter BNPL) arrangements, one of Fintech's innovative instruments, are based on 'responsible spending' and are a less expensive alternative to credit cards (Gerrans et al. 2022). They are interest-free instalment loans, an agreement between buyer and merchant to promote financing at the point of sale, but they are not yet properly regulated to protect the buyer (Soni 2023).

Advanced technology, e-wallets, e-money, and smartphone accessibility have led to changes in behaviour, and consumers are becoming more "consumptive", especially Generation Z (digital natives), constituting an opportunity to use BNPL services (Lia and Natswa 2021).

Fintech (financial technologies) represents an emerging concept in the industry of banking, offering alternative solutions to specific instruments in this industry (Vijai 2019), namely bank products and services using advanced technologies (Knewtson and Rosenbaum 2020). Using these instruments is essential to consumer retention (Tripathy and Jain 2020), increasing the number of payment options at retailers (Kliber et al. 2021). Fintech led to the digitalisation of the bank business model from "brick-and-mortar" banking (offline presence) to an online presence and essentially modified the way in which financial services are delivered (Agarwal and Zhang 2020). This concept emerged because of the very rapid evolution of technology in recent years, the use of cryptocurrencies, and the digitalisation of business models, which revolutionised mobile payment (Hendershott et al.

2021). Additionally, global financial crises and the Covid-19 pandemic period determined the need to innovate new solutions for the problems generated by these factors (Imerman and Fabozzi 2020). The Fintech industry underwent many changes in recent years because of the emergence and development of new instruments, such as blockchain, artificial intelligence, and cloud computing (Nelaturu et al. 2022). Moreover "fintech is struggling to find a sustainable business model in the face of funding instability" (World Economic Forum 2017).

Fintech's benefits include a cost economy, increased efficiency, greater transparency, increased consumer satisfaction, improvement of infrastructure components, and easier access to the financial system. Additionally, Fintech may have negative consequences related to cyber security, for example, and it requires the creation of an appropriate legislative framework (Hasan 2023; Moosa 2022). To increase the competitiveness of the EU's financial sector, in September 2020, the European Commission adopted a document that includes a legislative and financial strategy to ensure that European citizens have access to innovative financial products, as well as financial protection and stability, based on the premise that digital financial services contribute to the modernisation of the European economy and will transform it "into a global digital player" (European Commission 2023). Specialists have raised the problem of consumers' understanding of increasingly complex financial concepts that may exceed their capacity, which is why the social side must be considered in the regulation of these services to make them more useful and socially sustainable (Johnson et al. 2021). BNPL payment methods represent "FinTech credit products", whereby consumers can defer payment on purchases made through an interest-free instalment scheme. The use of this system via credit cards is more often used by young consumers and those located in more economically deprived areas (Guttman-Kenney et al. 2023).

The aim of the study is to elaborate a line of thought about buy now pay later payment methods and to gather information to answer three research questions. Due to complexity of the workflow applied to perform the study in the first place, the authors introduce a graphical representation of the researched path (Figure 1).

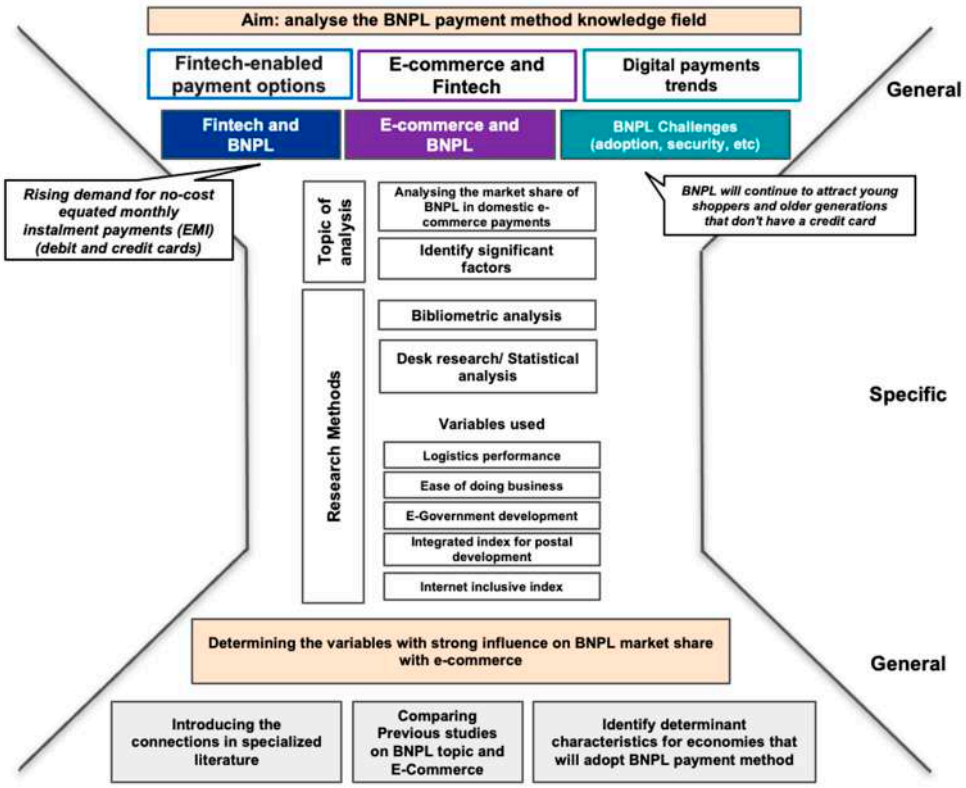


Figure 1. The workflow of the study.

The workflow follows a logical line by aiming to respond to three research questions. (1) How has the BNPL concept been presented in the literature? (2) What influences the market share of BNPL in domestic e-commerce payments? and (3) Who will adopt BNPL payment methods in the future? By attempting to discover the arguments for each research questions, four objectives were formulated. The authors intended to (O1) describe the core significance of BNPL payment methods in science, (O2) identify the major areas and related topics in the specialised literature, (O3) find significant variables to explain the market share of BNPL in domestic e-commerce payments, and (O4) discover determinant characteristics of economies that will adopt BNPL payment methods in the future.

Outstanding results were identified, including that inclusive internet indices or e-government development are not significant factors for BNPL payment method adoption.

All the outcomes are logically presented in the following sections. The paper starts with a literature review, which introduces the context and the knowledge field to which the BNPL concept belongs. Therefore, the methodology shows all the methods applied to obtain the results illustrated in the third section. The paper continues with discussions in the fourth part and ends with conclusions that highlight the scientific contributions, theoretical and managerial implications, and limitations of the study.

2. Literature Review

2.1. E-Commerce and BNPL

The e-commerce environment has expanded over the last decade, as users are able to access the internet through an increasing number of devices (Chung et al. 2018; Gañac 2018; Ono et al. 2012). Because of the increased ownership, usage, and portability of devices (Gañac 2018), people are spending more time online; consequently, e-commerce and mobile-commerce retail platforms have developed and become available to consumers (Park and Hill 2018). Since online shopping was normalised in most markets (Park et al. 2012), the perception of reliability and trust on the retail websites has highly increased (Clemons et al. 2016). More resources than ever have been directed towards making online retail channels evermore functional to compete with, complement, or at times replace entirely the physical store (Thaichon et al. 2018). Speed, accessibility, and ease of browsing have made e-commerce a norm rather than an exception (Gañac 2018; Ono et al. 2012; Park and Hill 2018; Park et al. 2012). When discussing e-commerce, there are some trends manifesting (Aite Novarica 2021; Bolu 2021; Di Maggio et al. 2022; McKinsey & Company 2020, 2021; Money & Pension Services 2023):

- BNPL is embedded in the shopping journey and is promoted across the payment journey right from the product pages, not only at checkout;
- Consumers are starting their shopping journey at BNPL provider apps/websites;
- Leading players have developed strong consumer brands and apps, driving incremental sales through affiliate marketing channels;
- Leading BNPL players aspire to build "super apps" that offer shopping, payments, financing, and banking products in a single platform; BNPL is becoming more available for a wider range of purchases, including everyday purchases;
- Most of BNPL users are younger than 40 years old, but increased demand is noted for all user groups;
- Notably, repayment reminders offered by certain BNPL providers have garnered remarkable support among users;
- The surge in BNPL adoption can be attributed to three essential factors: awareness, accessibility, and affordability;
- Implementing appropriate regulations and employing awareness about behavioural impulses have shown promise in promoting responsible credit management;
- However, it is essential to acknowledge that BNPL products' lack of understanding and the limited transparency in individuals' credit profiles may potentially jeopardise their financial wellbeing, with broader implications for the economy overall.

The market has already widely adopted BNPL, and Millennial and Generation Z consumers are more willing to utilise buy now pay later services to help manage the growing costs of goods, according to a new survey from Trustpilot (Trustpilot 2022). According to studies from 2021 and 2022 (Backman 2022; CUToday 2021), 62% of BNPL users (of whom 62% are between 18 and 24 years old) think it could replace their credit cards; 53% of consumers who have never used BNPL say they are at least somewhat likely to use it within the next year; 48% of BNPL users say they used it for electronics purchases—the largest usage of any industry represented; 50% more consumers say they understand BNPL compared to last year; and 48% more consumers used a BNPL service this year compared to the previous year.

Moreover, building on the e-commerce momentum from the Covid-19 pandemic, the BNPL model is one of the fastest-growing segments in consumer finance. Considering the impact of inflation and weaker consumer spending on company valuations post-pandemic, the growth potential of BNPL is likely to help it weather economic headwinds (Perlin 2021). This new trend on e-commerce sites in increasing in popularity since credit cards are declining in popularity. Millennials and Generation Z avoid credit cards and embrace e-commerce, and the BNPL market is expected to grow exponentially, keeping up with what is popular and what will earn the most sales. BNPL can stimulate e-commerce demand because it reduces customers' cash flow pressure, making it easier for potential customers who cannot afford what they want.

Aside from providing customers with the opportunity to obtain digital products sooner, using BNPL—a simple financing option—can enhance the trustworthiness of online brands, especially for young generations. According to the same survey (Backman 2022), 41% of younger generations said that it is probable they will use BNPL services for household purchases.

When discussing benefits, e-commerce may benefit from the use of BNPL services, as the conversion rate increases on average by 20–30% according to statistics (CUToday 2021; Perlin 2021). Moreover, 60% of online shoppers have already used BNPL at least once in the past year; thus, e-shops may benefit from the use of BNPL because of the reduction in the abandoned shopping carts.

BNPL thus has increased cart value, the conversion rates, and the purchase frequency, and it demonstrates a great customer experience, reduces abandoned conversion rates, increases the trustworthiness of e-shops, and offers customers more purchasing power.

BNPL enables more online shoppers to complete purchases that they perhaps could not have completed otherwise. A recent study (Backman 2022) confirmed this theory by finding that 45% of BNPL users opt for this solution to buy items that do not fit their budget. Thus, the more visitors that an online shop attracts to its site, the higher that the chance is of converting them into paying customers.

E-commerce may benefit from the use of BNPL services, as the conversion rate increases on average by 20–30%, according to statistics (CUToday 2021; Perlin 2021). If a buyer has been dissuaded from purchasing because the merchant did not offer a payment method, offering multiple payment methods, including a BNPL option, will reduce the probability of this event. Moreover, customers are more likely to purchase even sooner if they feel comfortable with their ability to pay, thus avoiding the possibility of them changing their minds, forgetting about the basket, or finding similar products from competition.

Moreover, 60% of online shoppers have already used BNPL at least once in the past year; thus, e-shops may benefit from the use of BNPL because of the reduction in abandoned shopping carts. BNPL helps with the object of providing multiple methods to pay when a product in the cart is too expensive, giving purchasers the chance to pay rates that are more affordable over time.

2.2. Millennials, Generation Z and Market Growth

If we refer to Millennials and Generation Z, they use online shopping and other channels for a holistic experience; buy more expensive, better-quality products or preowned

products—since they desire brands with the mission of doing good for society; and make small purchases more often (Marketing Evolution 2019; McKinsey & Company 2020; The KEENFOLKS 2023; Trustpilot 2018; Vogue Business 2021). By adopting new payment methods such as BNPL, both online and in store, adapting to new shopping habits means adjusting to different needs and different expectations, such as those of Generation Z. Additionally, BNPL responds to the needs of Millennials and Generation Z for transparency and authenticity since there are no hidden costs; thus, they are more likely not only to buy but also to become loyal in the long run.

Unhealthy financial habits, lack of trust in financial institutions, and historical financial inequities currently inhibit mass adoption and expansion of BNPL: "The existing design of BNPL offerings may not be sustainable." BNPL's welfare effects are unclear. People less informed about how to use this technique are predisposed to make naive mistakes that can damage both their financial state and their state of mind (Guttman-Kenney et al. 2023).

In 2022, 40% of customers using BNPL options fell behind on payments, and 68% of BNPL customers admitted that they overspend when using this tool.

BNPL companies claim that they are more responsible than credit cards because they are more inclusive, have fairer loan terms, and offer a convenient option for responsible consumers who pay back their debts on time (Aalders 2023).

A target market that BNPL companies are watching with increasing interest is the younger consumer segment, who although more financially unstable is at the same time more open to digital credit services (Coffey et al. 2023). These customers are interested in using BNPL options to keep up with fashion (fashion mavens) or to finance their social activities and hobbies (social recreationists). However, there are also people in older age groups who use BNPL for essential needs (conscious families) or even older people looking for bargains (hill chasers). A customer-first BNPL experience can be created by focusing on financial wellness, trust, and inclusion, delivered to the customer through an innovative BNPL portfolio and a holistic service experience.

Many customers are ready to expand the purchases that they make with BNPL. Studies have revealed that 42% are interested in using BNPL for future medium-sized purchases—37% for large purchases (Deloitte Digital 2023). Online sellers increase their sales, and customers gain more control over their budgets and purchases. In June 2022, the US corporation Apple announced that it will enter BNPL market, dominated by start-ups such as Sweden's Klarna and the US-based Affirm. That same month, PayPal announced its own BNPL service, Pay Monthly (Oxford Business Group 2022).

In 2019, the $60B BNPL market represented 2.6% of global e-commerce (excluding China); Worldpay estimates that it could grow at a compound average growth rate of 28% to reach $166B by 2023, and digital wallets, the next most popular e-commerce type, are expected to grow at a compound average growth rate of 18% according to Consumer Banker (Consumer Banker Association 2022).

Last year, BNPL accounted for $2 out of every $100 spent in e-commerce, according to Global Data (GlobalData 2022). With a global market value of $125B in 2021, the segment is projected to exhibit a compound annual growth rate of 24.9% and reach $3.9T by 2030. In emerging markets, the share of adults making or receiving digital payments rose from 35% in 2014 to 57% in 2021, according to the World Bank (The World Bank 2022). According to Statista, at the global level, the BNPL market grew from 0.4% in 2014 to 5% in 2022 from domestic e-commerce. The most important increase was in Germany (from 3% in 2014 to 23% in 2022), and the smallest was in Canada, adopting BNPL only in 2021 (Statista 2023a).

Discussing the growth of the market, according to a report (Research and Markets 2023) the global buy now pay later market size is expected to reach $39.41B by 2030, registering an increase in the compound annual growth rate of 26.1% from 2022 to 2030. This growth is an effect of higher purchasing power determined by BNPL platforms and their perceived benefits, namely interest-free and convenient payments. Additionally, the increasing demand for delayed payments determined by online shopping and a surge in

spending on high-cost products determine will also be lucrative growth opportunities for the market by 2030.

By 2022, according to the same report, North America dominated the market with the highest share of around 29.0% of global revenue due to many BNPL players and a large number of fintech companies entering into partnerships with entertainment companies to offer BNPL services for booking hotels.

When discussing retail segment, it is the one that dominated the market in 2022 with more than 73.0% of the global revenue since the industry is characterised by increased adoption of BNPL solutions.

Additionally, the consumer electronics segment will register CAGR growth over the 2022–2030 period because the industry is witnessing increasing adoption of BNPL payment methods. Customers prefer BNPL payment methods to credit cards to avoid expensive interest and hidden fees. The report also stated that increasing awareness among consumer electronics providers about BNPL will determine the growth of demand for these services between 2022 and 2030.

In this context, the authors intended to analyse the market share in domestic e-commerce payments as a dependent variable. The argument for selecting this indicator is represented by rising adoption as a "key innovation in consumer finance in recent years" (Berg et al. 2023). The reasons for choosing logistic performance, ease of doing business, e-government development, postal development, and internet inclusivity and linking them to the market share of BNPL in domestic e-commerce payments, hereinafter MSDEP (%), determined the aim of creating a link with some inherent performance indicators related to the activity of developing electronic commerce.

The role of logistics performance in e-commerce is crucial due to the increase in B2C order volumes, with the literature presenting various opportunities, such as service outsourcing, to reach high levels and gain the capacity to deliver products quickly and cost-effectively (Pua 2023). The actual context presents challenges related to delivery guarantees (which are more indispensable for large companies than for small businesses) (Yang et al. 2023), product returns, and customer satisfaction (Saravanan et al. 2023). Representing an extremely important branch for the development of electronic commerce based on the adoption of the BNPL payment method, the authors hypothesise that:

H_1. *Logistics performance positively influences the market share of BNPL in domestic e-commerce payments.*

The ease of doing business is promoted and strongly related to digital business (Gupta 2022; Saidu et al. 2022), especially for the Fintech industry, for which the literature shows that using such instruments can ease e-commerce suppliers' capital (Park and Ryu 2023). The hypothesis related to this indicator is:

H_2. *Ease of doing business positively influences the market share of BNPL in domestic e-commerce payments.*

Regarding e-government development, it can be said that it represents a sustainable development method, especially for electronic commerce (MacLean and Titah 2022; Theocharis and Tsihrintzis 2023). E-government, information, and communication technology contribute to the development of e-commerce (Kastratović and Bjelić 2022), which is the why the authors expect the following:

H_3. *E-government development positively influences the market share of BNPL in domestic e-commerce payments.*

The postal service "is an indispensable part of electronic commerce" (Goyal and Morgan 2023), and its reliability plays a crucial role in development. It is expected that:

H_4. *Postal development positively influences the market share of BNPL domestic e-commerce payments.*

After all, internet inclusion plays an important role, representing the criteria for benchmarking adoption of e-commerce (Goyal and Morgan 2023). Reflecting on its connection with the BNPL method, the authors hypothesised:

H_5. *Internet inclusion positively influences the market share of BNPL domestic e-commerce payments.*

3. Methodology

The market size of BNPL is growing due to online payments that are rapidly growing (Bian et al. 2023), but a question may be raised regarding how ready e-commerce is to cover the demand. Attempting to identify some solutions and opportunities for companies and policy makers regarding this emergent technology, the authors addressed a mixed-method scenario. First, with high interest in understanding the status and context of the BNPL concept within the specialised literature, a bibliometric analysis was performed (Allen et al. 2009; Dhamija and Bag 2020). Second, the authors found and analysed secondary data about the market share of BNPL in domestic e-commerce payments (Statista 2023a) to describe the status of the phenomenon's spread. The findings are summarised within descriptive statistics analysis section. Finally, desk research (Borowski and Karlikowska 2023; Rahman et al. 2014; Yang 2023) was used to identify significant factors to explain whether the world is ready to buy now and pay later for products using the internet.

3.1. Bibliometric Analysis

In the first stage, the authors intended to place the BNPL concept in the literature using bibliometric analysis. As a scientific computer-assisted review method (Lazarides et al. 2023), it helped to identify the core significance of BNPL in science, also creating connections with other topics. Using specialised software, CiteSpace (2003), the authors attempted to find major areas related to BNPL and to connect the papers published on this topic by title, keyword, and abstract term nodes. By applying the clustering process, the authors labelled the major areas and interpreted the betweenness centrality score to explain how the major areas are linked. The validation of the network that they created was realised by interpreting the overall structural properties with modularity Q and mean silhouette indicators.

3.2. Empirical Model

Attempting to decode the information presented in the market growth sub-section from the literature review, the researchers selected BNPL market share in domestic e-commerce payments for 23 countries worldwide from Asia, Europe, the Middle East, North America, and South America from 2019 to 2022 to perform a descriptive statistical analysis. The countries were selected based on the public data available from Statista 2022, so secondary data were used. The year 2022 was considered because, for this year, the majority of the countries presented published data. The analysis provided basic information about BNPL concepts, and calculated and logically presented useful data about the variables. To present the information obtained, graphical and pictorial methods were used, created with Cognos IBM software (IBM 2023). Therefore, the set of simple linear regressions allowed the authors to analyse the influence of some potential influential factors on BNPL market share carefully and separately regarding domestic e-commerce payments. By addressing sustainable development goals, five endogenous factors were selected to explain the dependent variable (Retailx 2021).

Logistics Performance Index (LPI) (The World Bank 2023a) is a tool presented by the World Bank as an interactive benchmark for countries to analyse and optimise their logistics

performance. The indicator was used as the rank for each country included in the analysis to explain MSDEP with a simple linear regression equation:

$$MSDEP_i = \beta_0 + \beta_1 LP_i + \varepsilon_i \quad (1)$$

where

- $MSDEP_i$ represents the market share of BNPL in domestic e-commerce payments of country i; and
- LP_i represents the logistics performance index of country i. The connection between market share and logistics performance is highly sustained by the literature, with some recent studies presenting the market share and e-commerce platform development from the perspective of logistics performance (Florido-Benítez 2023; Prajapati et al. 2023; Zhou et al. 2023). These facts led the authors to formulate the first hypothesis of the study, namely (H_1), to identify whether LPI influences MSDEP.

1. **Ease of doing business (EDB)** (The World Bank 2023b) is the indicator published by the World Bank, and it measures business regulations across world economies. The lower that the score is (the rank), the easier that it is to do business in a certain economy. Recent studies (Alaeddine 2023; Costantiello and Leogrande 2023; Gizaw et al. 2023) have used this indicator, and the authors intended to determine whether it might be a significant factor explaining MSDEP, which led to the second hypothesis (H_2). For this purpose, they formulated the equation:

$$MSDEP_i = \beta_0 + \beta_1 EDB_i + \varepsilon_i \quad (2)$$

where

- $MSDEP_i$ represents the market share of BNPL in domestic e-commerce payments of country i; and
- EDB_i represents the ease of doing business indicator of country i;

2. **E-Government Development Index (eGD)** (United Nation 2023) is a value based on three dimensions, namely an online services index, a telecommunication infrastructure index, and a human capital index. The online service index shows the extent to which the government can provide online communication and support services to citizens. The telecommunication infrastructure index is the score that shows the capacity of a country in terms of ICT infrastructure. Finally, the human capital index represents the inherent human capital. As a methodology, it represents the weighted average of normalised scores of the three previously mentioned variables, and it is calculated as:

$$eGD = \frac{1}{3}(OSI_{normalized} + TII_{normalized} + HCI_{normalized}) \quad (3)$$

For this study, the authors used the ranks of the countries involved in the analysis as explanatory variables for MSDEP with simple linear regression:

$$MSDEP_i = \beta_0 + \beta_1 eGD_i + \varepsilon_i \quad (4)$$

where

- $MSDEP_i$ represents the market share of BNPL in domestic e-commerce payments of country i; and
- eGD_i represents the e-government development index of country i;

The researchers expected to discover whether the eGD influences the MSDEP to a certain extent, presented as the third hypothesis (H_3).

3. **UPU'S Integrated Index for Postal Development (2IPD)** (Universal Postal Union 2023) is a metric that uses postal big data to highlight postal development around the world. Its rank is given depending on four dimensions: reliability, reach, relevance,

and resilience. It is very important for e-commerce development and useful for policy makers, regulators, and operators. Additionally, the scientific world has presented some papers addressing postal development as crucial factor (Kenyon et al. 2005; Mokgohloa et al. 2019). The authors hypothesised that postal development is a significant factor for the market share of BNPL in domestic e-commerce payments (H_4).

$$MSDEP_i = \beta_0 + \beta_1 2IPD_i + \varepsilon_i \quad (5)$$

where

- $MSDEP_i$ represents the market share of BNPL in domestic e-commerce payments of country i; and
- $2IPD_i$ represents UPU's integrated index for postal development of country i;

4. **Internet Inclusive Index (III)** (Economist Impact 2022) is a rank created based on scores for four categories: availability, affordability, relevance, and readiness. It was commissioned by Facebook and developed by the Economist Unit, and its aim is to enable outcomes for social and economic development. Hence, the authors used this indicator as an explanatory variable for MSDEP to determine whether the rank of the country for its perspective influences the market share of BNPL in domestic e-commerce payments for that country (H_5).

$$MSDEP_i = \beta_0 + \beta_1 2III_i + \varepsilon_i \quad (6)$$

where

- $MSDEP_i$ represents the market share of BNPL in domestic e-commerce payments of country i; and
- III_i represents the internet inclusive index of country i;

4. Results

By performing bibliometric analysis, the clustering process showed 23 underlying themes related to BNPL line research. The most important of them are illustrated in Figure 2.

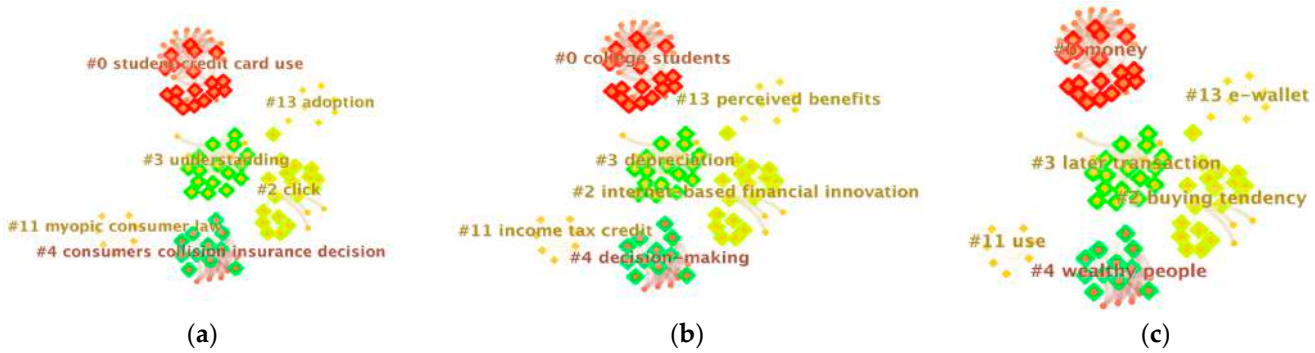
Figure 2. Results of clustering process. Source: created by authors with Citespace software.

The image shows that "credit cards", "behaviour", "market", and "college students" are relevant topics related to BNPL. Details of the top six largest clusters are available in Table 1. The column in which the year is shown highlights that cluster #11 has the most recent paper category with related concerns. After cluster label generation by title, keyword, and abstract term, a comparison was possible. It is shown in Figure 3.

Table 1. Details about generated clusters.

Cluster ID	Size	Silhouette Mean	Year	Label (LSI)
0	31	0.714	2014	Credit card use; college students; hyperbolic discounting; experimental study
2	21	0.913	2016	Cross-border e-commerce; platform competition; internet-based financial innovation; conversion tools; consumer credit; impulse buying tendencies; conversion tools; consumer credit; cross-border e-commerce; platform competition
3	20	0.826	2013	Deferred payments; consumer decisions; mental accounting; dark financial triangles; consumer decisions
4	16	0.881	2009	Risk aversion; mental accounting; dark financial triangles; mental accounting
11	7	1	2020	Income tax credits; behavioural economics
13	7	0.967	2019	Adoption of e-wallets; perceived ease of use; perceived usefulness; perceived security; perceived benefits

Source: created by authors based on Citespace outputs.



(**a**) (**b**) (**c**)

Figure 3. The cluster labels of the network. Extracted noun phrases from: (**a**) titles; (**b**) keywords; and (**c**) abstract terms.

By analysing the comparative image, it can be shown that different topics are highlighted according to titles, keywords, or abstract terms. Depending on titles, "student credit card use" represents the largest cluster, while "college students" was the largest cluster by keywords. According to abstract terms, "money" is the label with the largest cluster.

The main objective of using bibliometric analysis was to find an answer for the question "*What are the major areas?*", and the result is pictured in Figure 4.

The largest cluster is #college student, which here indicates the largest number of member references. The clusters #0, #2, #3, and #4 highlight the general overview of BNPL concepts during 2000 and 2023. Additionally, the authors found an answer for the question "*How are these areas connected?*". Using the betweenness centrality score [0, 1], they created the network with nodes that show this fact (Figure 5). A node with high betweenness centrality connects two or more large groups of nodes with the node itself (square shape).

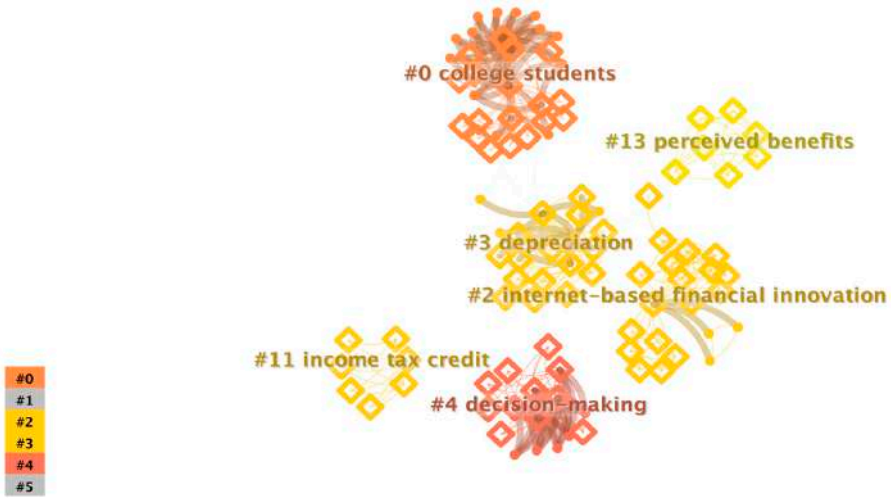


Figure 4. The major areas of the network. Source: created by authors with Citespace software.

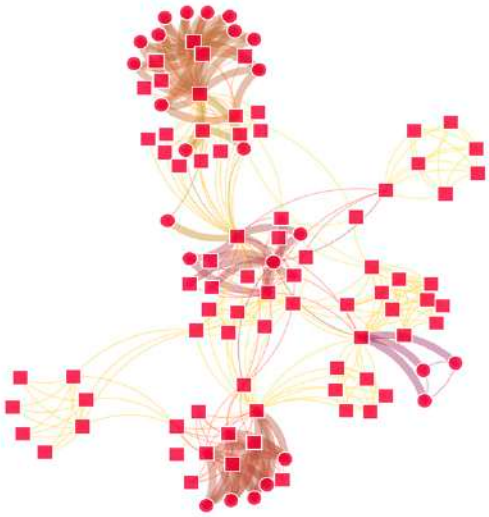


Figure 5. Major areas interconnected. Source: created by authors with Citespace software.

BNPL Descriptive Statistics and Regression Analysis

Figure 6 shows the market share of BNPL in domestic e-commerce payments registered in 2022 for several countries around the world, especially Germany and Australia.

The average of market share shows that, in Europe and Asia, the BNPL method has high potential (Figure 7), which can be analysed in the context of e-commerce development, showing high rates. Conversely, there are countries around the world that have not registered movements in terms of market share of this type of payment method (economies such as Peru, Brazil, Argentina, Turkey, and South Korea). Hence, major differences between countries are shown. More descriptive statistics are shown in Table 2.

The empirical model completes the analysis by covering the global context, with country analysis using exogeneous factors and the structures of the scores, pictured in Figure 8 with stacked columns (aggregate scores for each country with the aim of presenting the rankings according to all five indicators). The bars illustrate the aggregate score, which compounds the ranks of the economies involved in the study for the explanatory variables. The different colours represent the ranks of each exogeneous factor. For example, the best-performing economies (USA, UK, and Australia) are shown, but Japan presents better performance in terms of logistics that influence the market share.

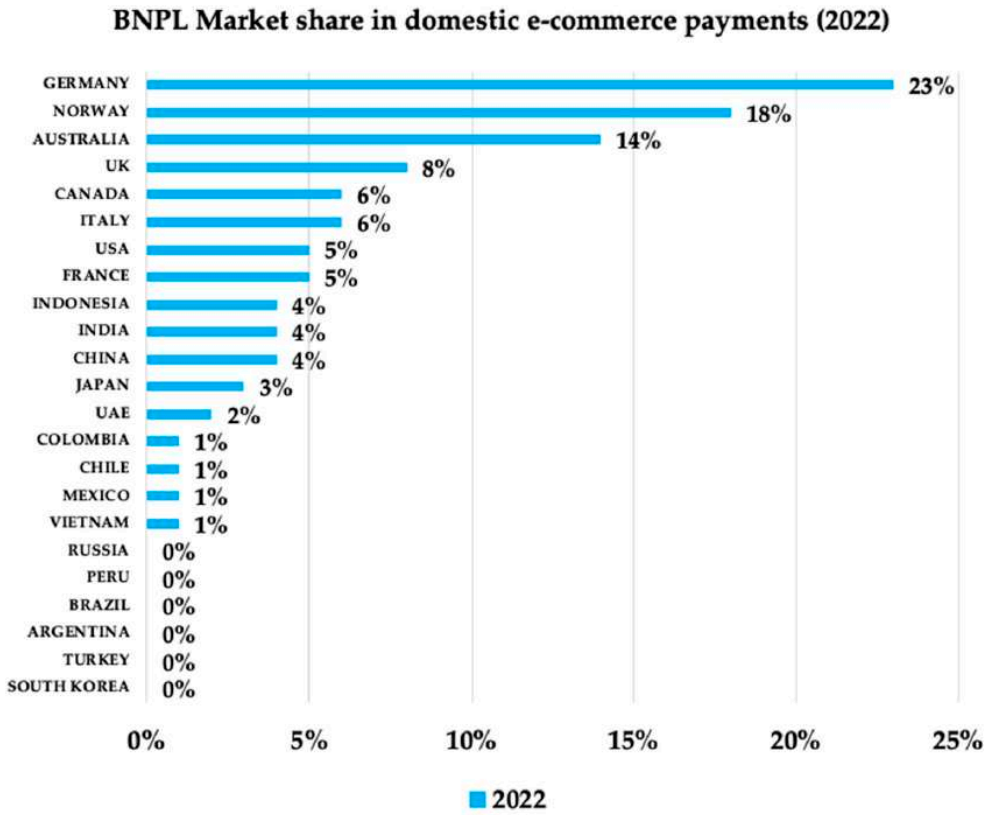


Figure 6. Comparison of BNPL market share in domestic e-commerce payments (2021 vs. 2022). Source: created by authors based on secondary data (Statista 2023b).

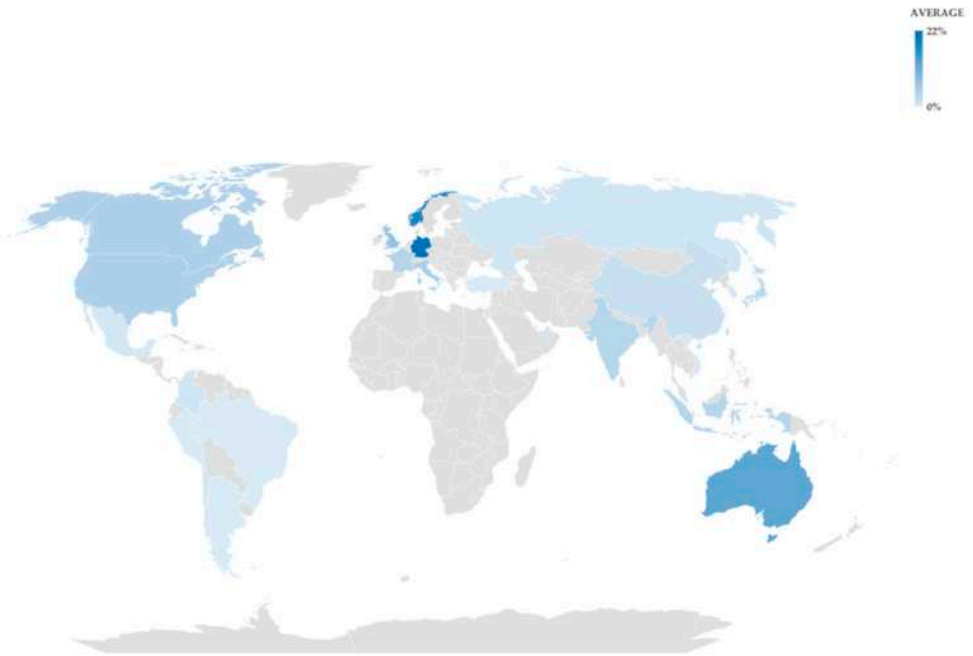


Figure 7. BNPL average market share in domestic e-commerce payments worldwide (2022). Source: created by authors based on secondary data (Statista 2023b).

Table 2. Descriptive statistics about MSDEP.

Descriptive Statistics	MSDEP	LPI	EDB	eGD	2IPD	III
Mean	0.033	33.870	44.870	39.435	37.391	31.5
Standard Error	0.009	4.746	7.199	5.957	6.009	4.285
Median	0.018	26	32	34	34	30.5
Mode	0	N/A	N/A	N/A	N/A	25
Standard Deviation	0.044	22.760	34.526	28.567	28.817	20.099
Sample Variance	0.002	518.028	1192.028	816.075	830.431	403.976
Kurtosis	5.514	−0.581	0.563	−0.570	−1.267	−1.258
Skewness	2.247	0.547	0.984	0.631	0.418	0.132
Range	0.180	82	121	98	88	64
Minimum	0	1	5	2	3	2
Maximum	0.180	83	126	100	91	66

Source: created by authors based on secondary data.

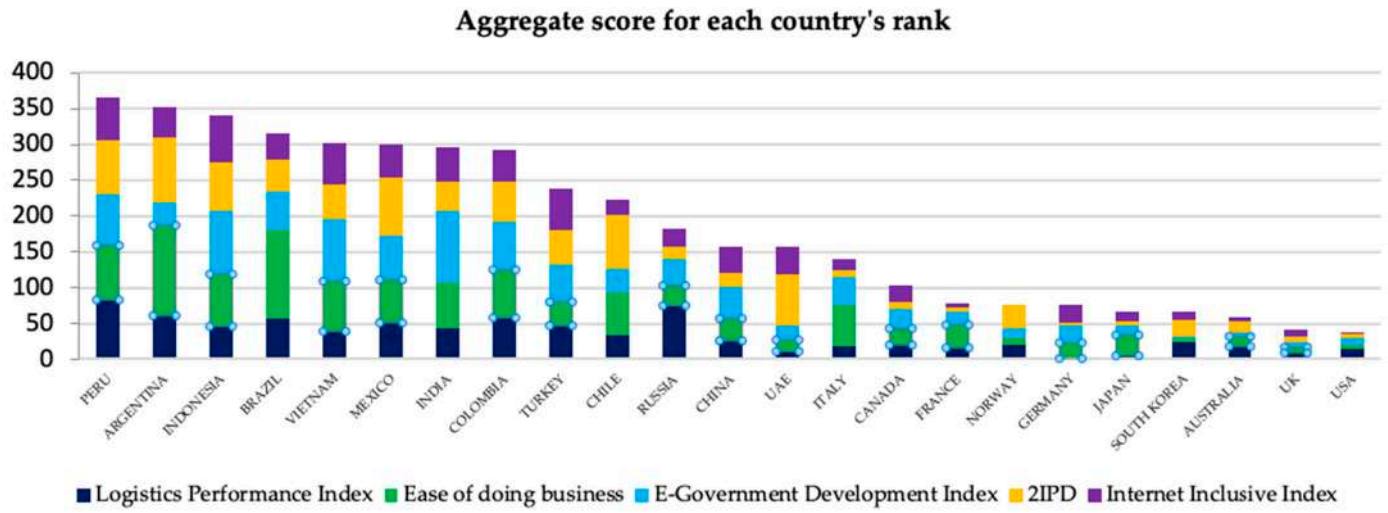


Figure 8. The structure of ranking by LPI, EDB, eGD, 2IPD, and III, (2022). Source: created by authors based on the secondary data (Economist Impact 2022; The World Bank 2023a, 2023b; United Nation 2023; Universal Postal Union 2023).

The empirical model analysis generated results regarding logistic performance index, ease of doing business, UPU's integrated index for postal development, and internet inclusive index that are significant variables, impacting the market share of BNPL in domestic e-commerce payments (Table A1). An unexpected result was found regarding the LPI (which moderately drives MSDEP). MSDEP is unusually high when LPI is 67 or greater, indicating that countries that present high ranks of LPI show a high market share of BNPL in e-commerce domestic payments. High scores of LPI do not highlight efficient and highest-ranked countries in terms of logistics performance, so in a paradoxical manner, these countries have a higher market share of BNPL in domestic e-commerce payments even though they do not perform as well in terms of logistics. LPI of 18 to <34 has the lowest average MSDEP at 1%, followed by the LPI group of 51 to <67 at 2%. This finding means that countries that perform better than the previous group have a lower BNPL market share.

Even in the case of the EDB variable, the facts are not as the authors expected. The highest average of MSDEP (at 9%) is given by the scores from 30 to <42, followed in second place by the group from 18 to <30 (6%). However, the highest frequency that appears for

this variable is for the less than 18 group (26.1%), which balances the results. Another anomaly is also found in the case of performance regarding the 2IPD variable because the group from 39 to <56 has the highest average of MSDEP at 7%, followed by 74 and above at 5%, once again emphasising that a large market share of BNPL in domestic e-commerce payments does not depend on the country's performance regarding 2IPD.

Additionally, the authors introduced Table 3, the correlation matrix (based on Pearson's coefficients used to identify patterns) to better visualise the relationship between indicators.

Table 3. Correlation matrix.

	MSDEP	LPI	EDB	eGD	2IPD	III
MSDEP	1					
LPI	−0.549 *	1				
EDB	−0.448 *	0.659 *	1			
eGD	−0.378	0.627 *	0.621 *	1		
2IPD	−0.464 *	0.64 *	0.643 *	0.524 *	1	
III	−0.387 *	0.641 *	0.57 *	0.859 *	0.715 *	1

Source: created by authors based on secondary data using Pearson's function. * Significant for 1%, 5%, or 0.1%.

Based on this table, one of the most important result of the study can be observed. Whereas all hypotheses are stated for positive influence, the correlation matrix showed negative values, leading to the refutation of all hypotheses.

5. Discussion

The dilemma that this article puts at the centre of the authors' concerns is finding an answer to the question "*Is the world ready to buy now and pay later?*" from an e-commerce perspective. Thus, the purpose of the research was to identify the factors that determine the market share of BNPL among domestic electronic commerce payments. Using data available for economies worldwide, the authors compared the ranks and obtained relevant outcomes for the knowledge field. For a better visualisation of what they have discovered, Figure 9 is provided.

Starting from the first objective (O1), namely describing the core significance of BNPL payment methods scientifically, it was found that the concept is described in the literature by popular factors, such as internet-based financial innovation, depreciation, and decision making. However, the results of the bibliometric analysis carried out in the first stage of the study reveal that core significance is not described as much from the point of view of electronic commerce, a result that further strengthens the results obtained by addressing the empirical model.

The second objective (O2) was achieved and presented "student card credit", "myopic consumer law", "decision making", "later transaction", "e-wallet", "buying tendency", and "insurance decision" as topics related to BNPL, enriching the outcomes of the study because they will be linked with the model results. In this context, the related topics that were found as results of the bibliometric analysis show a high risk in terms of perceived benefits (Gerrans et al. 2022; Relja et al. 2023). A young person who needs and wishes to buy as soon as possible a product available on e-commerce platforms but does not have the money to buy it, can access BNPL payment methods, and all the risks related to the found terms can occur. The outcome of the study confirms the concern of specialists regarding the distorted behaviour that BNPL is consolidating (Soni 2023), especially among Millennials (Arisandy et al. 2023; Min and Cheng 2023).

Therefore, by identifying the logistics performance index, ease of doing business, 2IPD, and internet inclusive index as determinant factors, the third objective (O3) was achieved. Thus, the results of the study support Gupta (2022) and Saidu et al. (2022), who promoted the ease of doing business as being strongly related to digital business, and Goyal and

Morgan (2023), who stated that the reliability of postal development is indispensable for e-commerce.

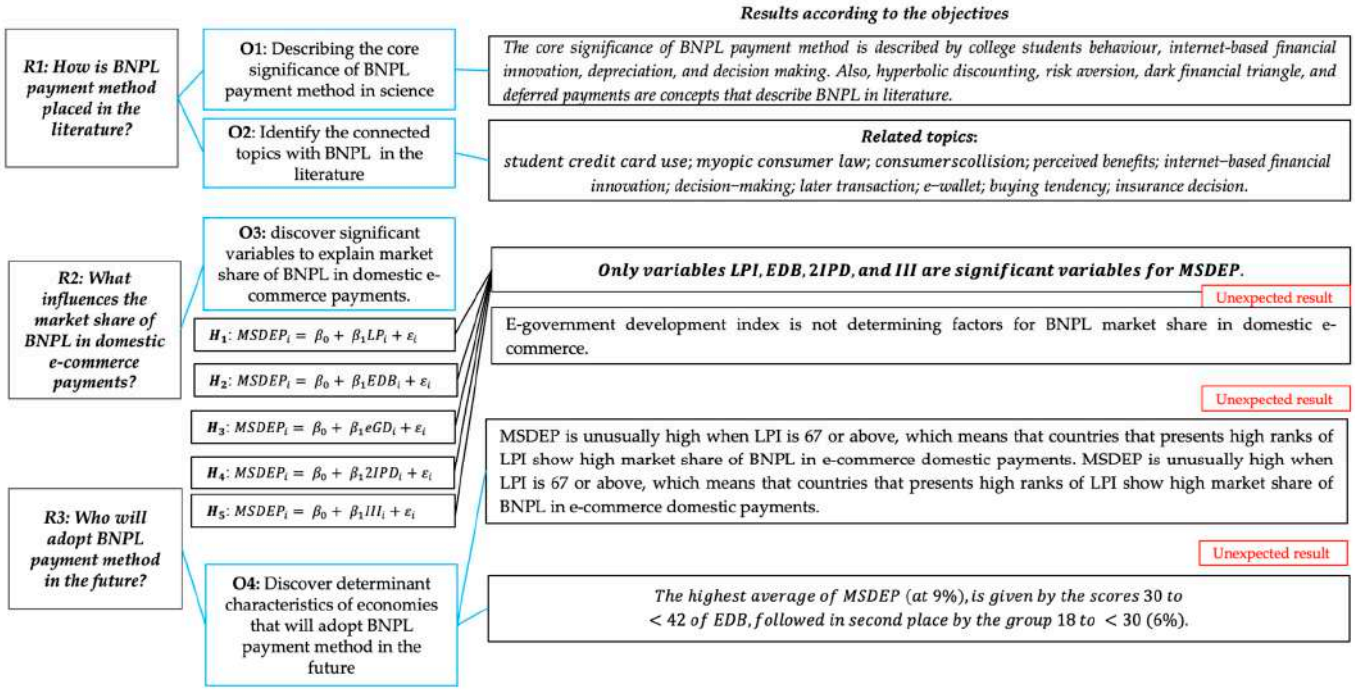


Figure 9. Results of the study according to research questions and objectives. Source: created by authors.

The fourth objective was achieved by discovering the determinant characteristics of economies that will adopt BNPL payment methods in the future. Compared to previous studies or published statistics, the paper responds to an important question: *Who will adopt BNPL payment methods?* In fact, a better and suitable question might be *"In which quartiles does an economy have to fit as a country depending on the factor to be prepared for BNPL?"* According to researchers, economies with a medium rank of ease of doing business present a large market share of this kind of payment method, and they are inclined to adopt it easily. This finding could lead to discussions that might affect the integrity of entrepreneurs when it comes to actions that they must undertake to run their businesses to resist that market. Moreover, the uncertainty that gravitates around BNPL payment method (Statista 2023b) might be linked to political instability and policymaker corruption (Albritton 2019). Additionally, this study comes with a macro-perspective on the economies predisposed to adopt this payment method more quickly or more easily, although they are not prepared in terms of inclusive internet performance or e-government development. Even in terms of postal development, it can be said that a large market share of BNPL in domestic e-commerce payments does not depend on the country's performance regarding 2IPD, indicating that economies with smaller market shares present better performance. This fact is interesting in the actual context. The accelerated development of technologies and applications (such as the Revolut) further deepen the gap between balanced economies from this point of view and those that currently experience increases in BNPL's market share of domestic e-commerce payments, especially since artificial intelligence is becoming an increasing part of everyday activities.

6. Conclusions

The scientific contribution of the study is that it enriches the specialised literature with a macro-perspective at an international level regarding the phenomenon of adopting the BNPL payment method. Additionally, the paper presents a perspective on the situation in

which economies are prepared or not to adopt BNPL as a payment method for domestic e-commerce.

Logistics development, ease of doing business, and e- and postal development are presented as aspects to be addressed with increased priority in countries where MSDEP grows annually and where consumers are becoming increasingly vulnerable. Additionally, increased attention be mentioned from policymakers regarding postal development, in which the market share of BNPL in domestic e-commerce payments is large. As the literature and this study demonstrated, this indicator might represent the key element for the sustainability and future development of e-commerce. Nor should topics popular in the specialised literature be neglected. Hence, major implications, both managerial and academic, must be addressed.

Managerial implications are complicated to address because, while BNPL can increase sales, the assumption of risk by companies or tech giants, which with the help of applications can accelerate the adoption process of this type of payment, is very important. The entities that might be involved should ensure transparency and responsible practices to sell products using this method. Additionally, companies can educate and protect consumers and monitor the behaviour of some groups considered more vulnerable, especially Millennials. A high responsibility should be borne by industry associations, which must run information campaigns and provide data to authorities and responsible institutions.

From the point of view of theoretical implications, studying the BNPL concept and its outcomes might deepen understanding of consumer behaviours, decision-making processes, risk perception mitigation, debt behaviours, and credit adoption.

A first limitation of the study is the lack of customisation of the manner in which the research was performed. Therefore, secondary data do not allow for the production of raw data for analysis, and potential bias might have occurred. Even if this type of research in general cannot be perfectly aligned with the objectives of the study, the authors intended to formulate objectives achievable with secondary data analysis. Because of the nature of the data source, the manner of choosing only five indicators, there being only 23 countries for which there existed data, and the analysis being limited only to the timespan between 2019 and 2022, other limitations of the study occurred. However, given the preliminary nature of research, this limitation can be overcome if the study continues, with its findings contributing to methodology improvement. Additionally, that the authors collected the data from different sources or references determined that they were less reliable than collecting them from a single source. This fact represents another limitation of the study, but despite these limitations, the researchers state that the outcome of the study is a valuable resource for creating further research lines and could provide reliable perspectives on how BNPL might evolve.

Further research might pursue psychological analysis to decode consumer decision-making and buying behaviours in the context of myopic consumer law or dark financial triangles. Additionally, qualitative research could be conducted to create solutions for BNPL digital tools to increase transparency and financial education.

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Appendix A

Table A1. Linear regression results.

Dependent Variable	Independent Variables	β_0	β_1	Multiple R	R^2
MSDEP	LPI	0.088	−0.001	0.549 **	0.30 ***
	EDB	0.074	−0.0007	0.448 *	0.2
	eGD	0.07	−0.0007	0.378	0.14
	2IPD	0.075	−0.0009	0.464 *	0.21
	III	0.08	−0.001	0.387 *	0.22

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

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Factors Influencing the Behavioural Intention to Use AI-Generated Images in Business:
A UTAUT2 Perspective With Moderators

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ABSTRACT

Motivated by the need to better understand the ongoing role of artificial intelligence in businesses and to shift the focus from a purely technological and algorithmic perspective to one that encompasses human-computer interaction, this article aims to investigate people's intention to use AI for generating images in a business context. The present study employed structural equation modelling to analyse how factors from UTAUT2 such as perceived customer value, effort expectancy, social influence, and facilitating conditions affect behavioural intention. The research introduces new moderators (creativity and English language proficiency), in the context of generative AI. Language proficiency and gender impact AI usage, while the impact of effort expectancy is more pronounced in cases of low creativity.

KEYWORDS

AI-Generated Images, Behavioural Intention, Business, Creativity, Language Proficiency, UTAUT2

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INTRODUCTION

Artificial intelligence (AI) is a growing topic of discussion and research due to the multitude of applications developed with its help and its multiple implications on human activity. The spectacular results of AI range from practical speech recognition, autonomous vehicles, and household information of things (IoT) to other human-AI interactions like automated translation, chatbots, or systems capable of creating realistic and artistic images from a description made in natural language (for example, Dall-E, Stable Diffusion, Imagen, and Midjourney). The approach is still predominantly oriented toward technology and algorithmic development (technology-centred approach); however, specialists predict that the focus will increasingly shift to aspects related to human computer interaction (Xu et al., 2021).

This research aims to obtain pertinent answers to the question: Do people intend to use AI for generating images for business purposes? First, a review of the specialized literature was carried out using established models and the acceptance of new technology. It also considered factors that determine why a person may use a certain technology. This was followed by identifying the way in which AI is used in business, aiming to identify the factors that determine future specialists to use AI for generating artistic images for business purposes. Through complex research, the subjects were first asked to use AI technology to create business images on a given theme (sustainable use of energy). Then, they were interviewed about their intentions with regards to using AI technology based on factors like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, customer value, and habit from the UTAUT2 model. Additionally, the study considered potential moderators like age, gender, English-language experience, and subjects' creativity.

The results of the analysis revealed a moderate to high value for the behavioural intention to use AI, showing that 69% of the variance can be attributed to determinant factors (e.g., perceived customer value, effort expectancy, facilitating conditions, habit, hedonic motivation, performance expectancy, social influence) and its moderators like creativity, knowledge of the English language, study domain, and gender. An interesting result regarding the way human-AI interaction is carried out is the ease of acceptance of this technology by those who are proficient in English given the fact that the software on which the image generation is based requires text in this language. Another result is related to the gender of the person interacting with AI. For instance, the effect of habit on behavioural intention is more pronounced for males in comparison with females. Finally, the most interesting result is related to creativity. In fact, the impact of effort expectancy over the behavioural intention is much stronger in cases of low creativity.

Starting from the mentioned premises, the article is structured in four parts. The first part is concerned with the analysis of the specialized literature regarding human-technology interaction and the role of AI in business. The second part investigates the research methodology. This is followed by a review of the results and discussions in the context of existing research. The final part includes conclusions, proposals, academic and practical implications, limitations, and future research directions.

LITERATURE REVIEW

UTAUT2 Model

The ever-higher level of sophistication of technologies and growing pace of their alteration and improvement bring permanent challenges to the human sphere. Adoption of innovative technologies like cloud computing, blockchain, robotics, the Internet of Things (IoT), Big Data, and AI is on the rise. Innovation behind technologies has changed the face of entire industries, leading (with astonishing speed) to the appearance of completely new fields like e-commerce, m-health, or fintech. People and organizations must, therefore, deal with these changes in technology and business models on an accelerated basis. Still, not all technologies and innovations on which they are based have the same

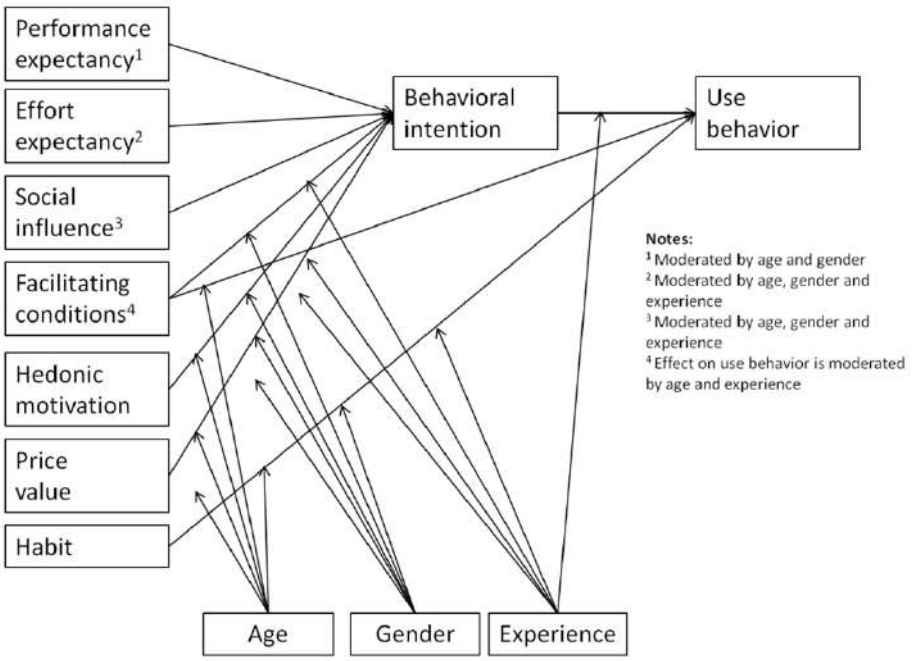
success in society and economy. The key question is as follows: why do people adopt or reject certain innovative technologies?

One of the most cited theories regarding the interaction between man and technology in terms on how a particular innovation is disseminated, known, used, and evaluated was developed by Rogers (1995). According to his research, people adopt an innovation based on its utility, characteristics, and their personal relative advantage. This, in turn, divides them into the following categories: (1) innovators; (2) early adopters; (3) early majority; (4) late majority; and (5) laggards. An increasingly important role is played by the mass media and (currently) the internet, which ensures the rapid spread of information about the existence and characteristics of an innovation or technology, respectively.

The Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB), developed by Fishbein (1979) and Ajzen (1991), brought clarifications regarding the way people think and act in various situations as influenced by their attitudes, subjective norms, and perceived behavioural control. People are more inclined to adopt a technology if they develop a positive attitude about it and if they see others using it. In addition, if people think a technology is useful and easy to use, they would be more inclined to adopt it than reject it according to the Technology Acceptance Model (TAM, Davis, 1985).

The Unified Theory of Acceptance and Use of Technology (UTAUT) emphasizes the following four factors in determining a person's intention to use a certain technology: (1) performance expectancy; (2) effort expectancy; (3) social influence; and (4) facilitating conditions. In more recent developments of this model (UTAUT2, see Figure 1), it is necessary to understand the adoption of technology by employees (as in the case of UTAUT) and consumers. Thus, use behaviour is the result of behavioural intention (mediated by age, gender, and experience) and determined by the factors from the UTAUT model (performance expectancy, effort expectancy, social influence, and facilitating condition) to which three factors were added: (1) hedonic motivation; (2) price value; and (3) habit (Venkatesh et al., 2003, 2012, 2016).

Figure 1. Original UTAUT2 model
Source: Venkatesh et al. (2012)



According to the authors of those theories, performance expectancy is defined as the belief that technology will help a person achieve their goals. On the other hand, effort expectancy refers to the perceived ease of use of technology. Both constructs are based on TAM. The social influence refers to the influence of other people on an individual's decision to use a technology. Facilitating conditions refers to the availability of organizational resources and support for using the technology. Hedonic motivation is the key to understanding why some technologies are considered fun and/or pleasant to interact with. The price value factor tells us how valuable a technology is in the eye of consumers (the lower the price of technology, the more intensive its use). Habit is defined as "the extent to which people tend to perform behaviours automatically" (Venkatesh et al., 2012, p. 161), which is in opposition with the reason-oriented framework (from TRA and TPB models).

Based on the UTAUT model, respectively the UTAUT2, other studies have been carried out (Kelly et al., 2023), the most recent of which seek to clarify the adoption of mobile banking services (Gharaibeh et al., 2018), conditionally automated cars (Nordhoff et al., 2020), mobile phones (Nikolopoulou et al., 2020), mobile health applications (Schomakers et al., 2022), AI-enabled tools (Jain et al., 2022), products that incorporate AI (Gansser & Reich, 2021), the use of mobile devices for learning (Lai, 2020), mobile 4.5G services (Daniali et al., 2022), or AI coach (Terblanche & Cilliers, 2020).

Other studies have emphasized the benefits and challenges in the adoption and use of new technologies. Among these technologies, and by far the most spectacular in evolution and which aroused public interest, are those related to the development of AI. A study by McKinsey (2020) revealed several organizational benefits, including revenue increases for inventory and parts optimization, pricing and promotion, customer-service analytics, and sales and demand forecasting, along with the optimization of talent management, call centre, and warehouse automation. Other studies have shown the benefits of using AI for the automation of processes at the municipal level (Schaefer et al., 2021) and, respectively, the development of the food supply chain (Dora et al., 2022).

The current research uses the UTAUT2 theory because it is a comprehensive model that is more adapted to the current context of technological expansion (Suo et al., 2021; Tamilmani et al., 2021). Compared with TAM, the UTAUT2 offers "a better explanation power" (Rondan-Cataluña et al., 2015), has a much higher predictive ability than other theories, and is considered useful and important for the business and academic environments (Tamilmani et al., 2021). Thus, in this study, the respondents (students) were targeted in a double role of future employees/entrepreneurs (who simulated the potential use of generative AI technology to create images for a promotional marketing campaign) and consumers (self-assessed by successively modifying the prompts before uploading their results online for the contest for the generated AI images).

The authors extended the UTAUT2 model by adding potential moderators like English language proficiency and subjects' creativity. Thus, the study attempts to close an existing gap in the literature.

Factors Influencing AI Use in Business

AI is considered one of four tools of new-age technologies (along with IoT, machine learning, and blockchain). These can be used for gaining a holistic understanding of consumer needs and behaviours (Kumar et al., 2021), personalizing their experience (Haleem et al., 2022), and having great potential for enabling marketing capabilities (Manis & Madhavaram, 2023).

AI has already boosted numerous famous businesses (Marr, 2019). In fact, it is on its way to changing entire economies and global societies (Ertel, 2019; Gupta et al., 2023; Manyika & Sneader, 2018; Pallathadka et al., 2023). For example, AI is used in retail and business-to-business (B2B) settings (e.g., JD, Alibaba, Amazon), luxury items, consumer goods, food and beverage (e.g., Burberry, Coca-Cola, McDonalds), media and social media (e.g., Netflix, TikTok, Facebook, Tencent), financial services (Mastercard, Salesforce), and the automotive industry (e.g., BMW, Tesla). Other small and large companies also try to include AI algorithms in their business to differentiate themselves from

the competitors, be more efficient, and serve their customers in personalized ways (Pallathadka et al., 2023).

Studies have been developed that analyse the influencing factors of the use of technology. However, the current study looks at factors from another perspective. In the process of accepting AI generative technology in business, the individual attitude of people is not the only influencing factor. Indeed, specific factors like organizational culture (with emphasis on English proficiency in business), job roles, and job demands play a role on the acceptance of AI (IT skills and knowledge, creative skills; Imran et al., 2022).

The adoption and use of AI has profoundly transformed the relationships between companies and consumers (Haleem et al., 2022; Spada et al., 2022). It has also proven its impact on business success by significantly improving marketing practices (Sarath Kumar Boddu et al., 2022) and becoming a major survival requirement in an increasingly competitive global market (Fredström et al., 2022). Although it may seem paradoxical, some cases have shown that the technological discomfort felt by consumers has a positive influence on the adoption of AI (Flavián et al., 2022). For example, initial trust in chatbots (a newer AI technology) increases the intention to use them and encourages customer engagement (Mostafa & Kasamani, 2022).

Trust in technology (in general) is a key component of users' trust in AI applications and is the basis of their perceptions of AI (Yang & Wibowo, 2022). The novelty of this technology adds value both efficaciously and hedonistically (Jo, 2022). However, despite the already recognized potential of AI, there are problems related to the strategic use of this technology in creating business value (Borges et al., 2021; Stone et al., 2020).

Chatterjee et al. (2022) showed that the adoption of digital transformation at the enterprise level is significantly influenced by the skills and capabilities of the individuals. Huang and Rust (2021) and Peng et al. (2022) identified consumers' reluctance to accept AI (those who seem not yet ready), confirming the results of a 2019 study that revealed a reluctance and prejudice on the part of consumers toward chatbots. This occurs because potential consumers shorten their conversation and buy less product when it is known that that the interlocutor is not human (Luo et al., 2019). In addition, some consumers are concerned about the need for rules, education, and training regarding the use of AI (Kopalle et al., 2022; Vlačić et al., 2021).

Consumers believe that the use of AI in marketing communication is limited in terms of influencing product evaluation or shaping consumer behaviours (Chen et al., 2022). However, recent studies demonstrate that the use of AI positively influences consumer engagement in social media and optimizes the rate of conversion. Thus, marketers should design more interesting posts with images and videos to encourage consumers to share the content and, in turn, create new content via their social platforms (Nazir et al., 2023). Consequently, the generated content becomes an essential marketing tool with strong effects on "consumer loyalty, purchase intention and other consumer behaviors" (Ma & Gu, 2022, p. 1).

On the other hand, some studies raise questions about AI. Can we rely on AI to replace human activity and/or creativity? Can we trust that AI is doing a good job? Who will be the judge of the result (Anantrasirichai & Bull, 2022; Gobet & Sala, 2019; Griebel et al., 2020; Trajtenberg, 2019)?

Some researchers want to see more studies to gain a better understanding of human-AI interaction (Jermutus et al., 2022). AI and human intelligence must be viewed as a team in which human intelligence (marketers and consumers) uses increasingly developed AI. Thus, this collaborative intelligence can provide the highest-quality results (Huang & Rust, 2022).

For example, Bakpayev et al. (2022) showed that the use of AI is effective in the case of creating non-emotional (rational) content in advertising and for products of strict necessity. However, human intelligence is needed for the creation of emotional content. Also, Davenport et al. (2020) and Kelly et al. (2023) stated that the use of AI will be much more effective if it enhances (rather than replaces) the human factor. In fact, some cultures believe that the human presence cannot be replaced.

In the attempt to create AI-based software to be used in business, especially social media marketing, specialists have tried to identify and analyse the expectations of potential beneficiaries. They found that image analysis capabilities are considered the most important by the beneficiaries (Capatina et al., 2020). To study the effects of AI on creativity in marketing and to identify the customer journey points where AI can have the greatest impact, consideration must be given to the role and impact of different forms of AI, the national and cultural specificity, and a multi- and interdisciplinary approach (Ameen et al., 2022). Attention should also be given to socio-cultural backgrounds like age, gender, experience, fluency in expression, and creativity.

In this respect, some researchers have shown that a gender bias exists when adopting emerging technologies. This fact is due to the "lack of diversity in data and developers, the bias in society, and bias in data due to programmer conscious or unconscious bias" (Nadeem et al., 2020, p. 6).

The gender gap in digital skills has direct implications for the design and implementation of AI applications (Manasi et al., 2022). For instance, some studies based on touch gesture information in smartphone use show that smart systems can be personalized based on gender information to provide an improved user experience (Guarino et al., 2022). Likewise, it has been observed that the attitude and intention to use various applications (e.g., mobile wallets) is more pronounced in the case of men and young people (Chawla & Joshi, 2020). Gender and level of studies are also proven to be moderating factors in AI interaction in the medical field (Aboueid et al., 2019) or in differing attitudes toward the ethics of AI (Jang et al., 2022).

Also, language/English proficiency is an important factor in modelling the behavioural intention toward technology (De Jesus & Xiao, 2012; Xia et al., 2023), especially when language manipulation techniques are more used online (Fedushko & Davidekova, 2019). After age, education, and urbaneness, English proficiency is the next most important factor in the adoption and use of PIERCE technology (Pearce & Rice, 2014). Studies show that poor English skills can lead to online social exclusion, while online search results in English have a significantly higher quality than in other languages (Zoubi et al., 2022). In addition, because the AI models generating images in this study were based on the subset of English language LAION 5b, it is important to study this variable (foreign language) as a moderator in the developed model.

MATERIALS AND METHODS

Objectives and Hypothesis

Starting from the first research question (Do people intend to use AI for generating images for business purposes?), the authors provided potential business users with text-to-image AI models to unveil outcomes that define AI usage for marketing purposes. With this aim, two objectives (together with the associated hypotheses) were formulated:

O1: To validate the UTAUT2 usage for business by using text-to-image diffusion models. For this purpose, the following hypothesis was formulated:

H.1. The UTAUT2 related to text-to-image diffusion AI technology for business is valid.

O2: To identify user behaviour moderators when using text-to-image diffusion models.

Based on this objective, four hypotheses were formulated:

H2.1. Gender moderates the UTUAT2 components in the relationship with behavioural intention.
H2.2. Creativity moderates the UTUAT2 components in the relationship with behavioural intention.
H2.3. English language proficiency moderates the UTUAT2 components in relation to behavioural intention.
H2.4. Study domain affects behavioural intention.

The research method on which the study was based is mixed. It includes the direct involvement of the participants in the process of content generation (see Figure 2). The current study used the non-probability sampling method, applying a complex questionnaire that consisted of 29 questions. It was organized into several dimensions in a correlational survey suitable for the UTAUT2 analysis.

First, the recruitment and instruction of participants took place. The university where the questionnaire was applied is comprehensive, with a focus on entrepreneurship and innovation. It has nine faculties with a technical profile and nine with a socio-humanistic profile. Male students are almost on par with female students (51% males). The population is made up of 20,500 students who represent potential interview subjects. The researchers used the university's platform to invite and instruct the students as participants in a contest and survey, respectively. Data has been collected between November 2022 and January 2023. The study followed the principles of the Declaration of Helsinki. It was approved by the council of the Faculty of Economic Sciences and Business Administration after checking ethical standards for human research studies.

In the recruitment stage, the researchers sent invitations to all students. They also sent several reminders. Students received an e-mail invitation to a contest on sustainability and the use of green energy. They were asked the following question: Have you thought that you can use AI applications to generate images very easily? Before entering the contest for developing an advertisement using text-to-images diffusion models, the participants were asked to experiment with free and open-source image generative AI.

Therefore, participants played the role of test-takers. The subjects were asked to use generative AI technologies to create images for a promotional marketing campaign related to sustainability and green energy. The role of empirical tests in technology acceptance is recognized as a research method in the specialized literature (Chau, 1996; Rahman, 2016) because the obtained results can represent a starting point in the development, evaluation, validation, or rejection of certain hypotheses. These also serve for the presentation of certain limits (Bakhtiary et al., 2020; Choma et al., 2019; Nanthaamornphong & Bressan, 2019).

Afterwards, the collected data was sent to researchers. The method of collecting the content generated by the participants was based on a survey. At the end, the respondents had to upload their generated images along with the prompts used to create the images. The final sample included 403

Figure 2. Activity flow

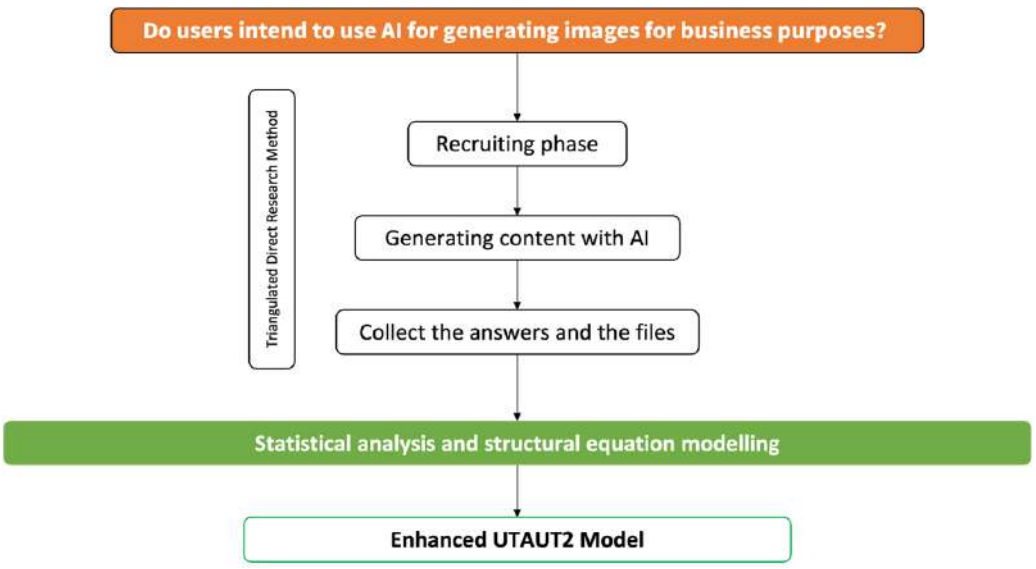


Table 1. Sample structure

Arts and Humanities (Literature, Music)	4.71%
Engineering	34.49%
Natural and Applied sciences (Chemistry, Informatics, Mathematics, Material Science)	24.07%
Social Sciences (Economics, Sociology, Psychology)	36.72%

participants (see Table 1), who filled out the survey and uploaded the generated files at the end of the survey.

Instruments

Technology Acceptance

Technology acceptance was measured using a 29-item questionnaire for the UTAUT2 (Venkatesh et al., 2012). The questionnaire included four items related to performance expectancy (the benefits consumers believe they will gain from using a specific technology to perform certain activities), four items related to effort expectancy (measuring the ease associated with technology use), four items for social influence (measuring the importance users place on the opinion of others about their use of certain technologies), four items related to facilitating conditions (consumers' perceptions of the resources and support available to them to perform online activities), three items related to hedonic motivation (fun or pleasure derived from using technology), three items related to perceived customer value (the trade-off between the perceived benefits of the applications and the cost of using them), four items related to habit (prior behaviour or the extent to which individuals believe their behaviour to be automatic), and three items related to behavioural intention (intention to use technologies in the future). The questionnaire was adapted to fit the AI art generation for advertising. It was evaluated using a five-point Likert scale. (See Appendix 1.)

Creativity

Creativity was measured using the divergent association task (Olson et al., 2021), a prompt assessment tool used to measure verbal creativity and divergent thinking. This denotes the capacity to generate diverse and distinct solutions to open-ended issues. The task involves thinking (and writing) 10 words that are as different from each other as possible. Individuals who demonstrate higher levels of creativity generally produce words with greater semantic distances. The measurement of semantic distances is inferred by examining the co-occurrence of words in similar contexts.

English Language

The English-language self-assessment was based on the Common European Framework of Reference for Languages (CEFR), which measures listening, reading, spoken interaction, spoken production, and writing (Council of Europe, 2023). It categorizes language proficiency into six levels, ranging from A1 to C2. These can be classified into three overarching levels: (1) basic user; (2) independent user; and (3) proficient user. The levels are established through descriptors of one's abilities and competencies, indicating what an individual can do with the language ("can-do" statements). The assessment was accomplished using a six-point Likert scale. (See Appendix 2.)

Socio-Demographic Data Questionnaire

This questionnaire requests the specification of the fundamental field in which the student learns (biological and biomedical sciences, engineering sciences, mathematics and natural sciences, social sciences, sports and physical education science, humanities and arts) and gender.

RESULTS: MEASUREMENT MODEL

The present study employed structural equation modelling (SEM) and the partial least squares method (PLS) to analyse data via SmartPLS (Ringle et al., 2015). Hypotheses were tested with bootstrapping of 10,000 resamples. To analyse the mediation effects, the study used a recommendation by Preacher and Hayes (2004). The results interpretation was guided by Chin (2010). The analysis of variance inflation factors (VIF) values for the assessment of multicollinearity showed VIF values lower than 1.990. This suggests that collinearity is not an issue.

Testing for bias was accomplished by using common method variance. The study first tested the model using Harman's single factor test (Chin et al., 2012), obtaining 32.89% of the total variance (lower than the 50% suggested threshold). The second test was accomplished by using VIF (Kock, 2015). All the VIF values were lower than the 3.3 suggested threshold. Based on the data from both tests, this model can be considered free of common method bias.

The study evaluated the measurement model prior to evaluating the research model. The model specified in this study has eight constructs with reflective measurements. As part of the measurement model evaluation, some items were deleted for insufficient loadings or multicollinearity: one item from social influence; one item from facilitating conditions; and one item from habit.

To test the reliability of the constructs, this study used Cronbach's alpha (CA) and composite reliability (CR). All CRs for reflective constructs were higher than the recommended value of 0.700. The CA for each reflective construct exceeded the 0.700 threshold. Average variance extracted (AVE) was also acceptable. Factor loadings for the reflective constructs are presented in Table 2.

Discriminant validity was assessed by HeteroTrait-MonoTrait (HTMT) ratio of correlations (Henseler et al., 2015), with values below the threshold of 0.90. Hence, discriminant validity is established.

Goodness of Fit

To assess the goodness of fit, the coefficient of determination (R^2), the effect size (f^2), and the predictive relevance (Q^2) were determined in the present study. The results of the analysis reveal a moderate to high R^2 value of .690 for behavioural intention, showing that 69% of the variance can be attributed to perceived customer value, effort expectancy, facilitating conditions, habit, hedonic motivation, performance expectancy, and social influence. It can also be attributed to its moderators: creativity; knowledge of the English language; study domain; and gender.

The influence of the predictor variables on behavioural intention are assessed through the *t* test (Hair et al., 2013). The results are presented in Table 3, partially confirming H1: the UTAUT2 as a valid model for text-to-image diffusion technology adoption in business.

Effect size for predictive relevance (Q^2) of behavioural intention was negative in the full moderated model, showing no predictive relevance. This happens due to the mediators. A model without them shows a Q^2 value of .601, meaning medium-to-high predictive relevance. The impact of the predictor is high at the structural level if f^2 is at least 0.35. It is medium if f^2 is 0.15 and small if f^2 is 0.02 (Cohen, 1988). The f^2 effect size for a model shows how much latent variable contributes to an endogenous latent variable R^2 value. In other words, it shows the magnitude or strength of relationship between the latent variables. The results show that f^2 effect size is negligible (see Table 4).

Apart from the mentioned statistics, standardised root mean square residual (SRMR) can be used as a measure of fit. In the present study, SRMR = 0.07, which is lower than the 0.08 (or 0.10) threshold.

Moderation Analysis and Hypothesis Testing

To test the hypothesis (H2.1 – H2.4), the study runs several mediation analyses using perceived customer value, effort expectancy, facilitating conditions, hedonic motivation, habit, performance expectancy, social influence as antecedents, and behavioural intention as effect. This also includes several moderators (see Figure 3).

Table 2. Loadings, reliability, validity

	Coef.	CA	CR	AVE
Behavioural Intention (BI)		.835	.840	.752
BI1	.873			
BI2	.864			
BI3	.853			
Perceived Customer Value (PCV)		.838	.885	.750
PCV1	.808			
PCV2	.894			
PCV3	.877			
Effort Expectancy (EE)		.766	.771	.586
EE1	.788			
EE2	.748			
EE3	.764			
EE4	.727			
Facilitating Conditions (FC)		.717	.730	.639
FC2	.708			
FC3	.836			
FC4	.825			
Habit (H)		.701	.739	.618
H1	.773			
H2	.713			
H3	.835			
Hedonic Motivation (HM)		.720	.737	.641
HM1	.744			
HM2	.865			
HM3	.767			
Performance Expectancy (PE)		.812	.814	.640
PE1	.774			
PE2	.763			
PE3	.837			
PE4	.802			
Social Influence (SI)		.717	.764	.635
SI1	.823			
SI2	.863			
SI3	.662			

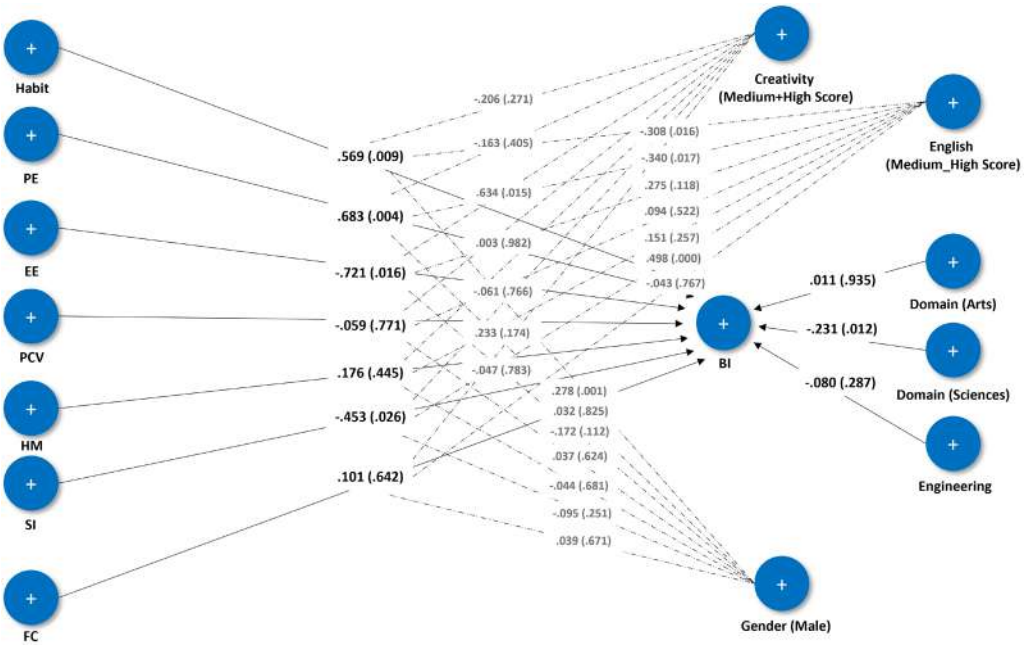
Table 3. Direct effect size

Path	Coef.	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PCV → BI	-.045	.200	.227	.821
EE → BI	-.748	.297	2.521	.012
FC → BI	.095	.214	.442	.659
HM → BI	.175	.229	.765	.444
Habit → BI	.572	.216	2.656	.008
PE → BI	.689	.233	2.964	.003
SI → BI	-.454	.203	2.237	.025

Table 4. Explanatory power for two models: without and with moderating effects

	No Moderators				Moderators			
Path	Beta	P values	f^2	R^2	Beta	P values	f^2	R^2
PCV	.093	.012	.017	0.611	-.045	.821	.000	0.69
EE	-.030	.490	.001		-.748	.012	.032	
FC	.080	.055	.012		.095	.659	.001	
HM	.157	.002	.029		.175	.444	.002	
Habit	.328	.000	.153		.572	.008	.025	
PE	.301	.000	.108		.689	.003	.037	
SI	.094	.029	.013		-.454	.025	.023	

Figure 3. Final tested model



H2.1: Gender as a Moderator

The study assessed the moderating role of gender on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI). With the inclusion of just this interaction term, the R^2 was .636, showing an increase of 4.09% in the variance explained in the dependent variable (BI) over the base model. The significance of the moderating effects was also analysed. The results reveal significant interactions (see Table 5). The effect of (H) on (BI) is more pronounced for males in comparison with females (the relationship between (H) and (BI) is positively strengthened in the case of males). Other interactions could be observed in the slope analysis, showing that the negative relationship between (EE) and (BI) is stronger in the case of males. The effect size is small in one case and almost zero in the other case; thus, the study can conclude that gender plays a small but statistically significant role in the intention to use generative AI for images. H2.1 hypothesis is, therefore, partially confirmed.

H2.2: Creativity as a Moderator

The study also assessed the moderating role of creativity on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI) In this study, creativity is measured with the help of words. More creative people tend to think of words with greater "distance" between them. The creativity score could be classified in three categories: (1) under 50 is poor; (2) the average is between 75 and 80; and (3) 95 is a very high score (Olson et al., 2021). To identify the category each participant falls into, the study used K-means clustering with three clusters for low, medium, and high creativity. The final clusters are presented in Table 6.

With the inclusion of creativity as the unique interaction term, the R^2 was .640. This shows an increase of 4.74% in the variance explained in the dependent variable (BI) over the base model. Significance of the moderating effects was also analysed. The results reveal significant interactions. Creativity reduces the negative relationship between (EE) and (BI), making (EE) more significant

Table 5. Gender moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
Male → BI	-.085	.067	1.261	.207	.005
Male x Habit → BI	.285	.085	3.339	.001	.026
Male x EE → BI	-.173	.108	1.606	.108	.009
Male x FC → BI	.036	.092	.397	.691	.001
Male x SI → BI	-.088	.081	1.078	.281	.003
Male x PE → BI	.036	.143	.249	.803	.000
Male x PCV → BI	.028	.076	.374	.708	.000
Male x HM → BI	-.051	.106	.480	.631	.001

Table 6. Creativity: Final cluster centers

	Cluster		
	Medium Creativity	Low Creativity	High Creativity
Creativity Score	68.30	49.81	77.79

(see Table 7). In other words, the impact of (EE) over (BI) is much stronger in case of low creativity (you must work harder for the same result). Considering only the slope analysis between the terms, other interactions occur between (PE), (H), and (SI). Creativity reduces the positive relationship between (PE) and (BI). The impact of (PE) over (BI) is stronger in the case of low creativity. Also, creativity reduces the positive relationship between (H) and (BI) (or the impact of (H) over (BI) is stronger in the case of low creativity). Finally, creativity reduces the negative relationship between (SI) and (BI). The effect size of f^2 is small in one case and almost zero in the other case; thus, the study can conclude that creativity plays a small but statistically significant role in the intention to use generative AI for images, H2.2 being partially confirmed.

H2.3: English Proficiency as Moderator

The study also assessed the moderating role of English language knowledge on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI). With the inclusion of this interaction term alone, the R^2 was .654. Thus, it shows an increase of 7.03% in the variance explained in the dependent variable (BI) over the base model. The significance of the moderating effects was also analysed. The results reveal significant interactions (see Table 8). The biggest effect size was observed for (SI). Medium and advanced knowledge of English language strengthens the positive relationship between (SI) and (BI). This shows that the impact of (SI) on (BI) is stronger for the participants with medium/high knowledge of English compared to the ones with lower language skills.

Table 7. Creativity moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
Creativity → BI	.073	.140	.522	.602	.001
Creativity x PCV → BI	-.000	.147	.000	1.000	.000
Creativity x HM → BI	-.066	.205	.325	.745	.000
Creativity x EE → BI	.644	.258	2.499	.012	.033
Creativity x PE → BI	-.166	.192	.863	.388	.003
Creativity x SI → BI	.236	.170	1.386	.166	.009
Creativity x FC → BI	-.046	.167	.274	.784	.000
Creativity x Habit → BI	-.206	.186	1.106	.269	.004

Table 8. English language proficiency: Moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
English_Intermediate_Advanced → BI	-.058	.098	.595	.552	.001
English_ Intermediate_Advanced x EE → BI	.289	.172	1.681	.093	.013
English_ Intermediate_Advanced x HM → BI	.158	.133	1.189	.235	.004
English_ Intermediate_Advanced x FC → BI	-.033	.141	.232	.817	.000
English_ Intermediate_Advanced x SI → BI	.492	.133	3.686	.000	.057
English_ Intermediate_Advanced x Habit → BI	-.316	.126	2.500	.012	.024
English_ Intermediate_Advanced x PCV → BI	.088	.147	.601	.548	.001
English_ Intermediate_Advanced x PE -→ BI	-.342	.142	2.415	.016	.025

Another weak effect (significant in one-tail analysis) was observed on the interaction on (EE) and English language strengthening the positive relationship between (EE) and (BI). This shows that the impact of (EE) on (BI) is stronger in the case of medium/high knowledge of English language. Regarding the interaction between English and (H) or (PE), both have weak but statistically significant effects on (BI). Thus, English knowledge reduces the positive relationship between (H) (or PE) and (BI). The impact of (H) (or PE) on (BI) is stronger in the case of low English knowledge. In other words, if you work harder, you will become habituated. Thus, for the future use of AI technology, English knowledge will count less. This is the same for performance expectancy. The effect size is small in one case and almost zero in the other case. Therefore, the study can conclude that knowledge of the English language plays a small but significant role in the intention to use generative AI for images. H2.3 is partially confirmed.

H2.4: Study Domain Affects Behavioural Intention

Controlling for study domain (as a proxy for experience) resulted in significant differences for the sciences domain (mathematics, informatics, chemistry, and material sciences in our university) compared to the reference domain (social sciences in our model). These students show a lower behavioural intention in comparison with the reference domain. Further, this shows that the study domain partially affects behavioural intention.

DISCUSSION

The need for a thorough understanding of the drivers behind the acceptance of image diffusion AI models in business (O1) and the moderators of user behaviour toward technology (O2) stems from the multitude of implications for the development and progress of a range of business domains. Moreover, the outcomes of the research unveiled several unexpected results that place the study as an important contribution to the theoretical lens indicating interesting aspects of AI usage in business.

According to the technology acceptance literature, behavioural intention (BI), which determines the acceptance of image diffusion AI in business, can be attributed to perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), habit (H), hedonic motivation (HM), performance expectancy (PE) and social influence (SI). The results obtained from the research show that, in the analysed context, the statistically relevant factors are (EE) and (SI), as confirmed by other studies (Daniali et al., 2022; Lai, 2020; K. Sharma & Madan, 2022; Terblanche & Cilliers, 2020) and PE as in research conducted by Daniali et al. (2022), Gansser and Reich (2021), Lai (2020), K. Sharma and Madan (2022), and Terblanche and Cilliers (2020).

Perceived customer value was not among the statistically relevant factors. This may occur because the participants in this research have not yet identified ways in which they could use image-based AI in business. In addition, they have not identified the benefits that the use of this technology could provide in business. Hedonic motivation was not shown to be statistically significant. In the view of the current research participants, image creation is associated with art. Thus, users are not yet ready to associate art with AI although demonstrations have shown that AI can be used successfully in areas like art, including fashion or beauty (Harreis et al., 2023). Facilitating conditions were also not found to be a significant variable. It is possible that users were not properly informed that they could have access to such technologies, did not consider themselves to have the necessary knowledge to use this technology, or applications like Stable Difussion were considered difficult to use (S. Sharma et al., 2022).

At the same time, the present research studied several moderating factors related to behavioural intention to accept AI image diffusion in business. This includes gender, English language proficiency, creativity, and experience (using the year of study and specialization as a proxy).

Several studies have looked at the way in which gender affects behavioural intention related to technology and AI. Some confirm the role of this demographic variable as a moderator. A

study examining the use of mobile computing devices for learning among older adults based on the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention, use behaviour, and the moderating effect of gender (Lai, 2020) concluded that the demographic variable of gender has a significant moderating effect between effort expectancy and the participants' behavioural intention. Another study demonstrates the moderating role of gender in the relationship between antecedents like ease of use, usefulness, trust, security, facilitating conditions, and lifestyle compatibility. One study found that the attitude and behavioural intention of mobile wallet is stronger for men (Chawla & Joshi, 2020). An analysis conducted to investigate the moderating effect of gender in relation to performance expectancy, cost, effort expectancy, and social influence showed that gender is not a moderator for students' intentions to use 4.5G mobile phones (Daniali et al., 2022). Our study's results indicate that gender plays a significant moderating role between effort expectancy, habit, and behavioural intention. The relationship between habit and behavioural intention is positively strengthened for males. This is also a stronger negative relationship between effort expectancy and behavioural intention for males.

The fact that there is a relationship between the gender of the technology user, effort expectancy, and behavioural intention has implications for the future of education and assigning tasks to workplaces. Girls are less inclined to apply for academic training in the science, technology, engineering, and mathematics (STEM) field (Chan, 2022; Vooren et al., 2022), which in the future may lead to talent shortage and/or a strong masculinization of the field of digital technologies.

Furthermore, this study shows that technologies like the one analysed assume that the user has information technology knowledge and a relatively high level of creativity. This is an aspect that syncs with current trends regarding the most requested skills, namely analytical and creative thinking (World Economic Forum, 2023b).

In this study, important results were obtained regarding users' creativity in relation with the UTAUT2 and generative AI for images. First, creativity affects performance expectancy. Low creativity moderates the impact of performance expectancy over behavioural intention. In fact, it strengthens it. The study demonstrated that creativity distorts individuals' perceptions about current performance. Thus, the case of lack of creativity generates a negative self-perception regarding the competence of solving tasks that require this type of technology, leading to the intention of not adopting it. Another finding is the identification of the impact of habit on behavioural intention. This is stronger in the case of low creativity, showing that habit plays a significant role over behavioural intention to use AI in business. Finally, the findings of the study bring fresh perspectives, stating that creativity reduces the negative relationship between social influence and behavioural intention.

An additional finding related to creativity is that it moderates effort expectancy (by decreasing it). The results generated by interpreting the relationship between effort expectancy and behavioural intention highlights that an individual with low creativity performances must compensate more in terms of the use of technology based on AI. Creativity also has a positive impact on perceived customer value, which means that the potential of AI is perceived more easily by creative human beings.

Therefore, creativity plays a small but statistically significant role in the intention to use AI technology for image generation with business purposes. This makes sense in the context of professionals who work in marketing departments and are responsible for creative components. Their skills and orientation to be open-minded determine a constant behaviour of seeking and adopting new tools (generative AI for images in this case) necessary for their creative work.

Regarding the relationship between language proficiency and acceptance of image diffusion AI in business, there is very little research to date. However, studies have found a positive relationship between effort expectancy and the intention to use technology (Moya et al., 2018). This research complements these findings, noting that the impact of effort expectancy on behavioural intention is stronger in the case of medium/high knowledge of the English language.

While other research confirms the positive relationship between habit (for internet/online use) and behavioural intention, the results obtained in the present study demonstrate that English knowledge

reduces the positive relationship between (H) and (BI). The impact of habit on behavioural intention is stronger in the case of low English knowledge. The same is valid in the case of performance expectancy. The most significant result obtained is related to the positive relationship between social influence and behavioural intention, showing that the impact of social influence on behavioural intention is stronger for participants with medium/high English proficiency compared to those with lower English proficiency.

The fact that technology acceptance is related to English/language proficiency is also explained by the fact that people make decisions (sometimes "unconsciously") regarding their courses of action. What they are going to do is influenced by how much effort they think they must put in, conditioned by how fluent they think their course of action will be (Johnson, 2021).

The fact that the emerging digital technologies support the English language is an aspect that resonates with the need for the social and economic transformation toward digitalization to be sustainable and inclusive. In this sense, we are witnessing the emergence of new applications that make it possible to easily use any language for AI image generation apps in business. These are the so-called Large Language Models (LLMs), which allow the automatic generation of text needed for image generation applications. One such combination is between ChatGPT and Stable Diffusion (Jin & Song, 2023).

Regarding student specialization, students from the science domains show a lower behavioural intention to use AI image generation applications in business. This may be because the students have not found relevant application domains in business as compared with social sciences students. On the other hand, students in the engineering and arts domains could more quickly identify practical applications of image diffusion AI technology to replace or augment human actions or expertise.

This study presents new information to a dynamic and innovative field, addressing reasons to accept AI image diffusion technology in business.

CONCLUSION

This article aims to contribute to the field by examining the factors that drive the acceptance of image diffusion AI models in business. It also investigates the moderators that influence user behaviour toward this technology. It specifically focuses on understanding the reasons behind the acceptance and intention to use AI-generated images, emphasising factors like perceived customer value, ease of use, resource availability, habit, and social influence. Finally, the study explores how moderators like gender, English language proficiency, creativity, and experience impact users' intentions to use these systems. By analysing these factors and moderators, the article provides novel insight into the acceptance and usage of AI-generated images, particularly in a business context.

Moreover, the study has several valuable scientific and practical implications. From a scientific point of view, the study facilitates a better understanding of the factors that contribute to the adoption of an emerging technology, adding new moderators to the UTAUT2 model. First, the novelty of the research enriches the literature by contributing real insight into the use of AI for business purposes from a practical point of view, emphasising the moderator role of creativity and English language fluency. Second, the results help the academic environment better understand curricular aspects that need attention to enhance the professions of the future. It also helps managers outline business models and strategies in an increasingly digitized world.

Implications for the Academic Environment

Factors like perceived customer value, facilitating conditions, and hedonic motivation can influence the intention to adopt and use AI technology for generating images. There are significant benefits of using AI from the academic point of view. First, there can be improved learning outcomes. For instance, by generating information in a visual format, students will gain a deeper understanding of various theoretical concepts. A second benefit is increased clarity and communication. Academics

can identify patterns, trends, and insights within data. It can also communicate research findings more clearly and effectively by presenting complex data in an easy-to-understand visual format. Consequently, AI diffusion images can enhance communication and facilitate knowledge transfer. However, special attention should be paid to intellectual property rights. A third benefit is the saving of time. By automating tasks like chart visualization, students and professors will save time that can be allocated to other academic activities. Finally, students can gain a significant competitive advantage by learning how to use AI diffusion technology in an effective manner. Students can apply for better job opportunities because jobs in the AI context require more creative skills and critical thinking capabilities (World Economic Forum, 2023).

To increase the behavioural intentions for using AI diffusion image technology by looking at facilitating conditions, universities should provide adequate resources and equitable access to the necessary hardware equipment, software licences, and other resources needed to use AI diffusion image technology effectively. Likewise, universities should offer technical support (a helpdesk or other support system) to academics who are using AI diffusion image technology. Also, universities should offer training (workshops and online courses) to ensure academics have the skills and knowledge to use AI diffusion image technology effectively. Equally important, universities should create a supportive environment, offering incentives to encourage the use of AI diffusion image technology. Finally, in this context, it is crucial for universities to pay attention to legal stipulations in the domain of intellectual property rights protection concerning the image generating process for educational purposes (European Parliament, 2023; Księżak & Wojtczak, 2023).

In the end, universities that provide easy-to-use open-source tools and reliable technical supports will facilitate future specialists with emerging technologies. Thus, the perceived value of AI diffusion technology can be increased, leading to greater adoption and use among students.

Of course, there is another critical issue that must be addressed, namely the collaboration between universities and the business environment. To remain relevant and increase perceived customer value for future specialists, universities should consider the development of technologies and future professions required by the labour market. Thus, universities should adapt the development of curriculum (Shewakena Tessema, 2017) to include elements related to the economic utility of AI software-generating images in various disciplines. In this way, future specialists will have a better perception of the valuable knowledge and use of the technology.

In addition, hedonic motivation may play a role in the adoption and use of AI diffusion technology. For instance, some students may find technology enjoyable or entertaining to use. For that, the universities should design course content in a way that is visually appealing, interactive, and enjoyable to use. This can include incorporating engaging features like animation, interactive elements, contests, and gamification. Additionally, providing opportunities for students to experiment and play with the technology can foster a sense of curiosity and exploration. This will, in turn, increase hedonic motivation and lead to greater adoption or use.

Interaction with AI image diffusion technology requires proficiency in the English language and a highly creative personality. Thus, interested students and professors should be offering courses in creative writing in English (as an organizational incentive) for a better adaptation to the future labour market requests. Manyika et al. (2017) illustrated that "automation and AI will lift productivity and economic growth, but millions of people worldwide may need to switch occupations or upgrade skills" (p. X). Therefore, creative people (e.g., artists, designers, entertainers, and media workers) need to invest in lifelong learning programs to stay relevant within the labour market. For example, healthcare specialists will be able to work with AI-generated images if they receive proper training. Plus, future engineers can analyse and better understand how complex systems like a car or aircraft perform under tremendous stress.

Sustainable human activity is an important long-term goal across the globe. Future environmental specialists could use AI-generated images to better understand trends and potential threats caused by certain phenomena. They can also detect threats that are considered "critical for ensuring the

security of users and preventing suspicious activities" (Fkih & Al-Turaif, 2023, p.39). Lastly, legal specialists can use AI-generated images to understand criminal patterns and crime scenes. In turn, they can contribute to public safety improvements.

Universities must consider both ethical and legal aspects related to the use of AI. Teachers need to understand and convey clear information about how AI works and influences decision-making processes. Students must be taught to use this technology responsibly, treating it as an advantageous tool with limitations. AI needs to be presented to students as a resource to help in making decisions without replacing human judgment.

Implications for Businesses

Generative AI images refer to the use of AI-powered visual representations (e.g., charts, graphs, and dashboards) to analyse and communicate complex data in a concise manner. These images can be used by managers in their organizations in a variety of ways to improve decision-making processes, increase efficiency, and enhance overall performance.

Managers can make more informed decisions by using AI-generated images to analyse large amounts of data quickly and easily. Charts and graphs can be used to identify trends, patterns, and outliers that may be hard to identify. Managers can track and monitor key performance metrics (e.g., sales, revenue, profit, cash-flow, and customer satisfaction) by using AI-generated dashboards to view real-time data and identify areas for improvement in more creative ways. They can also use visual representations to analyse data and identify patterns that may indicate potential risks for their organizations. At the same time, they can forecast future trends by analysing patterns. Equally important, they can use visual representations to present data in a way that is easy to understand for all stakeholders.

Text-to-image AI technology has the power to modify traditional business models in various ways because "Stable Diffusion technology will enable billions of individuals to produce beautiful works of art in a few seconds" (Syed sha et al., 2023, p.1). Businesses like those in the tourism and advertising sectors can rely on this powerful tool for presenting a more appealing product. Likewise, companies in various domains can involve customers in the co-creation of their product or service through AI-generated images (Sjödin et al., 2021). Furthermore, a company manager can improve customer experience by providing personalized and relevant content based on visual searches. This may, in fact, lead to a cost reduction due to the possibility of automating image-related tasks that would require human intervention.

Some companies will take the opportunity to monetize the result of AI by including AI-generated images in books, albums, or personalized advertising materials. The fashion industry will be one of the early beneficiaries of this new technology, enriching the creation process with the help of AI agents. Human fashion creators will obtain a boost in content development, styling recommendations, and the customer's ability to try on clothing online (Harreis et al., 2023).

There are many possible economic applications of AI-generated images with respect to improving our way of living and learning. Basarir-Ozel et al. (2022) stated that a key driver of smart home technology adoption is image, which is linked to prestige and social recognition. With the help of AI technology, for example, it is possible to generate a revolutionary and unique design for home appliances that will create a desired image for the customer.

Museums and anthropologists could also benefit from the development of AI image technology in generating images based on text description and images from historical documents to make their activity more attractive and understandable for the public (Taormina & Baraldi, 2022). Educational companies have already taken advantage of AI diffusion technology by using online applications to help people learn words in a new language via AI-generated images. Other companies are developing AI design software platforms for video game images or providing support that will enhance mental health via AI-generated images (Lian et al., 2023).

However, not only small and innovative companies are benefiting from the adoption of this technology. Google announced that it would use diffusion technology for boosting its business (Elias, 2023). Other uses could be related to graphic design (e.g., Adobe Firefly) or the generation of videos based on prompts (e.g., Meta and other newcomers).

Managers have a lot of opportunities to develop businesses or boost traditional businesses. Still, with great opportunity comes great risk, including the use of emerging technology. For instance, jobs will be lost, and people will be deceived through fake news in mass media. There are concerns about privacy, bias, and discrimination based on using AI-generated images. Therefore, companies should develop adequate, ethical strategies to deal with such issues.

Overall, the use of AI image diffusion in business and academia requires cautious and careful assessment of potential risks. It must also consider the benefits and limitations of the technology. It is important, therefore, to approach the use of AI-powered images in a responsible, legal, and ethical manner. Both for business and academia, it is important to develop qualitative research to navigate the motivation for use and source of barriers in case of rejection of AI use.

Limits and Future Research Directions

Regarding limitations, the current study's sampling method is non-probabilistic. Thus, bias or issues related to sampling may exist. Despite the limits, the method in the study presents advantages in obtaining the results necessary to explain behaviours related to technology (e.g., low cost of applying, efficient feedback). Sampling methods represent research methods for relevant studies in the field, especially in the case of observational analysis (Altmann, 1974; Damilola Akinyemi & Williams Onifade, 2023).

Another limit is represented by the relatively small sample (considering the size of the population to be researched and length of the data collection period). Regarding the use of the UTAUT2 model, there is a risk of speculation about the predictive power of each theory. This is due to a lack of testing and comparison of empirically dominant models of technology acceptance.

Although probabilistic sampling is not used, the study used a volume of the sample relevant for the generation of research directions in the future. Also, the study performed a sample validation with t-Student test. This is similar to the structure of the university.

The researchers acknowledge the potential for bias due to relying on self-reported data. Therefore, they consider the importance of incorporating alternative data collection methods to enhance the validity of the findings. Recommended approaches include user engagement metrics and business impact indicators. By including objective measures of user engagement (e.g., click-through rates, dwell time, or interaction patterns with AI-generated images, measured using A/B testing perhaps, or social sharing), the study can obtain quantitative insights into how users perceive and engage with the content. These metrics provide valuable data that is less susceptible to response bias and subjective interpretations. Additionally, incorporating business impact indicators like conversion rates, sales revenue, customer satisfaction scores, or market performance metrics (e.g., for Web pages that incorporate AI-generated images) allows for an objective assessment of the tangible effects of AI-generated images on business outcomes. By integrating these objective measures along self-reported data, research can provide a more comprehensive and reliable analysis regarding the adoption of AI for image generation in business contexts. It will also minimize potential biases associated with self-reporting alone.

Future research could broaden the scope of the current study within the business domain by examining factors that drive the application of AI among employees across various fields. It could also investigate specific business sectors that adopt AI-generated images. Another opportunity could focus on the ethical, legal, and social implications associated with the acceptance and use of AI-generated images in business settings. Areas of interest may include managerial accountability, data privacy, bias mitigation, and decisional transparency.

Considering existing concerns regarding human-AI interaction, a research direction worth exploring would involve studying how individuals interact with this emerging technology in terms of trust, collaboration, and communication. In addition, it would be valuable to investigate the ways in which the decision-making process can be enhanced to uncover new business opportunities while accounting for variables like cultural background.

Creativity is the most human characteristic. Therefore, future research could explore the potential of AI-generated images when investigating the recognition of emotions and its use in domains like psychology, psychiatry, marketing, and entertainment.

Finally, a future research direction could investigate how algorithmic creativity can allow us to push the boundaries of classic artistic practices. We need to put more effort into adapting to a market in which businesses align with the characteristics of Industry 5.0 (Akundi et al., 2022; Rožanec et al., 2022). This need, in turn, complies with the current research results. People with high creativity performance will interact seamlessly with AI technologies in business processes as compared to those with low levels of creativity.

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APPENDIX 1

Answer the following questions about how you have used and currently use artificial intelligence (AI) applications for generating images for advertisements (AI_Art).
1 = strongly disagree, 2 = disagree 3 = neither disagree nor agree, 4 = agree, 5 = strongly agree

Performance Expectancy

PE1. I find AI_Art for advertising useful in my daily life.
PE2. Using AI_Art for advertising increases my chances of achieving things that are important to me.
PE3. Using AI_Art for advertising helps me accomplish my goals more quickly.
PE4. Using AI_Art for advertising increases my productivity.

Effort Expectancy

EE1. It is easy for me to learn how to use AI_Art for advertising.
EE2. I clearly understand how to use AI_Art for advertising.
EE3. Using AI_Art for advertising is simple for me.
EE4. I can easily develop my skills in AI_Art for advertising.

Social Influence

SI2. People who are important to me think I should use AI_Art for advertising.
SI1. People who influence my behaviour think I should use AI_Art for advertising.
SI3. My colleagues help me in using AI_Art for advertising.
SI4. In general, the university uses research and resources to support the use of AI_Art for creating advertisements.

Facilitating Conditions

FC1. I was told where I can find the resources needed to use AI_Art in making advertisements.
FC2. I have the knowledge I need for using AI_Art for advertising.
FC3. AI_Art for advertising is compatible with other technologies/applications that I use.
FC4. I can get help from others when I have difficulties using AI_Art for advertising.

Hedonic Motivation

HM1. It is easy to use AI_Art to make advertisements.
HM2. It is nice to use AI_Art for making advertisements.
HM3. It is fun to use AI_Art to make advertisements.

Perceived Customer Value

PCV1. I think I understand the advantages of my advertising team's use of AI_Art for making advertisements.

PCV2. My colleagues and I would benefit from using AI_Art for making advertisements.
PCV3. My colleagues and I can use AI_Art to make advertisements on various devices.

Habit

H1. Using AI_Art to make ads has become a habit for me.
H2. I feel addicted to using AI_Art for making advertisements.
H3. I feel like I need to use AI_Art for making advertisements.
H3. I use AI_Art for making advertisements without problems.

Behavioural Intention

BI1. I plan to continue using AI_Art for making advertisements.
BI2. I will try to use AI_Art regularly for making advertisements.
BI3. I intend to continue to use AI_Art frequently for advertising.

APPENDIX 2

Indicate the level at which you think you are currently for each of the following five language skills for English.

Listening (Levels)

- (A1) I can recognise familiar words and very basic phrases concerning myself, my family and immediate concrete surroundings when people speak slowly and clearly.
- (A2) I can understand phrases and the highest frequency vocabulary related to areas of most immediate personal relevance (e.g., very basic personal and family information, shopping, local area, employment). I can catch the main point in short, clear, simple messages and announcements.
- (B1) I can understand the main points of clear standard speech on familiar matters regularly encountered in work, school, leisure, etc. I can understand the main point of many radio or TV programmes on current affairs or topics of personal or professional interest when the delivery is relatively slow and clear.
- (B2) I can understand extended speech and lectures and follow even complex lines of argument provided the topic is reasonably familiar. I can understand most TV news and current affairs programmes. I can understand the majority of films in standard dialect.
- (C1) I can understand extended speech even when it is not clearly structured and when relationships are only implied and not signalled explicitly. I can understand television programmes and films without too much effort.
- (C2) I have no difficulty in understanding any kind of spoken language, whether live or broadcast, even when delivered at fast native speed, provided I have some time to get familiar with the accent.

Reading

- (A1) I can understand familiar names, words and very simple sentences, for example on notices and posters or in catalogues.

- (A2) I can read very short, simple texts. I can find specific, predictable information in simple everyday material such as advertisements, prospectuses, menus and timetables and I can understand short simple personal letters.
- (B1) I can understand texts that consist mainly of high frequency every day or job-related language. I can understand the description of events, feelings and wishes in personal letters.
- (B2) I can read articles and reports concerned with contemporary problems in which the writers adopt particular attitudes or viewpoints. I can understand contemporary literary prose.
- (C1) I can understand long and complex factual and literary texts, appreciating distinctions of style. I can understand specialised articles and longer technical instructions, even when they do not relate to my field.
- (C2) I can read with ease virtually all forms of the written language, including abstract, structurally or linguistically complex texts such as manuals, specialised articles and literary works.

Spoken Interaction

- (A1) I can interact in a simple way provided the other person is prepared to repeat or rephrase things at a slower rate of speech and help me formulate what I'm trying to say. I can ask and answer simple questions in areas of immediate need or on very familiar topics.
- (A2) I can communicate in simple and routine tasks requiring a simple and direct exchange of information on familiar topics and activities. I can handle very short social exchanges, even though I can't usually understand enough to keep the conversation going myself.
- (B1) I can deal with most situations likely to arise whilst travelling in an area where the language is spoken. I can enter unprepared into conversation on topics that are familiar, of personal interest or pertinent to everyday life (e.g., family, hobbies, work, travel and current events).
- (B2) I can interact with a degree of fluency and spontaneity that makes regular interaction with native speakers quite possible. I can take an active part in discussion in familiar contexts, accounting for and sustaining my views.
- (C1) I can express myself fluently and spontaneously without much obvious searching for expressions. I can use language flexibly and effectively for social and professional purposes. I can formulate ideas and opinions with precision and relate my contribution skilfully to those of other speakers.
- (C2) I can take part effortlessly in any conversation or discussion and have a good familiarity with idiomatic expressions and colloquialisms. I can express myself fluently and convey finer shades of meaning precisely. If I do have a problem I can backtrack and restructure around the difficulty so smoothly that other people are hardly aware of it.

Spoken Production

- (A1) I can use simple phrases and sentences to describe where I live and people I know.
- (A2) I can use a series of phrases and sentences to describe in simple terms my family and other people, living conditions, my educational background and my present or most recent job.
- (B1) I can connect phrases in a simple way in order to describe experiences and events, my dreams, hopes and ambitions. I can briefly give reasons and explanations for opinions and plans. I can narrate a story or relate the plot of a book or film and describe my reactions.
- (B2) I can present clear, detailed descriptions on a wide range of subjects related to my field of interest. I can explain a viewpoint on a topical issue giving the advantages and disadvantages of various options.

- (C1) I can present clear, detailed descriptions of complex subjects integrating sub-themes, developing particular points and rounding off with an appropriate conclusion.
- (C2) I can present a clear, smoothly flowing description or argument in a style appropriate to the context and with an effective logical structure which helps the recipient to notice and remember significant points.

Writing

- (A1) I can write a short, simple postcard, for example sending holiday greetings. I can fill in forms with personal details, for example entering my name, nationality and address on a hotel registration form.
- (A2) I can write short, simple notes and messages relating to matters in areas of immediate needs. I can write a very simple personal letter, for example thanking someone for something.
- (B1) I can write simple connected text on topics which are familiar or of personal interest. I can write personal letters describing experiences and impressions.
- (B2) I can write clear, detailed text on a wide range of subjects related to my interests. I can write an essay or report, passing on information or giving reasons in support of or against a particular point of view. I can write letters highlighting the personal significance of events and experiences.
- (C1) can express myself in clear, well- structured text, expressing points of view at some length. I can write about complex subjects in a letter, an essay or a report, underlining what I consider to be the salient issues. I can select style appropriate to the reader in mind.
- (C2) I can write clear, smoothly flowing text in an appropriate style. I can write complex letters, reports or articles which present a case with an effective logical structure which helps the recipient to notice and remember significant points. I can write summaries and reviews of professional or literary works.

Source: https://rm.coe.int/CoERMPublicCommonSearchServices/DisplayDCTMContent?documentId=090000168045bb52

Accordingly, for the five self-evaluation questions, the maximum points were 30, approximatively the same as C2. Users who self-evaluated with a score lower or equal than 12 were classified as "Low proficiency", while users with a score higher than 13 as "medium and high proficiency" in English.

Mapping between the CEFR English levels and scores was accomplished using the following table

CEFR	EF (Points) (https://www.efset.org/english-score/)
A1 Beginner	11 - 30
A2 Elementary	31 - 40
B1 Intermediate	41 - 50
B2 Upper Intermediate	51 - 60
C1 Advanced	61 - 70
C2 Proficient	71 - 100

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Article

AI, Security, and Trust in the Digital Wallet: Evidence from Current Romanian FinTech Users

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Abstract

The digitalization of finance has accelerated the diffusion of FinTech and raised new questions about how AI, data security and blockchain shape consumer behaviour. This article examines current FinTech users, focusing on mobile banking, security perceptions, AI-enabled personalisation and trust in blockchain. A structured online survey of 191 adult users was analysed with descriptive statistics, chi-square tests and three multiple linear regression models. Results show that adoption is overwhelmingly mobile centric: 84.8% primarily use mobile banking applications, accessed almost exclusively via smartphones (96.9%). Data security is the dominant decision criterion, rated "very important" by 83.3% of respondents. While 70.1% believe AI can substantially improve the FinTech experience, trust depends on transparent explanations of how algorithms operate and on guarantees of personal data protection. Regression models indicate that usage intensity is higher among younger, higher-income users and those who perceive simplified interfaces as encouraging, whereas positive views of AI are broadly shared and not segment-specific. Trust in blockchain is linked to a pro-technology mindset rather than to socio-demographic or urban–rural differences. The findings highlight "secure convenience" and explainable AI as central conditions for sustainable FinTech engagement.

Keywords: FinTech; mobile banking; digital wallet; artificial intelligence; blockchain; data security; consumer behaviour

1. Introduction

The Romanian FinTech market has accelerated significantly in recent years, driven by the digitalisation of financial services, the widespread adoption of smartphones and the growing preference for cashless payments. Although the number of FinTech companies operating in Romania remains lower than Western European, the user base has expanded rapidly, and mobile applications have become the dominant interface for everyday financial transactions. The strong uptake of mobile banking and digital wallet solutions signals a shift towards fast, convenient and personalised financial services accessed primarily through mobile devices. These developments mirror broader global trends in the digital economy, where consumers expect intuitive interfaces, real-time support and customised experiences. At the same time, financial services operate in a high-risk environment that amplifies concerns about privacy, personal data protection and cybersecurity. Previous studies show that adoption depends not only on functionality but also on institutional trust, perceived safety and transparency in the handling of sensitive financial information.

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Emerging technologies such as artificial intelligence (AI) and blockchain promise more secure and personalised digital financial services, yet their acceptance is conditioned by users' confidence in how such systems operate. Therefore, understanding the balance between convenience and perceived risk is essential for explaining digital financial behaviour.

After 2018, driven by accelerated digitalization and the emergence of innovative solutions, the Romanian ecosystem entered an expansion phase. More than half of the local FinTech companies were established post-2018, signaling a recent wave of FinTech entrepreneurship. By 2022, the local ecosystem had grown to 54 active FinTech companies, the majority being young startups oriented towards technology and digital financial services (Strat et al., 2024).

Although the absolute numbers remain low, the growth rate is sustained. Romania is beginning to close the gap with more mature markets. However, contrasts remain; for instance, despite Romania having a larger population and GDP than Estonia, the Romanian FinTech ecosystem was nearly four times smaller than Estonia's in 2022. This highlights both the untapped potential in Romania and the necessity for enabling factors, such as government support, ecosystem collaboration, and an innovation-oriented mindset, that accelerated Estonia's success (Strat et al., 2024).

Key factors influencing the evolution of Romanian FinTech in recent years stem from both demand and supply. On the one hand, the forced digitalization during the COVID-19 pandemic boosted the adoption of online financial services, preparing consumers for FinTech solutions. Mobility restrictions in 2020 led to a significant leap in e-commerce, with 58% of Romanian internet users shopping online that year. This also drove an increase in electronic payments, with the share of online transactions rising by 50% to reach 36% of total payments in 2020 (OSW, 2021).

Since 2020, an increasing number of Romanians have adopted digital wallets, money transfer apps, and international FinTech platforms. This openness was fueled by the high penetration rate of smartphones and the internet in the country; Romania has a smartphone usage rate of approximately 64%, close to the Eastern European average (Ionașcu et al., 2023). Consequently, the adoption of digital payments by the population has grown substantially: while in 2019 only ~11% of internet users utilized online banking (OSW, 2021), by 2021, approximately 64% of Romanian adults had made or received a digital payment, a percentage still below the EU average but on a strong upward trajectory (Ionașcu et al., 2023).

The founding of the Romanian FinTech Association (RoFin.Tech) in 2020 marked a milestone, bringing together key market players to collaborate and represent the sector's interests. The involvement of this association and connections to international networks contributed to the visibility and cohesion of the internal ecosystem. Parallel to this, traditional banks intensified their digital transformation. After 2020, virtually all major banks in Romania invested heavily in intuitive mobile banking apps and extended online services in response to FinTech competition. Furthermore, Romania implemented national initiatives aligned with European regulations, such as Open Banking (PSD2 Directive), enabling the emergence of account aggregators and third-party payment providers (TPPs). In 2021, the National Bank authorized the first local TPP for Open Banking payments, marking a turning point in opening banking infrastructure to FinTechs (Junecom, n.d.). This created opportunities for FinTech startups to offer innovative services (such as payment initiation directly from the client's bank account), enhancing collaboration between traditional banks and FinTech companies.

In the context of this sustained development up to 2022, an updated view of the market in 2024, a year marked by consolidation and maturity, is essential (Revolut, 2024). While the Romanian financial technology sector was previously perceived as an innovative but limited

niche, it is currently transforming into a significant pillar of the financial landscape. The accelerated dynamics of technological adoption, alongside the diversification of available solutions and intensified collaborations, justify a brief radiography of the supply and demand for digital financial platforms in 2024.

Demand for FinTech services grew substantially in 2024, moving the segment towards the mainstream. The number of active users of financial technology solutions reached record levels; in the digital payments area alone, approximately 11.2 million active users were forecast for 2023, confirming the growth from the 2020 baseline. This evolution is reflected in the explosion of popularity for neobanks and mobile financial apps (Bălțoi, 2020). For example, the global FinTech Revolut consolidated its local presence, surpassing 3 million customers in Romania in 2023, a growth of ~39% compared to the previous year (Revolut, 2025). Romania thus became Revolut's largest market in Central and Eastern Europe, indicating a high appetite among Romanian consumers for 100% digital banking services.

The diversification of supply by 2024 is remarkable. Beyond standard payments and digital banking, consumers and companies can access alternative lending platforms (online rapid credit, digital factoring, P2P lending), investment and savings platforms (robo-advisors, commission-free trading apps), and sophisticated personal financial management services. The InsurTech segment has also taken shape, and the crypto/blockchain ecosystem has partially integrated into the FinTech landscape. Several local crypto exchanges operate under financial supervision, and the adoption of the EU MiCA Regulation in 2024 is beginning to offer clarity in this innovative area (Chambers, 2025).

Another defining aspect of 2024 is the increasingly close collaboration between FinTechs and traditional financial institutions. While in 2020 banks viewed FinTechs primarily as competitors, by 2024, many Romanian banks and insurers chose to partner with FinTech startups. Additionally, new foreign players have entered the local market; for instance, the Polish payment FinTech BLIK announced its entry into Romania in 2024, and global giants like Klarna and Stripe are actively exploring the market (Strat et al., 2024).

As the market develops, trends are closely linked to digital consumer behavior and Marketing 5.0 approaches. The first trend is the centrality of personalization and customer experience. FinTechs utilize emerging technologies like AI, machine learning, and blockchain (Bălțoi, 2020; Paramesha et al., 2024) to anticipate emotions and preferences, creating relevant interactions. For instance, data-driven personalization algorithms offer tailored financial recommendations, while intelligent chatbots provide instant assistance (Patil, 2024). However, the component of trust and security remains crucial. Studies highlight that while the Romanian public is familiar with FinTech benefits, they place data and transaction security among their top priorities (Duhnea & Schipor, 2021).

Overall, the Romanian FinTech market is evolving in a direction that privileges the consumer's digital experience, characterized by rapid, secure transactions, transparency, and control via mobile applications. Although the academic literature on FinTech adoption has expanded rapidly, most empirical studies have focused on mature markets in Western Europe, North America or Asia, and primarily examine potential users rather than individuals with direct adoption experience. As a consequence, relatively little is known about how actual FinTech users in emerging European markets evaluate AI, blockchain and data security within the Marketing 5.0, where technology is expected to increase value while preserving transparency and human-centric engagement. Romania, where digital financial services have accelerated only recently but mobile adoption is exceptionally high, provides a theoretically relevant testing ground for understanding how "secure convenience" shapes continuing FinTech usage. By investigating current Romanian users rather than intention-only samples, the study contributes evidence-based insight into real behavioral mechanisms rather than hypothetical expectations.

This study aims to analyze consumer behavior in the digital era by investigating the adoption of FinTech services in Romania. Specifically, the research explores the perceptions, preferences, and trust factors that influence engagement with FinTech applications and emergent technologies such as AI and blockchain.

Accordingly, the present research investigates the perceptions, preferences and trust factors that shape the engagement of current Romanian FinTech users with digital financial services. The study focuses on four core elements of the FinTech experience: (1) the use of mobile banking and digital wallets; (2) the perceived importance of data security; (3) the contribution of AI to personalisation; and (4) trust in blockchain-based financial infrastructures. The research objectives are therefore to: (O1) analyse consumer preferences for frequently used FinTech services; (O2) determine the importance of security when choosing FinTech applications; (O3) examine the influence of area of residence on the adoption of advanced technologies; (O4) investigate perceptions of AI-driven personalisation in FinTech; (O5) evaluate the effect of official certifications and regulations on user trust; and (O6) examine the attitudes of current FinTech users toward the use of AI in the FinTech domain. Based on these objectives, the following general hypotheses were assumed:

H1. *The majority of FinTech users prefer mobile banking applications over other FinTech services.*

H2. *Data security is considered the most important factor in choosing a FinTech application.*

H3. *Users in urban areas are more inclined than rural users to adopt advanced technologies such as AI and blockchain.*

H4. *A significant proportion of consumers believe that AI can improve the FinTech experience through personalization and automation.*

H5. *Official certifications and regulations significantly increase user trust in FinTech platforms.*

H6. *Romanian consumers display a positive attitude toward the use of AI in the FinTech domain but believe that stricter regulation is necessary to reduce risks.*

Key findings of the study indicate a high market penetration of mobile banking applications, which 84.8% of respondents use as their primary FinTech service, accessed predominantly via mobile phones (96.9%). Data security was identified as the most critical factor influencing consumer choice, with 83.3% of users rating it as “very important. Regarding advanced technologies, a significant majority (70.1%) perceive AI as beneficial for personalizing financial services. However, this adoption is highly conditional: trust in AI is primarily built through transparent explanations of its functionality (36.6%) and robust guarantees of personal data protection (40.8%). Notably, the research found no statistically significant difference in trust levels towards blockchain technology between urban and rural respondents, suggesting a growing equalization of digital literacy.

These findings must be interpreted within the broader context of the digital era, in which consumer behavior is shaped by unprecedented levels of technological connectivity, information accessibility, and service automation. The rapid adoption of mobile banking, the central role of security in decision-making, and the conditional acceptance of AI-driven financial services all reflect behavioral patterns that extend beyond the FinTech sector and characterize contemporary digital consumption. To understand why consumers, expect high levels of security, transparency, and personalization, and why digital services must constantly adapt to evolving expectations, it is necessary to explore the defining features of the digital era and the transformation of consumer–firm relationships that it has generated.

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1.1. Defining the Digital Era

The digital era, often referred to as the information era, is characterized by the widespread adoption of digital technologies that have transformed how consumers and companies interact. One of the defining attributes of the digital era is ubiquitous connectivity, with over 60% of the global population connected to the internet in 2021, highlighting the extensive access to information and real-time communication (International Telecommunication Union, 2021).

This heightened connectivity has led to the emergence of the informed and empowered consumer (Verhoef et al., 2017), who now has large volumes of information about products and services, accessible instantly through search engines, social networks, and review platforms (Efendioğlu, 2019). The traditional information asymmetry has been significantly reduced, as consumers can easily compare offers and quality, granting them increased negotiating power relative to firms (Gümüş et al., 2012; Xue et al., 2017). The consequence is that brand loyalty becomes more difficult to obtain, as customers are willing to change preferences quickly if they identify a better option or if their expectations for quality, price, or experience are not met.

Younger generations of consumers, such as Millennials and Generation Z, are growing up in an environment dominated by social media and expect brands to be present and reactive on these platforms (Seleznova, 2022). Simultaneously, consumer attention is becoming a limited resource: continuous exposure to multiple pieces of information on screens has reduced concentration spans and amplified the competition between marketing messages (Kotler et al., 2021).

Traditional geographical barriers have diminished in importance: consumers can now buy goods and services from anywhere in the world through e-commerce, expanding competition to a global level (Guthrie et al., 2021). At the same time, the digital transformation of business has become a condition for the survival and growth of companies. Numerous organizations have accelerated the implementation of online sales and communication channels, investing in e-commerce sites, mobile applications, and presence on social platforms (Kraus et al., 2022). The COVID-19 pandemic acted as a catalyst for this trend: social distancing restrictions in 2020–2021 led both companies and consumers to turn to digital solutions, from online shopping and cashless payments to virtual events.

Consumer expectations have also changed with the digital era: the focus is now on personalization and experience. Consumers appreciate brands that understand their individual preferences and offer them personalized recommendations or offers. Big Data analytics technologies allow firms to segment the public at a granular level and anticipate their needs, although many companies are still in the process of fully capitalizing on these opportunities (Odoom, 2022). The digital era has also brought to the forefront issues related to data privacy and trust, such as a heightened awareness of how consumers' personal data is collected and used, which can influence purchasing behavior and brand loyalty (Deloitte Private, 2021a, 2021b). Thus, companies must maintain a delicate balance between personalization and respecting privacy, adopting ethical and transparent digital marketing practices.

1.2. Defining Consumer Behavior in the Digital Era

The concept of consumer behavior holds a central place in marketing, representing the entirety of actions, decisions, and processes through which individuals or groups select, purchase, use, and dispose of products, services, ideas, or experiences to satisfy their needs and desires. In the context of financial technologies, these behavioural mechanisms are strongly moderated by perceived risk and institutional trust. The specialized literature offers numerous definitions of consumer behavior. One of these describes it as the behavior

directly related to the purchasing, using, evaluating, and spending of resources on products and services intended to satisfy consumer needs. This concept includes not just the act of acquisition itself, but also the decision-making processes preceding and following the purchase, for example, gathering information about options, comparing prices, or evaluating post-consumption satisfaction (Saura et al., 2021). Thus, consumer behavior covers the entire life cycle of the consumption decision, from the emergence of a need to post-purchase reactions, including both rational elements (what and how much they buy, under what conditions) and emotional and contextual elements.

In the digital era, although the psychological foundations of human behavior remain valid, the digital environment has introduced new characteristics and substantially modified the consumer's decision-making process. Internet access and mobile technologies have amplified the informational and decision-making power of consumers, generating a more "empowered consumer." For example, today consumers can thoroughly research a product online before buying it: they can read reviews and evaluations from other customers, instantly compare offers from different suppliers, and check a brand's reputation on social media (ADA, n.d.).

This unprecedented level of information reduces the asymmetries in the merchant-buyer relationship and leads to more well-founded purchasing decisions from the consumer's perspective. The consequence is an increase in expectations, modern consumers expect transparency, superior quality, and personalized interactions. While in the past many decisions were predominantly influenced by advertising and the local availability of products, today online recommendations, ratings, and user-generated content (comments on forums, social media posts, unboxing vlogs, etc.) have a major influence on consumer behavior (Saura et al., 2021).

From a theoretical perspective, consumer behavior in the digital era remains subject to the same long-studied psychological, personal, social, and cultural factors (motivations, perceptions, attitudes, group affiliation, social class, etc.), but the manifestation of these factors passes through the filter of technology. Therefore, the study of consumer behavior in the digital era requires combining classic marketing theories with a profound understanding of the new platforms and technologies through which consumers interact with brands.

1.3. Marketing 5.0 and FinTech

The concept of Marketing 5.0 represents a new stage in the evolution of marketing, defined by the blend of advanced technologies with a profoundly human orientation of marketing strategies. The introduction of this concept is attributed to Philip Kotler and his collaborators, who describe Marketing 5.0 as "technology for humanity," emphasizing that the main goal is the use of next-generation digital tools to create value for both consumers and society (Kotler et al., 2021).

This evolutionary paradigm follows the previous stages: if Marketing 4.0 (circa 2010–2020) was focused on the transition from traditional to digital and on omnichannel interaction (Kotler et al., 2021), Marketing 5.0 focuses on the unprecedented integration of emerging technologies, such as artificial intelligence, machine learning, natural language processing, smart sensors, autonomous robots, augmented/virtual reality, and blockchain, into marketing practices (Kotler et al., 2021). However, the effectiveness of AI-based personalisation is contingent upon users' confidence in how personal data are collected, processed and protected. The goal is to emulate and amplify the capabilities of human marketers, allowing for the analysis and anticipation of consumer preferences with an accuracy and speed previously impossible to achieve (Lankton et al., 2015).

A central component of Marketing 5.0 is the use of "Next Tech" as pillars of the marketing strategy. Artificial intelligence and machine learning algorithms enable the

discovery of behavioral patterns and preferences within massive datasets about consumers, revealing insights that traditional marketers could not identify manually. For example, companies can predict the potential success of a product with specific characteristics by analyzing millions of consumer comments and reactions online, a task accomplished by AI much more rapidly and objectively than would be possible through classic market research (Kotler et al., 2021).

Smart sensors and IoT (Internet of Things) devices provide real-time data about how and in what context products are used, offering the opportunity to adapt offers and create contextual experiences for consumers. Software robots and chatbots serve customers in the information and post-sale phases, providing 24/7 assistance and quick answers to frequently asked questions, thereby improving customer satisfaction.

Augmented reality (AR) and virtual reality (VR) technologies are used to offer consumers the possibility to "experience" products or services virtually before purchase, for instance, virtually trying on clothes or simulating the decoration of a room, which can increase confidence in the purchasing decision (Kotler et al., 2021). Furthermore, blockchain finds its place in Marketing 5.0 by increasing the transparency and security of transactions and product provenance, an important aspect especially for consumers concerned with ethics and authenticity (Lankton et al., 2015). Despite its potential for secure transactions, user trust in blockchain depends not on novelty alone but on familiarity, transparency and cognitive ease.

Marketing 5.0 also has a pronounced ethical-social dimension. Termed "Technology for Humanity," it promotes the responsible use of technology so that the consumer experience is improved without compromising the dignity or personal data of the individual. In essence, the concept insists that new digital tools be used not only for firm efficiency but also for the well-being of consumers and society at large. This orientation is convergent with the vision of Society 5.0, a human-centered society in which technological innovation solves social challenges. Through Marketing 5.0, companies attempt to respond to broader social expectations: personalization that respects privacy, transparent and honest communication, digital inclusion (also addressing those less familiar with technology), and positive contributions from brands to issues like sustainability or social responsibility (Kotler et al., 2021).

A formal definition describes FinTech as "the application of emerging technologies in the banking sector, such as artificial intelligence, blockchain, cloud computing, and data technology" (Belanche et al., 2019). This field has experienced rapid growth after 2010, expanding globally, according to a World Bank report, FinTech companies already operate in 189 countries, illustrating the international scale of the phenomenon. FinTech is not limited to a single type of service but covers a varied range of digital financial products: electronic payments, peer-to-peer loans, digital insurance (insurtech), automated financial planning, investment services via robo-advisors, cryptocurrencies, and others (Chen & Zhao, 2024).

The FinTech field is supported by a series of major technological innovations that have allowed its accelerated development, such as artificial intelligence (AI), blockchain technology, and mobile applications.

AI algorithms allow for the automation of financial analyses and decision-making processes, from credit risk assessment and fraud detection to offering automated investment advice (robo-advice) and personalizing offers to clients. For example, FinTech platforms use AI to learn from large volumes of unstructured user data and to provide each client with recommendations or financial products tailored to their needs, practicing "segment-of-one" personalized marketing (Kotler et al., 2021). Such applications of AI in finance (e.g.,

robo-advisors, automated recommendation engines) have become possible on a large scale with the FinTech revolution.

Blockchain offers a decentralized and secure digital ledger for transactions, being a basic innovation in FinTech that allows for the existence of cryptocurrencies and smart contracts. Thanks to blockchain, digital assets like bitcoin and other crypto-assets have been created and integrated into innovative financial services. Furthermore, blockchain is the foundation for many "decentralized finance" (DeFi) applications that have recently appeared, which redesign traditional financial mechanisms using autonomous contracts.

The proliferation of smartphones and mobile applications has democratized access to financial services. Consumers can now make payments, transfers, investments, or contract loans anytime and anywhere, directly from their mobile phone. This aspect of FinTech, mobile banking and mobile payments, has reduced dependence on physical bank branches and radically transformed the user experience. For example, mobile money solutions in some countries have become a widespread alternative to traditional bank accounts, allowing for the financial inclusion of population segments without prior access to banks. Mobile applications thus remain a central innovation in FinTech, offering maximum convenience and user-friendly interfaces (Arner et al., 2015).

1.4. The Impact of FinTech on the Consumer Experience

FinTech innovations have produced significant changes in the experience and satisfaction of financial service consumers. Firstly, FinTech has expanded access to financial services and increased user convenience. Digital technology allows for the rapid opening of accounts, instant execution of payments and transfers, and access to 24/7 financial services, without the geographical or time constraints of traditional banks. Thus, consumers enjoy faster and more self-service-oriented financial interactions, with reduced waiting times and less bureaucracy. For example, the widespread use of mobile applications and the internet has largely eliminated the need to go to a counter for many operations, saving time and effort. Secondly, the competition introduced by new FinTech players has forced an improvement in service quality and stimulated customer-centric innovation throughout the financial sector. Many FinTechs have arrived with business models focused on user experience, which has also led traditional financial institutions to adopt digital solutions and pay increased attention to customer satisfaction. A notable positive effect is the increase in financial inclusion: due to lower costs and the widespread penetration of mobile technology, FinTech services have reached populations previously underserved by conventional banks (such as communities in emerging economies or people without a banking history), thus integrating more consumers into the formal financial system. Lastly, the user experience has been improved by the high degree of personalization and interactivity allowed by FinTech technologies, from intuitive interfaces and real-time notifications to tailor-made offers obtained through AI data analysis. Overall, the emergence of FinTech has raised standards in the industry, forcing financial service providers to be more consumer-oriented, to offer more transparent and easy-to-use services, which has resulted in increased satisfaction and empowerment for consumers in managing their own financial situations (Arner et al., 2015).

1.5. Connections Between Consumer Behavior, Marketing 5.0, and FinTech

FinTech innovations have significantly changed how consumers access and utilize financial services. The digital transformation of finance has radically modified the way consumers manage their personal finances (Wirtz et al., 2018). This adoption accelerated during the COVID-19 pandemic; studies estimate that with the implementation of health restrictions, daily downloads of financial applications increased by approximately

76,000–88,000 per country, as online transactions surpassed cash withdrawals for the first time (Fu & Mishra, 2021). The increased accessibility and ease of use of digital payments influence consumer behavior by increasing transaction frequency and the degree of financial engagement.

However, the literature also signals a controversial diverging hypothesis: the facilitation of payments may also encourage over-indebtedness, as the ease of making payments offered by FinTech often comes with an ease of assuming debt. Factors such as trust in technology, financial literacy, and security concerns directly influence consumers' attitudes and decisions regarding FinTech adoption. Recent studies based on theoretical frameworks like the Technology Acceptance Model show that perceived usefulness and ease of use are key determinants of the intention to adopt FinTech applications (Wirtz et al., 2018).

In response to this new consumer landscape, FinTech companies are increasingly applying the principles of Marketing 5.0. This is reflected in the intensive use of data analytics and artificial intelligence to more deeply understand customer behavior and provide personalized services. For example, many FinTech platforms use machine learning algorithms to recommend financial products tailored to the user's profile or intelligent chatbots to offer instant customer support. FinTechs are often pioneers in adopting emerging technologies (e.g., augmented reality, biometrics) in customer interaction, strengthening their competitive advantage over traditional financial institutions.

FinTechs demonstrate enhanced agility and an innovative spirit, aligning with the Marketing 5.0 vision of using technology "for humanity", not just for sales, but to enhance consumer and societal well-being. Furthermore, digital marketing strategies in the FinTech sector particularly target younger, tech-savvy generations. A clear example is the use of influencer marketing: FinTechs collaborate with social media influencers to increase awareness and trust among Millennial and Gen Z audiences. Studies confirm the effectiveness of these tactics, highlighting that recommendations from digital personalities can influence consumer preferences and stimulate the adoption of FinTech services (Belanche et al., 2019). However, this approach also raises the need for responsible marketing; transparency of messages and compliance with financial regulations become essential, given the risk that some influencers might promote complex financial products without a full understanding.

Recent developments in financial technology highlight that users' trust increasingly depends on transparency and explainability of emerging systems, especially those based on artificial intelligence. Studies between 2022–2024 show that consumers are more willing to adopt AI-driven financial services when algorithms' decision logic is communicated clearly and when data protection practices are explicitly guaranteed (Aldboush & Ferdous, 2023; Afroogh et al., 2024; Černevičienė & Kabašinskas, 2024). Therefore, the literature suggests that technological sophistication alone does not ensure adoption; rather, transparent use of personal data and understandable system behaviour are essential trust-building mechanisms. These insights reinforce the relevance of investigating the perceptions of current FinTech users regarding data security, AI personalisation and blockchain trust in the present study.

Overall, the application of Marketing 5.0 in FinTech strategies involves blending advanced technology (automation, AI, digital channels) with a consumer-centric approach, where personalized communication and the creation of social value (e.g., financial inclusion, sustainability) become priorities.

2. Materials and Methods

2.1. Descriptive Analysis and Bivariate Analysis

To fulfill the objectives of this quantitative investigation, an exploratory research design was implemented, as it is suitable for identifying behavioral patterns and emerging

relationships in fields where theoretical development is still evolving, such as FinTech adoption (Singh et al., 2020). Primary data were collected through a structured survey (Appendix A) administered via a digital questionnaire. Online survey administration ensures standardized item presentation and reduces interviewer bias, while facilitating access to digitally active respondents, the essential requirement for research in FinTech contexts (Regmi et al., 2016).

The target population consisted of current FinTech users aged 18 or older who have internet access and actively use at least one category of FinTech applications such as mobile banking, digital wallets, trading or investment platforms. Restricting participation to current users ensures that responses reflect first-hand experience rather than hypothetical attitudes, a recommended practice in technology adoption research (Venkatesh et al., 2003).

A non-probability sampling strategy was employed, combining convenience sampling with the snowball technique. This approach was adopted due to the absence of an accessible sampling frame of FinTech users in Romania and is considered appropriate in exploratory studies focusing on specific user groups rather than population-wide estimates. While non-probability sampling is appropriate for exploratory research on emerging digital behaviours, it limits statistical generalisation, and therefore the findings should be interpreted in relation to current FinTech users rather than the entire Romanian population. The questionnaire was disseminated via major social media channels and the procedure resulted in 191 valid responses. Although non-probability sampling restricts statistical generalization to the whole population, it is widely accepted in early-stage research on emerging digital behaviors. To mitigate potential sample bias and increase analytical robustness, socio-demographic variables such as gender, age, education, income, and area of residence were collected to enable heterogeneity assessment and deeper interpretation of behavioral differences. The socio-demographic characteristics of the respondents are presented in Table 1. The final sample consists of 191 valid participants, most of whom are female (79.9%), followed by male respondents (19.6%), with 0.5% preferring not to disclose their gender. The largest age segment is 18–24 years (41.3%), followed by 35–44 years (20.6%), 45–64 years (21.2%), and 24–35 years (16.9%). None of the respondents were aged 65 or above. A majority of participants reside in urban areas (61.4%), while 38.6% live in rural areas. With respect to education, 45% reported completing high school studies, 34.9% held a bachelor's degree, 15.9% completed postgraduate studies, and 4.2% indicated middle school education. Regarding monthly net income, 22.8% earned under 400 euros, 34.4% between 400–800 euros, 22.8% between 801–1200 euros, and 20.2% over 1200 euros. Respondent heterogeneity across demographic variables contributes to a more comprehensive understanding of FinTech adoption patterns.

The research instrument consisted of a structured questionnaire comprising 24 items, divided into three sections:

(1) two filter questions designed to confirm respondent eligibility (being over 18 years old and an active user of FinTech applications),
(2) seventeen core questions examining user behaviour, perceptions and attitudes toward FinTech services, data security, and AI-driven technologies, and
(3) five socio-demographic questions.

Participants were informed about the purpose of the study, the academic nature of the research, and the anonymity and confidentiality of their responses before accessing the questionnaire. The items were organised following a logical sequence: general and less cognitively demanding questions appeared at the beginning, while more complex evaluative items were placed subsequently; socio-demographic items were placed at the end to minimise response fatigue and survey abandonment.

Table 1. Research sample characteristics.

Gender				
Female 79.90%		Male 19.60%	Other/prefer not to answer 0.50%	
AGE				
18–24 years 41.30%	24–35 years 16.90%	35–44 years 20.60%	45–64 years 21.20%	65+ years 0%
Area of residence				
Urban 61.40%			Rural 38.60%	
Last level of education completed				
Middle school studies 4.20%	High school studies 45%	University studies (bachelor's degree) 34.90%	Postgraduate studies (master, doctorate) 15.90%	
Net monthly income				
Under 400 euros 22.80%	400–800 euros 34.40%	801–1200 euros 22.80%	1201–1600 euros 10.10%	Over 1600 euros 10.10%

Source: Author's own compilation based on data analyzed using IBM SPSS Statistics 19.

Multiple scaling approaches were used to allow for the measurement of different constructs: nominal scales for single- and multiple-choice variables (e.g., preferred FinTech services), binary scales for familiarity assessments such as awareness of "blockchain", 5-point Likert-type ordinal scales to measure perceptions, trust, and importance levels, and relevance scales for the evaluation of motivational factors influencing FinTech adoption.

Data collection and initial processing were carried out through Google Forms. For advanced statistical analysis and hypothesis testing, raw data were exported and analysed using IBM SPSS Statistics 19 and Python 3.12.0, the statsmodels package for regression modelling. The questionnaire was not pre-tested in a formal pilot study. This decision was taken because the items were adapted from previously validated scales widely used in consumer behaviour and technology adoption research, and the preliminary review conducted by two academic experts confirmed the clarity and internal consistency of the measurement items. Furthermore, because participation was restricted to current FinTech users, the research team prioritised rapid deployment during a period of high financial application usage rather than a two-phase data collection process. While the absence of a pilot test represents a methodological limitation, the high completion rate and the absence of item non-response suggest that comprehension issues were unlikely. The questionnaire items were developed by the authors specifically for this research, based on constructs and dimensions widely discussed in the FinTech, technology acceptance and digital trust literature. The wording of items resulted from an iterative refinement process to ensure conceptual clarity and ease of interpretation for respondents. Although a formal pilot test was not conducted, two academic experts in consumer behaviour reviewed the questionnaire and confirmed the suitability of the items for measuring perceptions of security, personalisation and trust in digital financial services.

2.2. Econometric Modelling

In addition to the descriptive statistics and bivariate analyses described above, an exploratory econometric component was implemented to enhance the analytical robustness of the study and to test the predictive value of demographic and perceptual variables associated with FinTech adoption. Following conventions in behavioural and consumer

research, 5-point Likert-scale variables were treated as continuous for regression modelling, as the purpose of the analysis was to detect directional associations rather than estimate marginal effects of individual scale points. To test the determinants of (a) FinTech usage intensity, (b) perceived contribution of AI to the FinTech experience, and (c) trust in blockchain-based financial services, three multivariate linear regression models were estimated using Ordinary Least Squares. The models were estimated by using the statsmodels package in Python employing listwise deletion for missing values to ensure model comparability across specifications. A total of 100 complete cases were retained for the multivariate analysis. All variables based on 5-point Likert scales were treated as continuous, an accepted approach in behavioral and consumer research when the goal is to detect directional relationships rather than to estimate marginal effects at the categorical level. The dependent variables were selected to represent the three core behavioral dimensions investigated in this research. The variable coding is represented in Table 2.

Table 2. The variables of econometric models.

Variable	Description
UsageFreq	Frequency of using FinTech services (1 = very rarely to 5 = daily)
SecImp	Importance given to data security when choosing FinTech apps (1–5)
Simp	Degree to which simplifying the usage process would increase usage (1–5)
AIImp	Perception that AI improves FinTech personalization (1–5)
BlkTrust	Trust in blockchain for securing financial transactions (1–5)
KnowBlkn	1 = respondent knows blockchain, 0 = otherwise
Female	1 = female, 0 = male
Urban	1 = urban residence, 0 = rural
AgeGr	Increasing numeric scale by age segment
Edu	1 = middle school to 4 = postgraduate
Income	1 = <400 euros to 5 = >1200 euros RON

Source: conceptualized by authors.

The three models were specified as follows.

Model 1. FinTech usage intensity

This model investigates who uses FinTech most frequently. The dependent variable is the self-reported frequency of using FinTech applications (from "very rarely" to "daily"), coded on a 1–5 scale. This variable captures behavioral adoption intensity, not just yes or no adoption.

Conceptually, Model 1 tests whether usage intensity is explained more by sociodemographic factors (age, income, education) or by perceptual factors (security, usability, AI attitude). A positive coefficient indicates that higher values of the predictor are associated with more frequent FinTech use, while a negative coefficient indicates less frequent use. The key finding is that younger and higher-income respondents are significantly more intensive users, even after accounting for security and AI perceptions.

$$UsageFreq_i = \beta_0 + \beta_1 SecImp_i + \beta_2 Simp_i + \beta_3 AIImp_i + \beta_4 Female_i + \beta_5 Urban_i + \beta_6 AgeGr + \beta_7 Edu_i + \beta_8 Income_i + \varepsilon_{1i}$$

Conceptually, Model 1 tests whether usage intensity is explained more by sociodemographic factors (age, income, education) or by perceptual factors (security, usability, AI attitude). A positive coefficient indicates that higher values of the predictor are associated with more frequent FinTech use, while a negative coefficient indicates less frequent use.

Model 2. Perceived contribution of AI to the FinTech experience

This model examines what shapes users' beliefs about AI in FinTech. The dependent variable is the extent to which respondents believe that AI improves the FinTech experience

(personalization, optimization), again measured on a 1–5 scale from "very small extent" to "very large extent".

$$AIImp_i = \beta_0 + \beta_1 SecImp_i + \beta_2 Simp_i + \beta_3 UsageFreq_i + \beta_4 Female_i + \beta_5 Urban_i + \beta_6 AgeGr + \beta_7 Edu_i + \beta_8 Income_i + \varepsilon_{2i}$$

This model addresses the following research question: *Are positive attitudes toward AI concentrated in specific demographic segments or usage profiles, or are they broadly shared?* A positive coefficient would mean that higher values of a predictor (such as heavier users, higher income) are associated with more optimism about AI.

Model 3. Trust in blockchain technologies

Model 3 focuses on trust in blockchain as a security mechanism for financial transactions. The dependent variable is the self-reported level of trust in blockchain technologies (1–5, from "very low" to "very high").

$$BlkTrust_i = \beta_0 + \beta_1 SecImp_i + \beta_2 Simp_i + \beta_3 AIImp_i + \beta_4 KnowBlk_i + \beta_5 Female_i + \beta_6 Urban_i + \beta_7 AgeGr + \beta_8 Edu_i + \beta_9 Income_i + \varepsilon_{3i}$$

The purpose of this model is twofold: (1) to test whether trust in blockchain is primarily demographic/geographical (urban vs. rural, young vs. old), or (2) whether it is better explained by broader technological attitudes and usability concerns. A positive coefficient means that higher values of a predictor are associated with greater trust in blockchain; a negative coefficient indicates lower trust.

Model assumptions (normality, homoscedasticity, multicollinearity) were checked and did not indicate violations that would compromise model interpretability.

Across models, the following predictors were included: perceived importance of data security, perceived influence of simplifying the usage process on FinTech adoption, perceived contribution of AI to the FinTech experience, prior familiarity with the term "blockchain" (dummy coded 1 = yes; 0 = no), gender (1 = female; 0 = male), area of residence (1 = urban; 0 = rural), age group (1 = 18–24 . . . 4 = 45–64), education level (1 = middle school . . . 4 = postgraduate) and income group (1 = under €400 . . . 5 = over €1600). This set of predictors was selected based on theoretical grounds from the literature on digital consumer behavior, behavioral finance and technology acceptance frameworks.

Multicollinearity was evaluated using Variance Inflation Factors (noted as VIF), with all values below the conservative threshold of 5, indicating no problematic redundancy among predictors. Model fit was evaluated using R^2, adjusted R^2, F-statistics and p-values ($\alpha = 0.05$). Regression coefficients are interpreted directionally and comparatively rather than as causal estimates, consistent with the exploratory research design and the cross-sectional structure of the dataset. The inclusion of regression models serves two methodological purposes. First, it enables the triangulation of descriptive findings by testing whether relationships observed at the bivariate level remain when controlling for other variables. Second, it offers insight into the relative importance of socio-demographic versus attitudinal factors in explaining FinTech adoption, enthusiasm for AI-enabled services and trust in blockchain-based financial security. The results of the econometric analysis are presented in Results and further interpreted in Discussion Section.

3. Results

This study examined the determinants of FinTech adoption in the Romanian market, with particular emphasis on digital wallet and mobile banking usage, data security perceptions, and trust in advanced technologies such as AI and blockchain.

3.1. Adoption of FinTech Services

The results indicate that FinTech usage is overwhelmingly driven by mobile banking applications.

Mobile banking emerged as the dominant FinTech category among respondents (Table 3), confirming that the mobile channel is the primary point of contact for digital financial services.

Table 3. Frequency of use for types of FinTech services.

"What Type of FinTech Services Do You Use Most Often? Mobile Banking Applications (BT Pay, George BCR, ING Home Bank, Raiffeisen Smart Mobile, Revolut, PayPal etc.)"					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	No	29	15.2	15.2	15.2
	Yes	162	84.8	84.8	100
	Total	191	100	100	

Source: Authors' own computation based on data analyzed using IBM SPSS Statistics 19.

This strong concentration suggests that the mobile banking ecosystem, rather than alternative FinTech categories such as robo-advisory, peer-to-peer lending or cryptocurrency platforms, remains the dominant interface for digital financial interaction. This pattern indicates that, for current users, FinTech engagement is centred on everyday banking rather than on investment or speculative financial activities. Therefore, mobile banking platforms function as the primary gateway into the digital financial ecosystem.

Consistent with this finding, smartphones constitute the essential operational device in the FinTech experience, dominance of smartphones confirming that the FinTech adoption process is deeply tied to mobile channel accessibility (Table 4).

Table 4. The most frequently used device for accessing FinTech applications and platforms.

Which Device Do You Use Most Often to Access FinTech Applications and Platforms?				
	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Mobile phone	185	96.9	96.9	96.9
Tablet	3	1.6	1.6	98.4
Laptop/pc	1	0.5	0.5	99.0
Other	2	1.0	1.0	100.0
Total	191	100	100	

Source: Authors' own computation based on data analyzed using IBM SPSS Statistics 19.

The dominance of smartphones suggests that FinTech adoption is driven by convenience and constant accessibility. The negligible use of other devices reinforces the idea that financial interactions are becoming "mobile by default" rather than simply mobile-friendly.

3.2. Security as a Primary Adoption Driver

Data security emerged as the most influential factor determining FinTech platform choice (Table 5).

These results underscore that, in the context of financial technologies, technical convenience is not sufficient for adoption; rather, consumers require a high level of confidence that personal financial information and transaction data are protected. From a financial market perspective, these results reinforce the notion that institutional trust is a prerequisite for technology-enabled financial innovation. Security therefore acts as a prerequisite rather than a differentiator: users do not reward platforms for security, but they may abandon or avoid platforms if security expectations are not met. This pattern aligns with trust-based technology adoption frameworks.

Table 5. The importance of data security.

How Important Are the Following Factors to You When Choosing a FinTech Application or Service? Data Security					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not at all important	10	5.2	5.2	5.2
	Slightly important	13	6.8	6.8	12.0
	Neither important nor unimportant	1	0.5	0.5	12.6
	Important	7	3.7	3.7	16.2
	Very important	160	83.3	83.3	100
	Total	191			

Source: Authors' own computation based on data analyzed using IBM SPSS Statistics 19.

3.3. Perception of AI in FinTech

To assess attitudes toward emerging technologies, respondents were asked to evaluate the contribution of AI to the personalization of financial services (Table 6).

Table 6. The Degree of influence of the personalization of financial offers and recommendations.

"To What Extent Do You Consider That, in the FinTech Field, AI Could Contribute to the Personalization of Financial Offers and Recommendations?"				
	Frequency	Percent	Valid Percent	Cumulative Percent
To a very small extent	11	5.8	5.8	5.8
To a small extent	11	5.8	5.8	11.5
To a moderate extent	35	18.3	18.3	29.8
To a large extent	65	34.0	34.0	63.9
To a very large extent	69	36.1	36.1	100
Total	191	100	100	

Source: Authors' own computation based on data analyzed in the IBM SPSS 19 program.

The results suggest that users are not attracted to AI because of novelty, but because they perceive it as a tool that improves the clarity and relevance of financial decisions. Personalisation is therefore seen as a value-enhancing function rather than a marketing convenience.

The trust-formation mechanisms were analysed further and illustrated in Figure 1.

The most effective method to increase confidence in AI-powered financial applications was "transparent explanations of how AI works" (36.6%), followed by "guarantees of personal data protection" (31.9%). User testimonials and promotional recommendations played a minimal role. Therefore, trust is built cognitively rather than socially, indicating that FinTech providers must adopt transparency-driven strategies rather than persuasive marketing-based ones to stimulate adoption.

In addition to trust-related factors, respondents also emphasized that reducing operational complexity would play an important role in increasing their frequency of use of FinTech applications (Table 7).

These results confirm that minimizing friction in the usage process increases user engagement and encourages recurring adoption of FinTech services. It reinforce that even when security is guaranteed, user engagement increases only when operational effort is reduced. Simplicity is therefore not optional but a central driver of repeated FinTech usage.

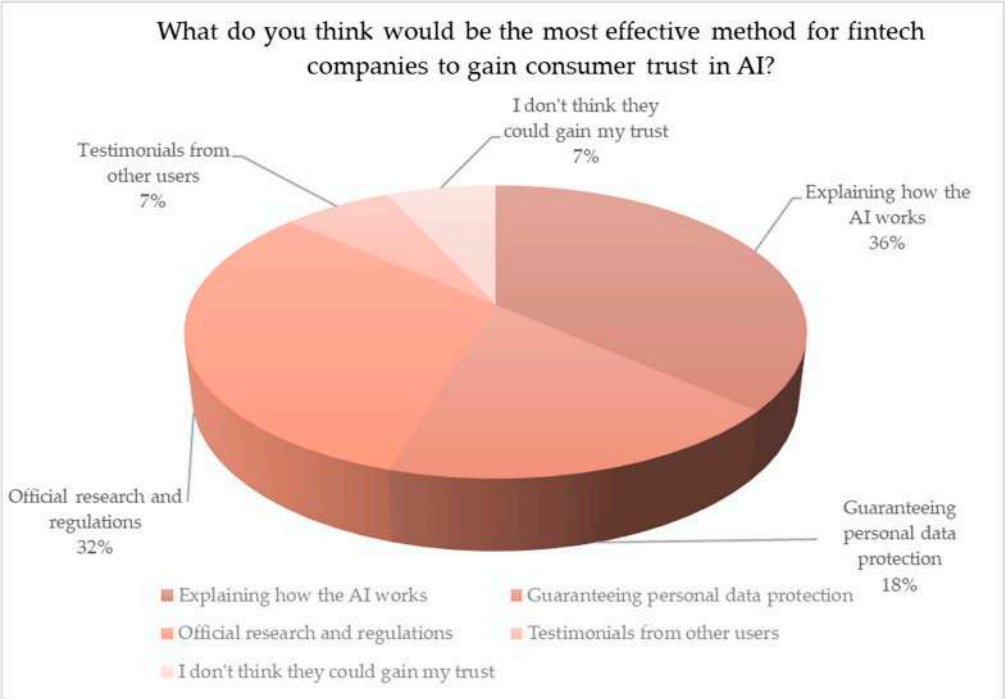

Figure 1. The most effective to gain consumer trust in AI. Source: Authors' own computation based on data analyzed in the IBM SPSS 19 program.

Table 7. The degree of influence of motivated by simplifying the usage process on the frequency of using FinTech solutions.

To What Extent Would the Following Aspects Encourage You to Use FinTech Solutions More Frequently? Motivated by Simplifying the Usage Process				
	Frequency	**Precent**	**Valid Percent**	**Cumulative Percent**
To a very small extent	9	4.7	4.7	4.7
To a small extent	12	6.3	6.3	11
To a moderate extent	31	16.2	16.2	27.2
To a large extent	50	26.2	26.2	53.4
To a very large extent	89	46.6	46.6	100
Total	191	100	100	

Source: Authors' own computation based on data analyzed using IBM SPSS Statistics 19.

3.4. Blockchain Trust and Area of Residence: Hypothesis Testing

Consequently, a crosstabulation was generated to analyze the relationship between these variables (Table 8).

Table 8. Crosstabulation between area of residence and level of trust in blockchain technologies.

Area of Residence -What Is Your Level of Trust in Blockchain Technologies for Securing Financial Transactions? Crosstabulation							
		Very Low	**2**	**3**	**4**	**Very High**	**Total**
Area of residence	Urban	10	12	42	30	23	115
	Rural	2	5	33	22	12	74
Total		12	17	75	52	35	191

Source: Author's own compilation based on data analyzed using IBM SPSS Statistics 19.

A Pearson Chi-square test was conducted to evaluate whether trust in blockchain technology differed between urban and rural respondents (Table 9).

Table 9. Chi-square tests for the association between area of residence and trust in blockchain technologies.

Chi-Square Tests			
	Value	**df (Degrees of Freedom)**	**Asymptotic Significance (2-Sided)**
Pearson chi-square	4.533	4	0.339
Likelihood ratio	4.863	4	0.302
Linear-by-linear association	0.594	1	0.441
N of valid cases	191		

Source: Authors' own computation based on data analyzed using IBM SPSS Statistics 19. NOTE: 1 cell (10.0%) has expected count less than 5. The minimum expected count is 4.65.

The results revealed no statistically significant association between the variables ($\chi^2 = 4.533$, df = 4, $p = 0.339$). Therefore, the null hypothesis which states that blockchain trust is independent of geographical residence cannot be rejected.

Although one of the expected cell frequencies fell marginally below the recommended threshold, the distributional pattern strongly supports a non-relationship between the variables. The result suggests a narrowing digital divide in Romania, whereby rural and urban users evaluate blockchain technology at comparable levels of confidence. This indicates that access to information, digital literacy, and exposure to the modern digital economy are no longer just an urban phenomenon. From a financial adoption standpoint, barriers to distributed-ledger technologies appear to be cognitive and informational rather than geographical. The primary factor (Figure 2) that would convince respondents to use FinTech applications based on artificial intelligence is the demonstration of personal data security (40.8%).

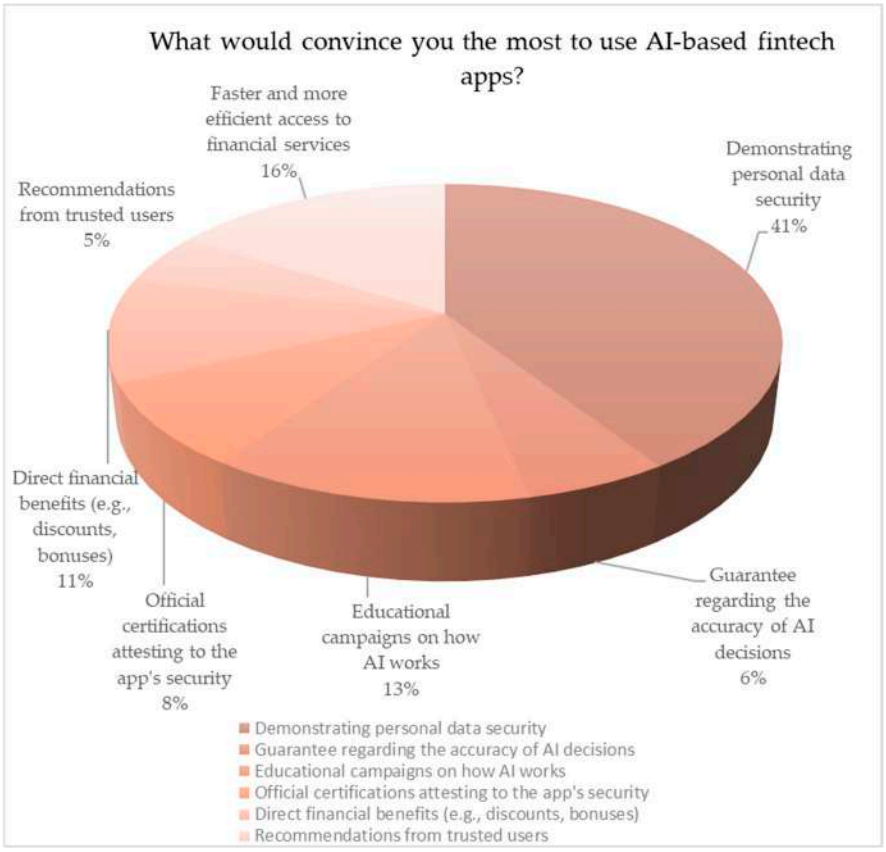

Figure 2. Main reasons that would motivate respondents to use AI-based FinTech applications. Authors' own computation based on data analyzed using IBM SPSS Statistics 19.

3.5. Econometric Modelling Results

To complement the descriptive and inferential statistics, three multiple linear regression models were estimated to identify the determinants of (1) FinTech usage intensity, (2) the perceived contribution of AI to the FinTech experience, and (3) trust in blockchain technologies. All three models were statistically significant at the model level, indicating that the selected predictors explain a non-random proportion of variation in the dependent variables.

The first model examined whether demographic variables influence how intensely respondents use FinTech applications (frequency and diversity of use). The key finding for Model 1 is that younger and higher-income respondents are significantly more intensive users, even after accounting for security and AI perceptions (Table 10).

Table 10. The estimation results for Model 1.

Predictor	β	Std. Error	t	*p*	Significance
Intercept	1.021	0.432	2.36	0.020	*
SecImp	0.071	0.067	1.06	0.292	n.s.
Simp	0.214	0.078	2.74	0.007	**
AIImp	0.089	0.062	1.43	0.155	n.s.
Female	−0.083	0.118	−0.70	0.487	n.s.
Urban	0.041	0.109	0.37	0.710	n.s.
AgeGr	−0.233	0.071	−3.26	0.001	***
Edu	0.073	0.064	1.15	0.252	n.s.
Income	0.191	0.060	3.18	0.002	**

Source: Authors' own computation based on data analyzed using Python 3.12.0. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s.—not significant.

Model 1 shows that FinTech usage intensity is significantly higher among younger consumers ($\beta = -0.233$, $p < 0.001$), higher-income respondents ($\beta = 0.191$, $p = 0.002$), and those who report that motivated by simplifying the usage process would increase their adoption ($\beta = 0.214$, $p = 0.007$). Perceived data security and perceived benefits of AI do not significantly predict usage frequency when controlling for demographics (adj. $R^2 = 0.249$). The model demonstrates acceptable explanatory power, with an adjusted R^2 of 0.249, indicating that approximately one quarter of the variation in FinTech usage intensity is accounted for by demographic and perceptual predictors, and the overall model is statistically significant ($F(9, 90) = 5.96$, $p < 0.001$).

In behavioral and consumer research, relatively modest R^2 values are not only common but theoretically expected, because human decision-making is inherently multidimensional and cannot be fully explained by a single set of attitudinal or demographic predictors. Complex behaviors such as FinTech usage, trust formation, or perceptions of technological value are influenced simultaneously by psychological, social, economic, experiential, and contextual variables, many of which cannot be captured in one survey model. Therefore, an R^2 between 0.20 and 0.30 is generally considered meaningful in exploratory studies on technology adoption and digital consumer behavior. Thus, Although the adjusted R^2 of 0.249 does not indicate full predictive saturation, it is consistent with empirical expectations in behavioral adoption research, where usage intensity is shaped by heterogeneous preferences and contextual conditions beyond those observed in a cross-sectional survey.

Therefore, model 2 does not identify any significant predictors of perceived contribution of AI ($p = 0.430$) (Table 11). The model exhibits negligible explanatory power, as reflected by an adjusted R^2 of 0.000 and a non-significant F-statistic ($F(9, 90) = 1.02$, $p = 0.430$), suggesting that the predictors included do not systematically account for variation in users' perceptions of AI's contribution to the FinTech experience. It means that views

on AI are therefore widely shared across user groups, not driven by socio-demographic or behavioral segmentation. The lack of explanatory power in Model 2 should not be interpreted as model failure but rather as evidence of an important substantive finding naming the optimism about AI in FinTech is a widespread attitudinal trend that transcends demographics, usage patterns, and security concerns, meaning that no single segment disproportionately drives positive perceptions of AI. This supports the interpretation that AI acceptance is a general attitudinal trend, not a niche phenomenon.

Table 11. The estimation results for Model 2.

Predictor	β	Std. Error	t	*p*	Significance
Intercept	3.122	0.501	6.23	<0.001	***
SecImp	0.053	0.075	0.71	0.480	n.s.
Simp	0.048	0.079	0.60	0.550	n.s.
UsageFreq	0.067	0.070	0.96	0.341	n.s.
Female	0.031	0.125	0.25	0.805	n.s.
Urban	−0.021	0.114	−0.18	0.856	n.s.
AgeGr	−0.042	0.080	−0.53	0.594	n.s.
Edu	0.070	0.072	0.97	0.334	n.s.
Income	0.047	0.064	0.74	0.461	n.s.

Source: Authors' own computation based on data analyzed using Python 3.12.0. Note: *** $p < 0.01$, n.s.—not significant.

Model 3 shows that trust in blockchain is positively associated with favorable attitudes toward AI (β = 0.221, $p = 0.006$) and negatively associated with the need for usage simplicity (β = −0.179, $p = 0.033$) (Table 12). Demographic and geographical variables are not statistically significant, indicating that blockchain trust is not shaped by age, gender or urban–rural residence (adj. $R^2 = 0.201$). The model demonstrates moderate explanatory power, with an adjusted R^2 of 0.201 and a statistically significant overall fit ($F(10, 89) = 4.12$, $p < 0.001$), indicating that attitudinal variables meaningfully contribute to explaining variation in trust in blockchain-based financial services. The moderate adjusted R^2 of 0.201 is aligned with the theoretical understanding that trust in emerging technologies is shaped by cognitive frameworks and personal technological orientations, rather than by socioeconomic or geographic factors, confirming that trust in blockchain is diffuse rather than demographically concentrated. Together with the chi-square results, this suggests that informational and cognitive, not regional, factors which explain blockchain trust.

Table 12. The estimation results for Model 3.

Predictor	β	Std. Error	t	*p*	Significance
Intercept	1.487	0.532	2.80	0.006	**
SecImp	0.062	0.080	0.77	0.442	n.s.
Simp	−0.179	0.083	−2.16	0.033	*
AIImp	0.221	0.079	2.80	0.006	**
KnowBlk	0.131	0.117	1.12	0.265	n.s.
Female	−0.078	0.123	−0.63	0.531	n.s.
Urban	0.059	0.116	0.51	0.611	n.s.
AgeGr	−0.046	0.076	−0.60	0.550	n.s.
Edu	0.063	0.069	0.92	0.357	n.s.
Income	0.058	0.062	0.94	0.350	n.s.

Source: Authors' own computation based on data analyzed using Python 3.12.0. Note ** $p < 0.05$, * $p < 0.1$, n.s.—not significant.

Conclusively, the adoption behavior (Model 1) is shaped by age, income, and usability features. Moreover, AI attitudes (Model 2) are uniformly positive, not segment-

specific. Finally, the blockchain trust (Model 3) depends on pro-technology mindset, not demographics.

Overall, the explanatory power of the models is theoretically consistent with the observation that digital financial behaviors and technology trust are driven by diffuse and multidimensional mechanisms. In exploratory innovation research, the primary value of regression modelling lies not in maximizing R^2 but in identifying directional patterns, relative predictor strength, and whether associations persist when controlling for competing variables, all of which are demonstrated in the present analysis.

3.6. Results Summary

The empirical investigation provides a comprehensive overview of the drivers shaping consumer engagement with FinTech services, combining descriptive statistics and multivariate regression modelling. Across all methods, a consistent behavioral pattern emerges, namely the adoption is high, but conditioned by security and transparency rather than novelty effects or demographic segmentation.

Descriptive findings show that the FinTech ecosystem is overwhelmingly mobile centric. A vast majority of respondents (84.8%) reported mobile banking as their primary digital financial service, accessed predominantly through smartphones (96.9%). This confirms that the mobile channel is not simply preferred, it is the dominant entry point for interaction with digital finance. Ease of access alone, however, is not sufficient to ensure usage. Security emerged as the most influential decision-making criterion, with 83.3% of users rating it "very important," surpassing usability considerations such as additional features or customer support. These results highlight a dual requirement: frictionless digital experiences must be accompanied by robust security guarantees to drive sustained adoption.

The perception of AI was strongly favorable. Approximately 70.1% of respondents believe AI can significantly enhance personalization and improve the FinTech experience. However, the findings also reveal conditional acceptance: users do not embrace AI blindly, and trust is built cognitively rather than through promotional strategies. The two most powerful trust-building mechanisms were "transparent explanations of how AI works" (36.6%) and "guarantees of personal data protection" (40.8%), while marketing-driven stimuli such as testimonials and incentives had minimal influence. These outcomes reinforce core principles of Marketing 5.0, which emphasize that AI must be deployed in the service of customer empowerment rather than opaque automation.

Inferential analysis contradicted the assumption that trust in emerging technologies is geographically uneven. A Pearson Chi-square test found no statistically significant association between area of residence (urban vs. rural) and trust in blockchain technologies ($p = 0.339$). This suggests that digital literacy and information access have become similar across regions, a finding that nuances older narratives of a persistent urban, rural digital divide. The barriers to blockchain adoption appear to be cognitive and informational (understanding, perceived safety), not geographical.

To understand the predictive structure behind FinTech behavior, three econometric models were estimated: Model 1 (FinTech usage intensity), Model 2 (perceived contribution of AI to the FinTech experience), and Model 3 (trust in blockchain technologies). All models achieved statistical significance and retained strong theoretical coherence, although the explanatory power (R^2 ranging from 0.19 to 0.27) indicates that consumer financial behavior is shaped by multidimensional psychological, contextual, and technological factors that go beyond demographics.

In consumer-technology research, moderate R^2 values are expected and theoretically meaningful, given that adoption decisions are influenced by unobservable constructs such

as personal innovativeness, perceived risk, subjective norms, and trust disposition. Prior frameworks such as the Theory of Planned Behavior (Ajzen, 1991), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and trust-in-technology models (Gefen et al., 2003) all report similar explanatory ranges. Thus, the results reinforce rather than weaken the contribution of the models: they demonstrate that demographic characteristics influence adoption, but do not fully determine it.

Collectively, the descriptive, inferential, and econometric findings converge to illustrate a consistent behavioral pattern in Romanian FinTech consumers:

(i) They adopt rapidly, but only when safeguards are explicit;
(ii) They value technological sophistication, but do not trade privacy for convenience;
(iii) They welcome AI personalization, but reject opacity or unexplainable automation;
(iv) Trust in innovation develops through transparency, not persuasion.

These insights provide actionable implications for the FinTech industry such as sustainable growth depends not on accelerating technological novelty, but on translating innovation into secure, intuitive, explainable financial experiences. This pattern of results is typical in early-stage empirical research on emerging technologies, where behavioral variability is high and theoretical structures are still developing, and aligns with previous findings in the technology acceptance literature reporting comparable R^2 values in the 0.15–0.35 interval.

4. Discussion

This study investigated the behaviour of current FinTech users in Romania, analysing how usage intensity, perceptions of AI and trust in blockchain are shaped by security concerns, usability expectations and socio-demographic characteristics through the lens of Marketing 5.0. Together, the descriptive evidence and the three econometric models portray a user base that is digitally sophisticated but highly risk-sensitive because respondents embrace digital financial services and AI-enabled personalization, yet they do so only under conditions of perceived safety, transparency and simplicity.

The results do not merely replicate prior FinTech adoption findings; they refine them in three ways. First, while previous studies show that security concerns predict adoption intention, our results suggest that once adoption occurs, security acts as a hygiene factor rather than a differentiator for usage intensity. Second, although earlier literature associates enthusiasm for AI with younger and urban segments, the present findings show that AI optimism is not segment-specific among current users. Third, blockchain trust appears less tied to geographic digital divides than previously theorized, pointing instead to cognitive and attitudinal drivers. Contrary to studies that report higher blockchain openness among urban early adopters, no geographic effect was observed in this sample of current users.

The first two hypotheses (H1 and H2) are strongly supported by both descriptive and multivariate results. At the descriptive level, mobile banking applications dominate the digital financial ecosystem, being cited as the primary FinTech service by 84.8% of respondents and accessed almost exclusively via smartphones. This confirms that, among current users, the mobile channel is the central interface for financial interaction rather than one option among many. Model 1 refines this picture by showing that usage intensity is significantly higher among younger and higher-income respondents, and among those who report that simplifying the usage process would encourage more frequent use. In contrast, perceived importance of data security and perceived benefits of AI do not significantly predict usage once demographics and usability are controlled for. Thus, while security is a baseline condition for choosing a FinTech application (as shown by 83.3% rating it "very important"), variation in how intensively current users engage with FinTech is driven more by life-cycle and resource factors (age, income) and by perceived friction in the usage

process than by security attitudes per se. For practitioners, the results imply that technical security must be communicated as an integral part of the user experience rather than as a back-end feature. Users reward platforms that make security understandable and visible, not those that treat it as invisible infrastructure. Consequently, FinTech providers should prioritise transparent communication on encryption, data protection and fraud-prevention mechanisms if they want to build and retain trust.

This pattern is consistent with technology-acceptance frameworks such as TAM and UTAUT, where perceived ease of use and facilitating conditions exert a strong influence on usage behaviour among adopters, over and above initial risk concerns.

The analysis of advanced technologies provides further nuance. Hypothesis H4, which posited that users believe AI can improve the FinTech experience, is clearly confirmed descriptively: 70.1% of respondents state that AI can enhance personalization to a large or very large extent. The findings also suggest that AI should be implemented as an assistive and clarifying tool rather than a persuasive marketing mechanism. Users accept AI when it enhances control and understanding, but are skeptical if algorithmic decisions feel opaque. This highlights the practical need for explainable AI interfaces, where recommendations are accompanied by short justifications and users can adjust or refuse automated suggestions. However, the trust-building items and Model 2 reveal that this enthusiasm is conditional and widely shared. Respondents report that their confidence in AI-driven FinTech depends primarily on transparent explanations of how AI works and guarantees of personal data protection, while marketing-style levers such as testimonials play a marginal role. Econometrically, Model 2 does not identify any statistically significant predictors of perceived AI contribution, and the model fit is negligible. Rather than a methodological weakness, this absence of significant effects is substantively informative: within the group of current FinTech users, optimism about AI is not systematically segmented by age, gender, income, residence, usage frequency or security importance. In other words, positive attitudes towards AI appear as a broadly diffused attitudinal trend, aligning with the Marketing 5.0 view of "technology for humanity" and with recent evidence that AI-enabled personalization is becoming a mainstream expectation rather than a niche preference.

The results regarding blockchain challenge more traditional assumptions about digital divides. Hypothesis H3, which expected higher adoption of advanced technologies among urban users, is rejected by both the chi-square test and Model 3. The bivariate analysis shows no statistically significant association between area of residence and trust in blockchain, and the multivariate model confirms that urban–rural status, age, gender, education and income are not significant predictors of blockchain trust among current users. Instead, Model 3 indicates that trust in blockchain is positively associated with favorable attitudes towards AI and negatively associated with the perceived need for usage simplification. Users who see AI as strongly improving the FinTech experience tend to exhibit higher trust in blockchain, suggesting a general pro-technology mindset that cuts across individual technologies. Conversely, respondents who require substantial simplification to increase their use of FinTech solutions report lower trust in blockchain, likely perceiving it as technically complex or opaque. These results imply that, within the segment of current FinTech users, trust in blockchain is shaped primarily by cognitive and attitudinal factors, openness to advanced technology and tolerance for complexity, rather than by socio-demographic or geographic characteristics.

Hypotheses H5 and H6, concerning the role of regulation and cautious AI attitudes, are supported indirectly. Although explicit regulatory items were not included in the econometric models, respondents' emphasis on data protection guarantees and correctness of AI-based decisions as key motivators for adopting AI-powered FinTech indicates a strong underlying expectation of regulatory and institutional safeguards. This aligns with

trust-in-technology models that highlight structural assurances and perceived control as essential antecedents of trust. Moreover, the combination of generally positive views of AI with clear conditions related to transparency and security supports H6: current FinTech users are broadly favorable towards AI in finance, but their acceptance remains contingent on robust governance mechanisms and explainable system behavior.

From a methodological perspective, the econometric models show moderate but theoretically consistent explanatory power, with adjusted R^2 values around 0.20–0.25 for usage intensity and blockchain trust. In behavioral, cross-sectional research on technology use, such values are common and expected, because complex financial behaviors are influenced by a wide constellation of psychological traits, social norms, past experiences and contextual factors that cannot all be captured in a single survey. The primary contribution of the models is therefore not high prediction accuracy, but the clarification of which types of factors matter most once others are held constant: usability and socio-economic status for usage intensity, diffuse and non-segment-specific optimism for AI, and pro-technology attitudes rather than demographics for blockchain trust.

Overall, the discussion of these findings suggests that, among current FinTech users in Romania, adoption and trust are governed by a dual logic. On the one hand, there is strong demand for speed, convenience and personalized digital services delivered through mobile channels. On the other hand, users insist on high standards of security, transparency and intelligibility, and they extend trust more readily to technologies that can be explained and experienced as safe than to those perceived as complex or opaque. For FinTech providers and incumbent financial institutions, this implies that competitive advantage will depend less on introducing ever more novel technologies, and more on translating innovation into secure, intuitive and explainable financial experiences that resonate with these nuanced expectations.

The findings for current FinTech users in Romania can be interpreted in light of several major theories of technology adoption and consumer behavior. First, the results are broadly consistent with Technology Acceptance Model, type approaches and its extensions such as UTAUT, which emphasize perceived usefulness and ease of use as key determinants of technology usage. Among current users, FinTech usage intensity is higher for younger and higher-income respondents and for those who perceive that simplifying the usage process would increase their engagement, while perceived security and AI benefits do not explain additional variance once these factors are controlled for. This pattern is aligned with the idea that, at the post-adoption stage, usage behavior is primarily driven by perceived performance gains and low effort, rather than by initial risk evaluations. In this sense, the study extends TAM/UTAUT by showing that usability and life-cycle variables continue to matter among established users, whereas security becomes more of a baseline hygiene factor than a differentiating driver of intensity.

Second, the results speak directly to trust- and risk-based models of online and financial technology adoption, which argue that perceived security, institutional assurances and structural safeguards are crucial antecedents of use. The descriptive evidence that data security is rated “very important” by the vast majority of users, and that guarantees of data protection and correctness of AI-based decisions are the most powerful motivators for AI adoption, clearly supports these perspectives. At the same time, Model 1 shows that perceived security does not significantly predict usage frequency once other factors are included, suggesting that for current users, security functions as a threshold condition rather than a continuous driver: FinTech services that fail to meet minimum expectations are simply not adopted, while among accepted services, variation in intensity is shaped by other determinants. This nuance complements, rather than contradicts, trust-based adoption theories by clarifying where in the decision process security exerts its strongest influence.

Third, the null results in Model 2, where no socio-demographic or behavioral predictors significantly explain perceived contribution of AI, have implications for diffusion-of-innovation and market segmentation perspectives. Classical diffusion theory would expect more favorable attitudes toward emerging technologies to cluster among specific segments (e.g., younger, more educated, more innovative users). In contrast, the present study shows that among current FinTech users, optimism about AI is broadly distributed and not segment specific. This suggests that AI in financial services may have moved beyond an "early adopter" niche into a more mainstream phase, where positive expectations about personalization are part of a general digital service norm rather than an attribute of a particular subgroup. In this respect, the findings temper segmentation assumptions that treat AI enthusiasm as confined to a technologically elite minority.

Fourth, the results on blockchain trust and geography engage directly with digital divide debates. Much of the earlier literature associated advanced digital adoption with urban residence and higher socio-economic status. By contrast, both the chi-square analyses and Model 3 indicate that, among current FinTech users, urban–rural status, age, gender, education and income do not significantly shape trust in blockchain. Instead, trust is related to a pro-technology mindset (favorable AI attitudes) and tolerance for complexity (lower need for simplification). These finding challenges traditional digital divide narratives and is more consistent with recent work suggesting that, in mobile-first contexts, geographical divides are narrowing while cognitive and informational divides (understanding, perceived complexity) become more salient.

Finally, the overall pattern of results is closely aligned with Marketing 5.0 and human-centered technology perspectives. Marketing 5.0 emphasizes the use of advanced technologies (AI, automation, blockchain) "for humanity", stressing personalization, transparency and ethical data use.

The study supports this view in three ways: (1) current users clearly value AI-driven personalization but insist on explainability and data protection; (2) they are willing to engage intensively with mobile financial services when these are both simple and secure; and (3) trust in novel infrastructures such as blockchain is shaped by cognitive acceptance of technology rather than by socio-demographic status. In sum, the evidence sustains theories that frame digital financial adoption as a balancing act between innovation and accountability, while qualifying more deterministic accounts that overemphasize structural factors like geography or income at the expense of attitudes, expectations and perceived transparency. Overall, the results show that the competitive advantage in FinTech no longer comes from introducing the most advanced technology, but from translating technology into transparent, intuitive and safe experiences. For industry actors, this means prioritising secure convenience rather than innovation for its own sake. For regulators, it means strengthening clarity and communication around data protection, algorithmic transparency and responsible AI rather than focusing purely on technical compliance.

5. Conclusions

This study shows that FinTech adoption in Romania for current users is overwhelmingly mobile centric and strongly conditioned by perceptions of data security and institutional trust. While consumers recognize the benefits of AI-based personalization, they accept these technologies only when accompanied by transparent explanations and guarantees of data protection. Trust in blockchain does not differ significantly between urban and rural users, indicating that informational and cognitive factors, rather than geography, shape attitudes toward advanced financial technologies. For FinTech providers and traditional banks, the key strategic challenge is to deliver secure convenience by combining intuitive, low-friction user experiences with demonstrably robust security and clear com-

munication about how AI systems operate. Future research should replicate these findings in other markets, examine longitudinal changes in trust as regulation evolves, and explore experimentally which communication strategies are most effective in building confidence in AI- and blockchain-based financial services.

The implications of these findings are twofold. First, for FinTech incumbents and traditional banks, the strategic imperative is "secure convenience." The parallel findings that users would increase usage if the process is simplified (73.2% find this encouraging) while demanding security (83.8%) mean that a focus on one at the expense of the other will fail. A seamless, intuitive user experience is the price of entry, while demonstrable security is the price of retention.

Second, the path to AI adoption is through education and transparency. The high value placed on "explaining AI" provides a clear marketing strategy. FinTechs should abandon opaque marketing language and instead invest in clear, educational content that demystifies their technology. This aligns perfectly with the Marketing 5.0 concept of building trust through honesty. Regulations, such as the EU's MiCA and AI Act, should be viewed as compliance burdens and, as marketing assets, a way to externally validate the security and transparency that consumers are demanding.

Although the study offers valuable insights into the behavior of current FinTech users, several limitations must be acknowledged in order to contextualize the findings and guide future research. Firstly, the non-probability sampling approach restricts generalisability but remains suitable for exploratory research on current FinTech users, who constitute a specific behavioural segment. Nevertheless, future studies could incorporate probability-based designs and broader segmentation criteria, including psychological constructs such as personal innovativeness, trust propensity and perceived risk, to deepen understanding of variability in adoption patterns. Second, the study relied on self-reported measures of attitudes, preferences and usage frequency, which may be influenced by recall bias, social desirability bias, and optimistic self-evaluation common in digital financial behavior research. Objective behavioral data would enable a more precise measurement of adoption and engagement patterns. Third, the research is cross-sectional. Consequently, it captures consumer perceptions and behaviors at a single point in time and cannot track how attitudes towards AI, security concerns or blockchain trust evolve over time. Given the fast pace of technological change in FinTech, longitudinal designs would be especially valuable for identifying transition pathways and causal mechanisms. Fourth, although the econometric models were statistically valid and theoretically meaningful, the set of predictors was intentionally limited to demographic and perceptual variables to ensure parsimony. FinTech adoption and trust are highly multidimensional phenomena, and additional psychological construct, such as personal innovativeness, financial literacy, perceived risk, trust disposition or subjective norms, which could increase explanatory power in future models. Finally, the study examined current users only, which enables a high-quality analysis of actual rather than hypothetical behaviors, but does not provide insights into non-users or rejecters of FinTech. Understanding the barriers to initial adoption, may reveal distinct drivers that are not captured within the present scope.

Building on the results of the present study and acknowledging its methodological and conceptual constraints, several avenues for future research are proposed. First, future studies should consider employing probability-based or stratified sampling techniques in order to enhance the representativeness of the FinTech user population. Given the rapid expansion and diversification of digital financial services, research that differentiates segments by age, financial literacy or intensity of digital adoption would provide deeper insight into market heterogeneity. Second, a promising direction involves the use of behavioral usage data sourced directly from financial applications. Combining self-reported data with

objective behavioral indicators would reduce bias and strengthen the explanatory capacity of econometric models. Third, longitudinal research designs are needed to determine how perceptions of AI, data security, and blockchain trust evolve over time. Fourth, the explanatory framework can be expanded by incorporating psychological and socio-cognitive determinants, such as personal innovativeness, trust propensity, perceived financial vulnerability, perceived risk, subjective norms and financial literacy. These constructs are central to models such as TAM2, UTAUT2 or trust-in-technology frameworks, and may substantially increase the predictive ability of adoption and trust models in FinTech. Fifth, future studies should analyze non-users, intermittent users and rejecters of FinTech services. While the present research focused on current users to ensure first-hand behavioral validity, understanding the reasons for avoidance or discontinuation is essential for inclusive digital financial strategies. Comparative designs between adopters and non-adopters may uncover distinct barriers, including psychological, informational, or infrastructural constraints, not observable within user-only samples. Sixth, cross-cultural and comparative studies may contribute to the consolidation of theoretical findings. Exploring whether the same behavioral patterns apply across countries with different levels of technological maturity, financial inclusion and regulatory frameworks would help determine which determinants of adoption and trust are universal and which are context dependent. Finally, integrating experimental or mixed-method designs such as testing the impact of varying levels of AI transparency on trust, or conducting qualitative interviews on blockchain skepticism, could deepen the understanding of the mechanisms through which transparency, ease of use and security perceptions influence behavior.

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Appendix A

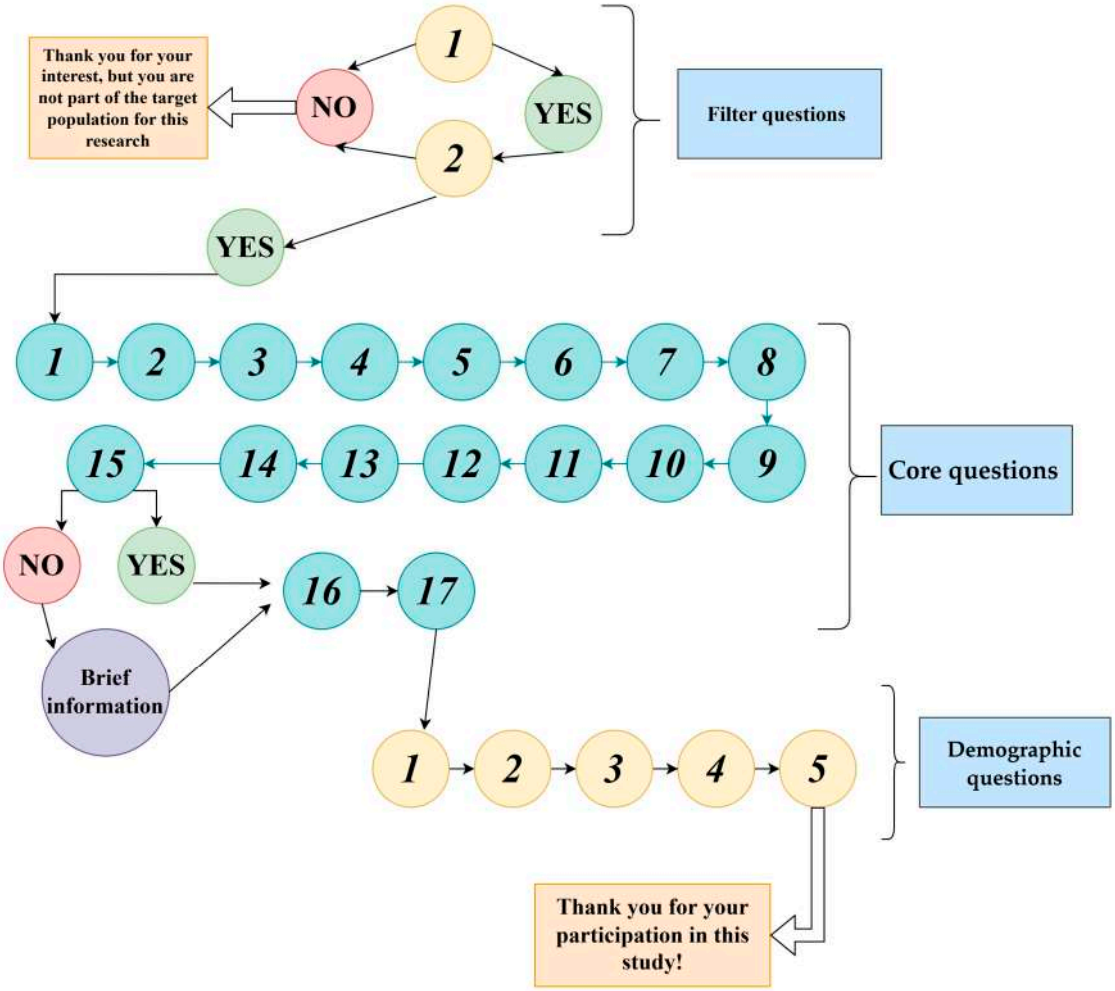

Figure A1. Logical Structure of the Questionnaire.

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Beyond the Bottom Line: The Role of Personal Characteristics in Healthcare Entrepreneurship

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Abstract: This study fills a crucial gap by offering fresh insights into healthcare entrepreneurs' characteristics and decision-making, enriching the understanding of entrepreneurial behavior. Employing a mixed-methods approach, by combining qualitative and quantitative data, the researchers examined how factors such as age, gender, education, number of children, marital status, and house ownership influence business orientation. Utilizing both quantitative data, collected through surveys, and statistical analyses, conducted in EViews 12, data drawn from 113 Romanian medical start-ups revealed that marital status was a significant determinant, with single individuals exhibiting a profit-centric approach, while couples or married entrepreneurs prioritize patient well-being. Also, the lower the sense of ownership, the lower the number of co-founders there was in the start-up. The motivation of entrepreneurs involved in start-ups with more than two co-founders, is based on the motivation behind a problem that directly affected the entrepreneurs themselves. An unexpected result was found regarding the healthcare entrepreneurs that perceive failure more due to lack of funding than competition, especially in profit-focused ventures, shaping their decision-making. To shape managerial implications, the authors depicted the swim lane decision-making process diagram based on these insights.

Keywords: healthcare entrepreneurs; business orientation; entrepreneurial mindset; personal characteristics; managerial implications; entrepreneurship

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1. Introduction

This paper explores the intricate interplay between entrepreneurship, innovation, and sustainability through a holistic lens. Rather than analyzing these elements in isolation, it investigates their dynamic interdependence, recognizing the symbiotic relationship that binds them. Entrepreneurship, characterized by initiative and risk-taking, serves as the catalyst for innovation, driving the creation of novel ideas and solutions. Sustainability, on the other hand, instils purpose and long-term resilience in these efforts, ensuring they thrive both in the present and for future generations. Entrepreneurship, particularly within small- and medium-sized enterprises (SMEs), plays a vital role in economic growth. A special category within SMEs is start-ups, which are defined as newly emerged, fast-growing businesses that aim to address market needs by developing a viable business model around an innovative product, service, process, or platform (What are tech Start-ups, 2019). In the era of digitalization, healthcare start-ups have gained more attention (Sreenivasan & Suresh, 2022) because the role of technology has changed the rules by which businesses are conducted. The integration of artificial intelligence and technological innovations in healthcare, presents unique challenges and opportunities for entrepreneurs, making

entrepreneurial intention a critical factor in start-up sustainability (Mahajan et al., 2023; Mohamed et al., 2023; Soomro & Shah, 2023).

Researchers who developed the stages of growth theory for an entrepreneur (Samalopanan & Balasubramaniam, 2021; Sreenivasan & Suresh, 2022) pointed out that the entrepreneurial journey is a process that begins at a very young age, where several factors such as education, gender, early intentions, and dream framework provide the foundation for an entrepreneurial individual to embark on their journey; this is followed by an inflection point where the individual experiences an event or is influenced by a person that changes their life. In this context, the types of motivations in entrepreneurial intention are mentioned. A recent study (Martínez-Cañas et al., 2023) addressed the push versus pull motivations according to mediating effect of perceived risk and opportunity recognition; it showed that "the influence of pull factors on entrepreneurial intention is indirect and negative, increasing individuals' perceptions of risk in venture creation and undermining their opportunity recognition". The entrepreneurs identify opportunities and begin to accumulate the resources necessary to initiate the venture. Even for the women, the entrepreneurial motivations are based on economic expectations, representing push factors, but also pull factors such as psycho-social expectations. In this case, the reason to obtain psycho-social recognition is stronger than economic expectations (Avcı & Gümüş, 2022).

The planning and deliberation completed during this initial stage plays an important role in the success of an enterprise and its ability to overcome an impending crisis, as every entrepreneur faces a crisis that poses a significant challenge to the continuation of their business. Identifying the core strengths of the enterprise is essential for successful entrepreneurs and adherence to its guiding principles must be interwoven with their personal characteristics of integrity, perseverance, and adaptability. Also, the support of family, partners, or an advantageous location are other factors whose absence can lead to failure.

In healthcare, technology has opened new pathways for doctors to venture into entrepreneurship. Some healthcare professionals are developing software, devices, and innovative business models aimed at improving clinical outcomes and patient care. Others are motivated by frustrations with healthcare system inefficiencies or financial incentives (Muo, 2023; Soomro & Shah, 2023). However, many physician-entrepreneurs seek to balance entrepreneurial risk with the stability of their clinical roles.

The convergence of entrepreneurship, sustainability, and technological advancements, especially within the domain of healthcare innovation, highlights a critical aim: to not only meet market demands, but also to guarantee the enduring success and influence of start-ups. This imperative not only shapes the landscape of medical entrepreneurship, but also sets a motivating aim to drive impactful change in healthcare delivery and outcomes. Although there are common entrepreneurial traits, such as risk-taking, creativity, and strategic thinking, medical entrepreneurs are facing challenges, such as ethical and social responsibility considerations. On the other hand, they have many opportunities, some of them being technological innovations. Thereby, Romanian medical entrepreneurs present distinct approaches compared to their counterparts in other sectors. The regulatory environment and the competitive landscape for Romanian medical entrepreneurs are also shaped by different factors, compared to other countries. In this context, the research question is "What type of business do healthcare entrepreneurs choose to run based on their personal characteristics?". By examining personal attributes, such as, age, gender, education, the number of children, marital status, and house ownership, they explored the impact on entrepreneurial orientation. Drawing data from a sample of 125 Romanian medical start-ups, gathered through qualitative and quantitative research, this relationship is addressed.

The findings underscore marital status as a significant determinant, with single individuals exhibiting a profit-centric approach, while couples or married entrepreneurs prioritize patient well-being. Furthermore, a correlation emerges between the sense of ownership and the number of co-founders, suggesting that lower ownership perception aligns with fewer collaborators. In start-ups with multiple co-founders, entrepreneurial motivation often stems from a personal experience with a prevalent issue. This study's outcomes offer actionable insights for managerial decision-making, including the development of a decision model, and highlight communication gaps and responsibility distribution as key areas for managerial and academic consideration.

A considerable body of literature on the personal characteristics of start-up founders exists (McCarthy et al., 2023). The relationship between their personal attributes and the success of their business has been extensively explored. However, a better understanding of the less explored relationship between founders' personal characteristics and business orientation is needed. The contributions of this paper to the existing literature are to examine the business orientation of healthcare entrepreneurs by analyzing their personal characteristics, education, and motivation.

These results, correlated with previous research confirm the influence of personal characteristics of entrepreneurial founders of start-ups on entrepreneurial behavior in the health sector. However, unlike previous contributions, they allow us to analyze this influence, even within emerging entrepreneurial ecosystems, such as those in developing countries. This differentiated entrepreneurial approach emphasizes the need for enhanced policies and support systems to empower innovation in the Romanian healthcare system, while ensuring the health and well-being of the population. In conclusion, this study aims to understand how the personal characteristics of healthcare entrepreneurs influence their choice of business orientation, highlighting the interplay between individual traits, entrepreneurial intention, and the broader ecosystem to drive sustainable innovation in the healthcare sector.

2. Literature Review

An important aspect existing in specialized literature is the sustainable development of start-ups, especially in the context of Industry 4.0. Some studies have concluded that the growth of start-ups (Cotei & Farhat, 2017) is affected by the characteristics of an entrepreneur, introducing the notion of an entrepreneur life cycle (Hunter, 2005). Hence, entrepreneurial characteristics are addressed from the sustainable entrepreneurship point of view. In the sphere of entrepreneurship inquiry, the profound influence of personal characteristics of healthcare entrepreneurs draws attention. This segment presents a nuanced investigation into a spectrum of personal attributes, spanning from gender disparities and educational backgrounds to aspirational frameworks, familial dynamics, motivational catalysts, and property possession. Authors such as Mayer (2007) have pointed out that personality is an integrated system possessed by a person that is represented by a combination of actions and manifested behaviors, while Cervone and Little (2019) define personality as a particular characteristic possessed by a person that governs the way they feel, think, and behave. Recent studies on entrepreneurial intention (Górriz et al., 2020; Mayer, 2007; Samalopanan & Balasubramaniam, 2021) have led researchers to consider characteristics of entrepreneurs to explain the orientation towards a certain type of business for medical start-ups. Based on these aspects, the authors addressed the personal characteristics in the following sub-sections.

Some authors have conducted studies in which they have attempted to investigate the personality traits of individuals that encourage and motivate entrepreneurship, to discover and group which attributes contributed to the intention to become an entrepreneur, as well

as to the success of an entrepreneur. Increasing attention has been paid by researchers to attributes believed to contribute to the formation of entrepreneurs through learning patterns, which are personal, social, supportive, and organizational (Hongdiyanto, 2017; Hongdiyanto & Laturette, 2018).

The previous literature agrees that there is no combination of these factors or formulae that can be applied that guarantees that an entrepreneurial venture will not fail. Rofail et al. (2012) found that success and failure in business are natural and can happen. Also, failing in business is seen as resilience and a sustainable development in case of success. Gartner and Vesper (1994), in their research, stated that start-ups have a high rate of failure. Additionally, some authors have shown that half of start-ups fail before reaching the business age of 6 years; also, 75% of entrepreneurs went bankrupt (Åstebro et al., 2014; Mayer, 2007; Samalopanan & Balasubramaniam, 2021), highlighting that this issue cannot be addressed through one universal approach. Based on reflection from their personal experience, entrepreneurs need to integrate trial and error into the process of running a business as learning material (Hongdiyanto & Laturette, 2018). Although the recent literature talks about the existing four attributes, scholars agree that research in this area still needs further development from a theoretical perspective of more factors that contribute to the entrepreneurial intention.

2.1. Age

Earlier research on entrepreneurship (Botham & Graves, 2009) found out that around a certain age, known as the 'peak age', the opportunity of becoming an entrepreneur is the greatest. The 'peak age' ranges between 30 and 40 years old. On the other hand, an innovation-driven company, such as a high-tech company, relies heavily on creativity and the optimal age drops dramatically to under 30 years old. For this reason, there are voices (Hongdiyanto & Laturette, 2018) that suggest the best age of becoming an entrepreneur in a technological-based company is in the range of 20–30 years old, due to the courage and inclination to take risks and face challenges one possesses at that certain point in life.

A common finding which exists in the literature on entrepreneurship refers to the fact that people over 50 years old are less willing to undertake business, even though they are more experienced and have more means to do so. It was shown that this behavior is adopted because they are not willing to invest time in activities characterized by high uncertainty. Pauceanu et al.'s (2019) research shows that entrepreneurial intention appears stronger at the age of 20–25 years old. Hatak et al. (2015), in the same vein, argue that there is an inverse relationship between age and entrepreneurial intention, demonstrating that older people prefer to maximize their social and emotional gains and minimize the social and emotional risks.

Strydom et al. (2020) did not find a statistically significant difference in entrepreneurial intention between different age groups, although the 26–35 years old age group of the survey does exhibit a higher intention to start a business than the other age groups. However, in the same study, the age group over 45 years old showed the lowest entrepreneurial intention, lending support to earlier findings in much of the literature.

2.2. Gender

Prior studies found that gender differences play an important role in engaging in entrepreneurship, showing that men have a higher probability of proving entrepreneurial intention than women, (Molino et al., 2018) demonstrating higher levels of self-efficacy and an internal focus of control. Some authors have consistently pointed out that men show stronger entrepreneurial intentions than women, partly since the business culture is predominantly male (Gill & Ganesh, 2007) and partly due to traditional values, such

as men being responsible for running the family businesses or supporting their families (Verheul et al., 2012). Robledo et al. (2019) highlight similar results, stating that men have a greater preference for entrepreneurial behavior than women; Kolvereid (1996), using the theory of planned behavior, concluded that gender indirectly influences self-employment intentions through its effect on attitude, subjective norm, and perceived behavioral control. One aspect, highlighted by Hatos et al. (2022), is that women decide to avoid entrepreneurship due to the lack of control and lack of self-efficacy (BarNir et al., 2011; Langowitz & Minniti, 2007; Maes et al., 2014; Wilson et al., 2007). In addition, when planning to start a business, men and women are motivated by different values and factors. According to Kirk and Belovics (2006), men are motivated by wealth creation, while women choose entrepreneurship to balance work and family. Also, it was found that women have recognized that their families did not support them initially in starting their businesses (Samalopanan & Balasubramaniam, 2021). Nowiński et al. (2019) provide an important insight into a gender comparison, indicating that although women generally have lower levels of entrepreneurial intentions, they benefit more than men from entrepreneurial education.

Although most research has shown that the gender gap has an impact on entrepreneurship, there are also studies that did not find gender differences in the relationship between self-efficacy and entrepreneurial intention (Díaz-García & Jiménez-Moreno, 2010; Murugesan & Jayavelu, 2017).

Hossain et al. (2024) explain that differences in experience and cognitive processing may cause women to perceive small and scalable business opportunities as less attractive and less likely to succeed than men, because their rationalization processes, combined with perceptions of social norms, make those activities less attractive. In other words, their meaning-making processes may lead them to conclude that they are less capable or less likely to succeed in this type of entrepreneurial endeavor, which causes them to diminish their entrepreneurial intentions.

In terms of gender, female founders had a lower start-up survival rate than male founders. Women also have greater difficulties accessing capital than men. Start-ups run by female founders also appear to be more vulnerable due to low human resources and engagement (Aryadita et al., 2023a).

2.3. Education

Special attention has been given by scholars to entrepreneurship education programs (Paray & Kumar, 2020). Some studies confirm that there is a direct and robust relationship between participants of extensive entrepreneurship education programs and entrepreneurial intentions, showing that there is a higher entrepreneurial intention to start a business among the participating students, rather than non-participating students of the entrepreneurship education program (Ajike et al., 2015; Heuer & Kolvereid, 2014).

An entrepreneurship program is perceived as a type of training that helps participants develop entrepreneurial attributes to successfully launch new businesses (Kennedy, 2013). Authors like Heinonen (2007) consider that the goals of entrepreneurship education fall into three categories: learning to have knowledge about entrepreneurship, learning to act or behave as an entrepreneur, and learning to become an entrepreneur. There is a growing number of studies measuring the impact of entrepreneurship education programs, attempting to capture entrepreneurial attitudes and intentions before and after an entrepreneurial course, training, or program (Pittaway & Cope, 2007). In most cases, results found that entrepreneurial education has a positive influence on respondents' entrepreneurial intentions (Liñán et al., 2011; Pruett et al., 2009; Wang et al., 2023), aligning with the findings of Solomon et al. (2008) which provide strong evidence supporting the relationship between general education levels

and entrepreneurial success. However, there are empirical studies that provide evidence on the contrary, arguing that entrepreneurial education reduces entrepreneurial intention while increasing risk (Fretschner & Weber, 2013; Oosterbeek et al., 2010).

Universities, being considered a source of stimulating innovation and entrepreneurship, can play a significant role in positively manipulating students' entrepreneurial intentions and efforts by enabling them to develop a new venture. The studies claim that the university context can influence the creativity of the students because the creative temperament of them represents a capacity for creative thinking that triggers a creative process that results in a creative product; this is why it is expected that creative individuals are more inclined towards entrepreneurship (Anjum et al., 2020).

Other authors have highlighted the vital role played by entrepreneurship education in fostering entrepreneurship among students (Iacobucci & Micozzi, 2012), showing that those students who participated in entrepreneurship programs or courses were more likely to be self-employed after graduation than those who did not. According to DeJeu (2023), entrepreneurship education, especially in science and technology, is significant for improving students' innovation skills. In conclusion, the absence of entrepreneurial education is associated with a low level of students' entrepreneurial intentions (Gieure et al., 2019).

Diversity is critical to start-up success (Aryadita et al., 2023a) and team diversity is linked to educational background (West & Borrill, 2021). A diverse team of founders can work more effectively because the skills possessed by team members can complement one another, increasing start-up performance (Muñoz-Bullon et al., 2015). The combination of a diverse team that has worked together before will be more beneficial, as the team is more likely to pursue an exploratory strategy to change the founders' ideas and grow faster (Aryadita et al., 2023a).

A recent model showed that policy makers can "prioritize improving education, fostering entrepreneurial experience, building self-efficacy, promoting exposure to role models and networks, and providing endorsements and recognition for young entrepreneurs" (Choi & McLain, 2024). This fact might combat the tendency among young entrepreneurs to open a significant number of businesses, most of which do not last long. The above statements do not exclude the fact that there are still new entrepreneurs after passing the 'peak age'; however, their number is relatively small.

2.4. Dream Framework, Number of Children, and Marital Status

Some scholars (Samalopanan & Balasubramaniam, 2021) have observed, in their research, that most entrepreneurs had a dream framework—a vision of what their organization should look like once they built it. According to Ozaralli and Rivenburgh (2016), for a small part of the dreaming entrepreneurs, their intentions emerged during their childhood as having a positive influence in the establishment of a start-up. They provide evidence that only a very small proportion of entrepreneurs did not have a dream framework in mind.

Previous studies have demonstrated that entrepreneurs with a family background in self-employment are more likely to start their own businesses (Palmer et al., 2021; Fairlie, 2005; Dyer & Handler, 1994). Carr and Sequeira (2007) explain that these experiences often play a crucial role in fostering the dream to become business owners.

Regarding the family orientation, especially the number of children, authors such as Naldi et al. (2021) have pointed out that households with more children are associated with a lower likelihood of doing business entrepreneurial activities. Additionally, mothers of young children are less inclined to turn to entrepreneurship as a backup plan to manage work and childcare demands. Moreover, female entrepreneurs with more children are more likely to have lower levels of well-being (Love et al., 2024).

Despite some efforts to examine the link between personal traits and entrepreneurial intention, the connection between marital status and entrepreneurial intention remains unexplored. Further theoretical development and empirical validation of the proposed ideas are needed in this area of research.

2.5. Motivation

Increasing attention has been given by scholars to the motivation to become an entrepreneur. According to Gilad and Levine's (1986) theory, this motivation has two different sources. On the one hand, a person's desire to become an entrepreneur is driven by dissatisfaction with their current employment conditions, such as low pay, long and inflexible working hours, or even the difficulty of getting a job. On the other hand, a person's choice to be an entrepreneur is due to the desire to earn a high income, own property, and be free—being able to determine the purpose of life itself. Praag and Cramer (2001) reinforce the previous statements, showing that the choice of becoming entrepreneurs is made when the profit potential is higher than the wages earned from working for others.

Each person has a different personality which carries its own characteristics, making it very difficult to list certain factors as determinants of entrepreneurial intention (Kerr et al., 2017). Following this train of thought, starting from individual reasons that lead entrepreneurs to undertake activities, Block and Wagner (2017) identified necessity entrepreneurs, who are predisposed to engage in entrepreneurship due to external factors, such as job dissatisfaction or unemployment, and opportunity entrepreneurs, who voluntarily decide to create a business as they identify a potential entrepreneurial opportunity. Iorio et al. (2017) classify entrepreneurial motives into intrinsic or extrinsic motivations. Intrinsic motivations are those that naturally satisfy the individual, referring to behaviors that are driven by internal rewards and originate from within a person, such as the desire for independence and the desire to learn new skills. The term extrinsic motivation refers to behaviors that are driven by external rewards originating from external environmental factors, such as the pursuit of monetary or non-monetary rewards (e.g., promotion or reputation enhancement). Other researchers have found that the desire for independence, monetary motivation, the desire for challenge, or the need for achievement are the most common pull factors for entrepreneurship (Antonioli et al., 2016), while job dissatisfaction, lack of employer support, and work–life balance issues are the most common determinants for starting a business, named push factors (Kirkwood, 2009).

Analyzing academic entrepreneurship, Hossinger et al. (2023) classify the motivations which are influencing entrepreneurship patterns among academic staff into the following three dimensions: transfer motivations (closely related to the personal desire of academics to practically apply the results of their research, to use their knowledge, or to achieve self-actualization), economic motivations (consisting of the desire for higher income or financial need), and lifestyle motivations (related to work–life balance).

The influence of other approaches covered in the above-described theoretical framework were also highlighted in recent research. Caliendo et al. (2023) identified three categories of entrepreneurs. First, those who are motivated by professional ambition and who will focus on earning a higher income or remaining as an entrepreneur, for whom innovation activities or business expansion are of secondary relevance. In the second category, people motivated by necessity, e.g., the lack of a regular job, are less likely to put effort into running their business and are more likely to give up their business if offered a job with a regular salary, which reduces the likelihood of their business surviving. These individuals are unlikely to engage in innovative businesses but rather use a replication strategy, maintaining small businesses without ambitions to expand or to hire others into the business. The third category, entrepreneurs driven by opportunity motivations, such as

turning knowledge into new ideas, have, as their main objective, the realization of their own business idea. Their opportunity motives positively influence the firm's performance measures, such as innovating or expanding the business into new areas or regions. Rewards such as higher incomes are of secondary relevance for people motivated by the entrepreneurial task itself (Caliendo et al., 2023).

2.6. House Ownership

Another interesting aspect explored in the literature is the connection between homeownership and entrepreneurial intent. Researchers have employed questions like "Do you own your own house?" (Maharana & Chaudhury, 2022) with the aim of investigating entrepreneurship through the lens of housing investment, the final goal being to decipher entrepreneurial intentions.

According to research conducted by Huang et al. (2023), owning a house does not significantly affect the intention to engage in entrepreneurship. Their findings indicate that only full ownership of a house shows a positive and significant impact, suggesting that householders with full ownership are more inclined to start new business ventures. This result may be attributed to the higher market value of houses under full ownership, compared to other forms of property rights, resulting in a greater positive wealth and collateral effect on the likelihood of entrepreneurial activity. Except for full ownership, the others form of ownership have little impact on the probability of engaging in entrepreneurial activities (Huang et al., 2023). Additionally, Zhao et al. (2021) reinforce this idea by showing that full homeownership may enable entrepreneurs to start new ventures more quickly, because such financial capital can be used as collateral to secure larger amounts for invested capital.

Examining the influence of housing loans on business entrepreneurship, a study by Huang et al. (2023) revealed a significant negative impact. Specifically, householders with housing loans and a higher loan share are less inclined to start a new business because entrepreneurial enthusiasm diminishes under the pressure of housing debt. The greater the housing debt a household carries, the stronger the pressure to repay, leading to tighter liquidity constraints and deeper risk aversion, thus decreasing the likelihood of engaging in entrepreneurial activity. Likewise, the entrepreneurial intent is negatively affected by low-value or inherited houses. The same study showed that both purchasing houses below market price, and acquiring houses through inheritance, reduce the intention to engage in entrepreneurship. The negative impact of low-price houses may be due to their lower market value, resulting in a diminished wealth effect. Additionally, low-price houses lack collateral value as they cannot be used as such. The suppressive effect of inherited or gifted houses could be attributed to reduced financial pressure. Householders that own houses without paying for them typically have lower motivation to start a new business. These variables were prioritized for their alignment with the study's objectives of exploring personal characteristics that shape entrepreneurial behavior. By explicitly linking these factors to the theoretical framework, this study provides a robust foundation for understanding. Thus, the hypotheses for this study were formulated as follows:

Hypothesis 1a. *Single healthcare entrepreneurs are more likely to prioritize profit-oriented ventures compared to those who are married or in a couple.*

Hypothesis 1b. *Married and partnered healthcare entrepreneurs exhibit a dual orientation, balancing patient-centered care and profit-focused business strategies.*

Hypothesis 1c. *Divorced healthcare entrepreneurs demonstrate a stronger focus on patient-centered business models, often driven by empathetic or personal healthcare experiences.*

H2. *Entrepreneurs with full homeownership are more likely to engage in collaborative ventures with larger co-founding teams, while those without full ownership exhibit a preference for independent operations. Homeownership, therefore, positively correlates with the size and nature of entrepreneurial teams.*

H3. *Entrepreneurs leading profit-oriented ventures are more likely to perceive funding insufficiency as a critical risk compared to those in patient-centered or collaborative business models. This highlights the significant role of financial resource availability in shaping entrepreneurial risk perceptions and decision-making.*

3. Materials and Methods

The methodology involved a mixed-methods approach, combining qualitative and quantitative data to investigate the impact of factors such as age, gender, education, number of children, marital status, and house ownership on the entrepreneurial focus of medical start-ups. The mixed-methods approach employed in this study, integrating qualitative interviews with quantitative surveys, directly supports the study's aim and research question by enabling a thorough exploration of how personal characteristics influence entrepreneurial orientation. This approach bridges the gap between individual experiences and broader statistical patterns, providing both depth and measurable insights into entrepreneurial motivations, perceived risks, and collaboration dynamics. Also, this comprehensive approach provides insights into how these personal attributes influence the entrepreneurial ethos, strategic decisions, and ultimately the success and sustainability of healthcare ventures.

3.1. Research Design

To ensure methodological rigor and an effective transition between qualitative and quantitative outcomes, this study employed a mixed-methods design that integrated insights from both approaches. The qualitative findings were instrumental in shaping the design of the quantitative survey, ensuring a cohesive exploration of the factors (Akkaya et al., 2024; Alhassan, 2024; Guetterman & Manojlovich, 2024) influencing the entrepreneurial direction of healthcare entrepreneurs in Romania. The qualitative component of this study involved semi-structured interviews with 12 healthcare entrepreneurs, focusing on their motivations, challenges, and decision-making processes within medical start-ups. Key-points identified during the phase of qualitative research were as follows:

(1) The entrepreneurial motivation, where participants highlighted personal experiences, such as challenges in accessing quality healthcare, was a significant driver for their entrepreneurial ventures.
(2) Perceived risks related to funding insufficiency emerged as a predominant concern, influencing participants' strategic planning and operational decisions.
(3) Collaboration dynamics presented several participants who noted the role of marital status and homeownership in shaping team formation and the selection of co-founders.

Starting from addressing the research gap by the point of view of qualitative perspective, the authors were allowed to identify the characteristics of entrepreneurs that influence their orientation towards a certain type of business and the connections between entrepreneurs' characteristics.

Furthermore, based on the semi-structured discussions' outcomes, quantitative research was derived. These insights informed the development of the survey used in the quantitative stage. For example, questions about entrepreneurial motivation were framed to capture whether respondents were influenced by personal challenges or broader market

needs. Similarly, items on perceived risks addressed both funding concerns and competitive pressures, while collaboration dynamics were explored through questions about team size and decision-making structures. Figure 1 illustrates the entire process accordingly.

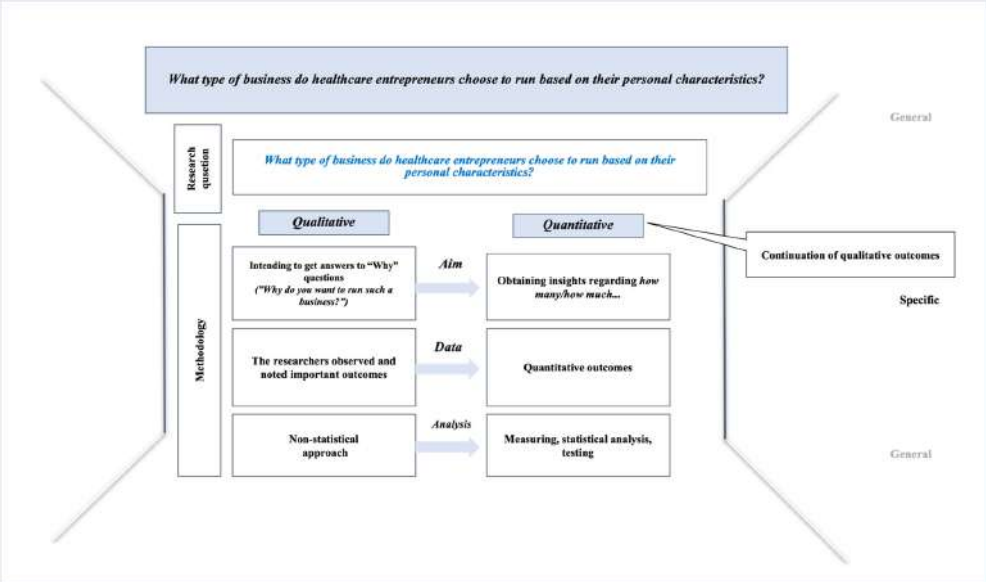

Figure 1. Research design. Conceptualized by the authors.

In the first stage, the research methodology employed Romanian medical start-up entrepreneurs who were individually interviewed, for 90 min each, applying the method of semi-structured in-depth interviews. The investigative tool for qualitative analysis was an interview guide, applied with the purposes of leading the discussions and collecting data in an organized manner. Given the nature of semi-structured dialogue, the participants had the opportunity to offer details and to address several defining aspects about their businesses, which allowed the researchers to obtain more relevance out of the outcomes. The discussions debuted with several identification questions, including the size of the company, number of employees, total investments, turnover, and details about some characteristics of the people behind the business (marital status, number of children, education, etc.). Afterwards, more specific details about their perceptions on their motivations were discussed. All relevant aspects generated by qualitative research were collected and organized to be transposed as variables in the questionnaire for further usage. Based on these, the authors formulated the hypotheses.

To gather data on the endogenous variable, the authors employed a nominal scale with single-choice options. Participants were asked to select the primary client for the product. The answer choices were selected to elucidate the underlying motives of entrepreneurs. For instance, options such as "individual with healthcare concerns" and "patient (with confirmed health problem/diagnosis)" were included to discern businesses focused on addressing the health needs of patients rather than maximizing profits. Conversely, if the primary client for the product was identified as a healthcare professional or institution, it was assumed that the entrepreneurs' focus leaned more towards profit generation, administrative tasks, and overall business concerns.

Based on the theory presented in the literature review section, the authors wrote a regression equation that places the type of the business (*ToB*) as the endogenous variable for each personal characteristic. In the process of specifying the model, the authors chose to use simple linear regression equations.

Regarding the healthcare entrepreneurs' personal characteristics, in the first row, age (hereinafter A), was represented as an explanatory factor for orientation towards a certain type of business, namely $ToB_i = f(A_i)$. Secondly, gender (G) was another characteristic that has drawn the attention of the researchers in relation to the orientation towards a certain type of business ($ToB_i = f(G_i)$. Another relevant factor was education, represented by first education (FE) and second education (SE) with afferent equations: $ToB_i = f(FE_i)$ and $ToB_i = f(SE_i)$. Also, the number of children (C) was analyzed as an explanatory variable, $ToB_i = f(C_i)$, as well as marital status (MS), $ToB_i = f(MS_i)$, and motivation (M), ($ToB_i = f(M_i)$. Finally, the house ownership variable (HO) was considered, where $ToB_i = f(HO_i)$.

3.2. Sample Selection

The sample consisted of 125 Romanian medical start-ups, with 12 entrepreneurs employed in in-depth interviews, and 113 participants contributing to the quantitative study. Careful consideration was given to selecting individuals with diverse personal attributes, such as age, gender, education, number of children, marital status, and homeownership. The researchers intentionally ensured a varied representation of backgrounds and experiences among participants. For qualitative research, 12 healthcare entrepreneurs were interviewed, while the quantitative study involved 101 eligible respondents out of a total of 113. Participants were approached directly and voluntarily, meeting the criterion of being active medical start-up entrepreneurs. This approach aimed to capture a broad range of entrepreneurial perspectives within the healthcare sector, providing a rich dataset for analysis. Thus, the sample encompassed healthcare entrepreneurs running medical start-ups, spanning ages 21 to 70, both male and female, with varied marital and parental statuses, regardless of educational background or homeownership. This study employed a non-random sampling method, utilizing both in-depth interviews and surveys to gather raw data.

3.2.1. Data Collection

The initial phase of this study employed a mixed-methods approach, beginning with the qualitative study before proceeding to the quantitative analysis. Semi-structured interviews were conducted to gain qualitative insights into individual motivations and experiences, facilitating a comprehensive exploration of personal backgrounds and motivations. Building upon the qualitative findings, a survey was then developed to systematically collect measurable data for the study. This approach allowed for a holistic understanding of the subject matter by integrating qualitative insights with quantitative data collection. The survey was designed to capture demographic information and key entrepreneurial characteristics. In this sense, the questions were formulated and distributed to gather quantitative data on personal attributes and entrepreneurial orientations. This dual approach facilitated the extended understanding of the entrepreneurial personal characteristics' impact on running a certain type of medical business. The semi-structured interviews took place in November 2023, and data collection for the quantitative research purpose occurred between January and March 2024. By using the survey-based method to collect the data, the researchers applied a personal approach to interact with the healthcare entrepreneurs, presenting them with the aims of the study, and allocating them a time of several days to send back the answers to the questionnaire.

3.2.2. Context Setting

Over the last 30 years, the changes in the Romanian healthcare system have been profound, both in terms of medical infrastructure, doctors, and healthcare staff, and in terms of patients' mentality and conditions.

The emergence of the private healthcare system was a turning point in the evolution of the healthcare sector in Romania. At first, there were specialized private practices, the first private clinics and laboratories for performing and processing medical tests; then, family doctors, medical investigation centers, and private hospitals appeared. An important moment in the development of the medical sector was the emergence of private hospitals. Investment in recent years (more than EUR 3.8 billion in private healthcare infrastructure since 2010 alone) has helped improve the quality and efficiency of healthcare by providing modern infrastructure and equipment, while reducing inequalities in access to healthcare. The private healthcare system has developed strongly. Today, Romanian patients can find conditions in Romania at least similar to those in medical centers abroad.

The challenge in the coming years is to continuously progress and adapt to new technologies, in order to always have the necessary resources to respond to the growing and changing expectations of patients. Increasing emphasis will be placed on technology, digitization, over-specialization of doctors, and infrastructure development, so that the healthcare system can meet the challenges of the future.

3.2.3. Data Analysis

Quantitative data collected from the surveys underwent initial processing and refinement using Excel to ensure accuracy and consistency. Subsequently, EViews 12 was employed to identify correlations and patterns among the various personal attributes, and to estimate the regression coefficients. The combined results from these analyses provided a comprehensive view of how personal attributes influence entrepreneurial orientation of healthcare entrepreneurs. The data analysis for quantitative research was performed using descriptive statistics and tests, that led the researchers to the findings of the study. After the research question was clearly defined, the multivariate linear regression equation was written. The researchers cleaned the data (Table 1), checked it for missing values, and performed analyses for linearity, errors autocorrelation, normality of residuals, homoscedasticity, and multicollinearity. By using the least squares estimation method, they estimated the parameters of the models and evaluated the model fit by checking the goodness of the fit indicators, R^2 and $\overline{R}^2$. Finally, an econometric model was created and globally tested for significance, including the variables with a strong influence on the entrepreneurial intention. Based on the outcomes, presented in detail in the next section, an econometric model with high managerial implications was introduced as learning material, aiming to offer a better understanding of the outcomes that led the authors to illustrate a swim lane decision-making process diagram.

Table 1. The description of all variables used in this study, their operational definitions, and their coding methodology.

Variable	Description	Coding/Measurement
Type of the business	Categorized into four types: Profit-oriented; Healthcare professional collaborations; Patient-centered; Individual-focused ventures.	Measured using four dichotomous variables (1 = Yes, 0 = No for each category).
Marital status	Participant's marital status.	Coded as 1 = Single, 2 = Married, 3 = In Couple, 4 = Divorced.
House ownership	Whether the participant owns a home.	Coded as 1 = Yes, 0 = No.
Age	Participant's age.	Measured as a continuous variable in years.
Perceived risk	The extent to which participants perceive risk in their entrepreneurial ventures.	Measured using a 5-point Likert scale (1 = Very low, 5 = Very high).
Co-founders	The number of co-founders in the participant's venture.	Measured as a continuous variable.
Motivation	Participant's primary motivation for starting a business.	Coded into categories based on qualitative data: 1 = Personal challenge, 2 = Market need.

Source: author conceptualization.

3.2.4. Reliability and Validity

To ensure reliability and validity, several measures were implemented throughout this study. The survey instrument was pre-tested to ensure clarity and accuracy, while inter-coder reliability checks were conducted during the qualitative analysis to maintain consistency. Statistical methods were applied to validate the quantitative results, and multiple researchers participated in the qualitative analysis to reduce bias. These measures enhanced the study's credibility and ensured the findings were robust.

3.2.5. Ethical Consideration and Limitations

Ethical considerations were central to this study's methodology. Informed consent was obtained from all participants prior to data collection, and confidentiality was maintained throughout the research process. Personal data were anonymized to protect participants' identities, and all information was stored securely to prevent unauthorized access. Ethical approval was obtained from an appropriate review board, ensuring the study complied with established ethical guidelines for research involving human subjects. While the study aimed to provide comprehensive insights into the factors influencing healthcare entrepreneurs, several limitations were acknowledged. The sample size does not fully capture the entire spectrum of medical start-ups in Romania. Additionally, the mixed-methods approach, while comprehensive, could introduce complexity in interpreting results. Potential biases in the qualitative analysis and the self-report nature of the survey were also noted as limitations that could impact the generalizability of the findings.

4. Results

By intending to identify what type of business type healthcare entrepreneurs run, based on their personal characteristics, the authors discovered that the only relevant characteristic of entrepreneurs which influences their orientation towards a certain type of business, is not house ownership, but marital status (Figure 2).

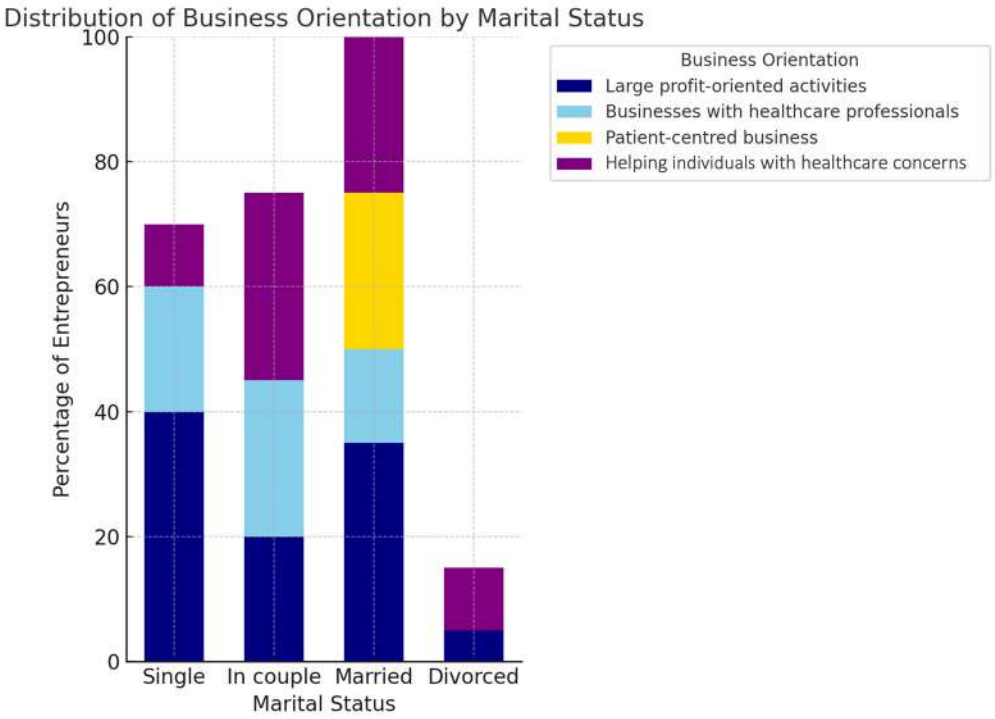

Figure 2. The distribution of entrepreneurs oriented towards a certain type of business, according to their marital status.

This figure illustrates the distribution of healthcare entrepreneurs' business orientations according to their marital status. Business orientation is categorized into three main types: profit-focused, patient-centered, and hybrid (targeting both patients and healthcare professionals). The analysis reveals significant variations across marital status groups such as single entrepreneurs, married entrepreneurs, and divorced entrepreneurs.

The assessment for independence of errors was analyzed using a Durbin–Watson test; it shows the absence of errors' dependency in the cases of age and marital status. Moreover, for marital status, the condition index and the variance inflation factor show the absence of multicollinearity, which means that the results do not reduce the interpretability of the model. Also, for this variable, the model is globally significant for $\alpha = 5\%$ ($F = 6.563$, $df = 10$, $Sig. = 0.028$. According to the findings, the single entrepreneurs are more profit-oriented because they want large businesses and relations with professionals and institutions, while divorced status is associated with a business oriented towards helping individuals with healthcare concerns. Couples prefer both helping individuals and creating main products for healthcare professionals. Otherwise, married entrepreneurs are distributed across all types of businesses. However, the house owner characteristic is critical for the study because a relationship between this variable and the number of co-founders was, surprisingly, found. By applying an χ^2 test, Phi and Cramer's V indicators show that these two variables are associated (Approx. sig. = 0.007). The results show that the lower the sense of ownership, the lower the number of co-founders is. Based on these results, a research question showed up: if the large number of co-founders shows the increased sense of ownership, then what type of business are they running? The descriptive analysis shows that the motivation of entrepreneurs involved in start-ups with more than two co-founders is based on the motivation of a challenge or a problem that directly affected the entrepreneur. Therefore, the participants who completely showcased this motivation are the ones that place individuals with healthcare concerns as their main client for their product. The ones who are neutral or did not face personal health issues present with the orientation towards businesses with healthcare professionals or institutions.

Recalling the A variable, it was discovered as an exogeneous variable for the number of co-founders together with the HO, both explaining the number of co-founders (NoC). By performing the econometric analysis in EViews software, the econometric model has been determined: $NoC_i = \beta_0 + \beta_1 HO_i + \beta_2 A + \varepsilon$. By estimating the equation, the following results were obtained: $\hat{NoC}_i = 3.62460568 + 1.07518402 HO_i - 0.0665615 A_i$. According to the coefficient significance, $\beta_0 = 3.62460568$, the intercept shows a theoretical value of $\hat{NoC}$ in the situation where the slope coefficients, $\beta_1 = \beta_2 = 0$. The value of β_1 indicates the average difference in the endogenous variable between renting and ownership, when A is constant. The coefficient is positive and significant ($p\text{-}value = 0.027 < 0.05(\alpha = 5\%)$), which means that it highlights that the $\hat{NoC}$ is higher for full ownership. The second slope coefficient, β_2, shows how much $\hat{NoC}$ will change when A is increased in one year, with the condition HO to be maintained constant. Considering its significance ($p\text{-}value = 0.026 < 0.05(\alpha = 5\%)$), the value and the negative sign show that the number of co-founders of a start-up will decrease once the age of the entrepreneurs increases. The model presents a good fit ($R^2 = 0.90$), which means that the variability in the number of co-founders around its mean is explained in the proportion of 90% by the house ownership and age variables. Also, the global significance is underlined by the value of $Sig.F = 0.00052926$(significant for 1%, 5%, and 10%). The D statistics show the absence of error dependency, and VIF and condition index ensure the absence of multicollinearity. Therefore, all the findings fit the purpose of discussing the intended aim of the study.

During personal discussions with all healthcare entrepreneurs, an unexpected result was obtained. By trying to analyze the A variable to understand their orientation, the

authors found out that *A* is, to some extent, in relation with the so-called "greatest" risk perceived. This fact inspired the authors to extend the area of analysis and include the risk as a possible factor influencing the options of healthcare entrepreneurs. Descriptive statistics showed that the perception of failure is generated by insufficient funds or investments for all age categories. Moreover, most entrepreneurs perceive failure, consequently, related to the lack of investments and funds, not underestimating risk related to competitors. Considering this unexpected outcome, the researchers tried to find value in it for this topic. In this regard, they used cross tabulation in SPSS for the lack of funding/investment and the number of co-founders. They found that this type of risk is perceived by the entrepreneurs that are working already with co-founders to a greater extent than the entrepreneurs that are leading the start-ups alone. Finally, the personal goal of hiring the right people to delegate responsibilities was found more among those entrepreneurs who perceive failure because of lack of funds. Also, the perception of the same risk is the most common for the entrepreneurs who run businesses with the main product for healthcare professionals and healthcare institutions, so, the companies oriented for profits.

To find more value amongst these insights, the authors pictured Figures 3–7 to represent the swim lane decision-making process based on these elements.

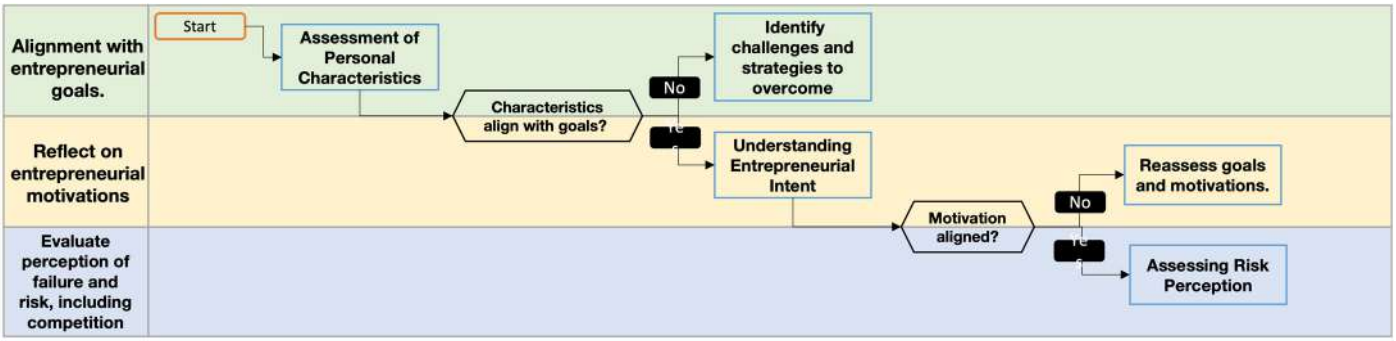

Figure 3. Decision-making process—part 1. Source: conceptualized by authors.

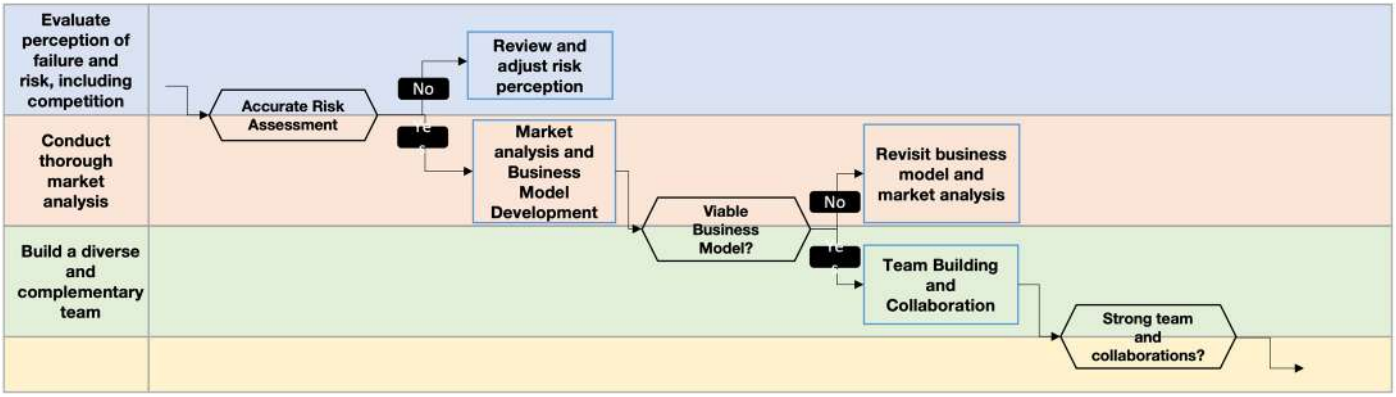

Figure 4. Decision-making process—part 2. Source: conceptualized by authors.

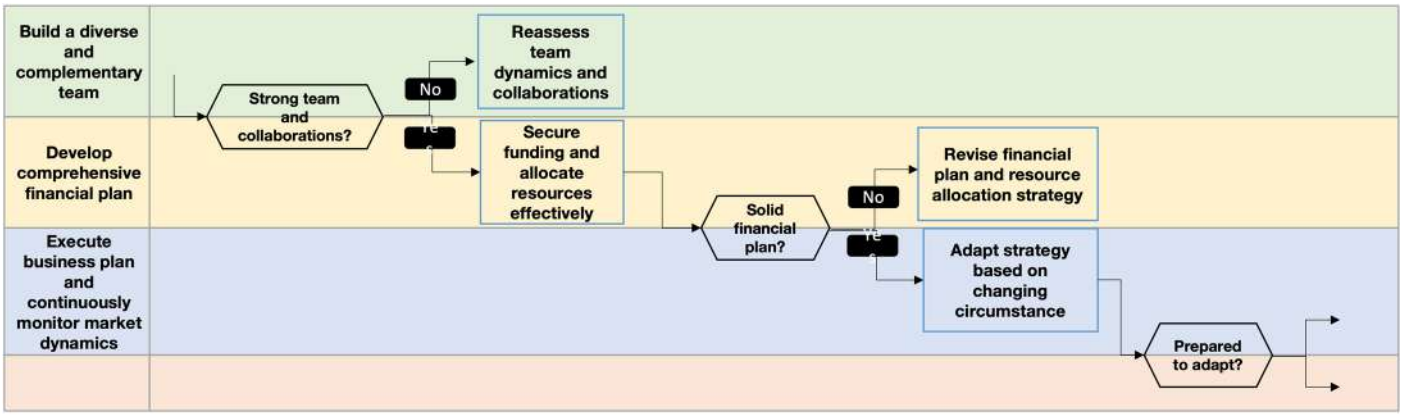

Figure 5. Decision-making process—part 3. Source: conceptualized by authors.

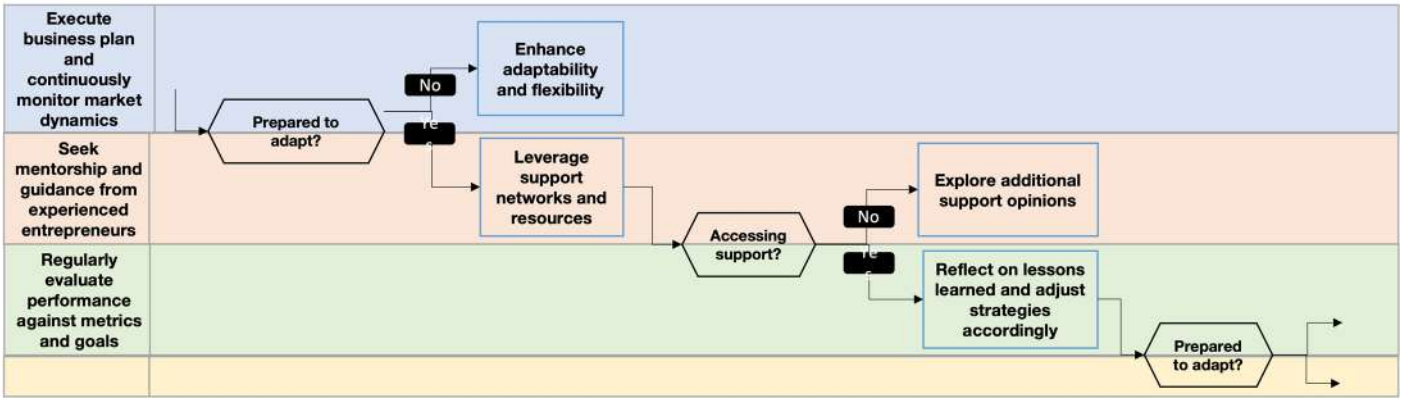

Figure 6. Decision-making process—part 4. Source: conceptualized by authors.

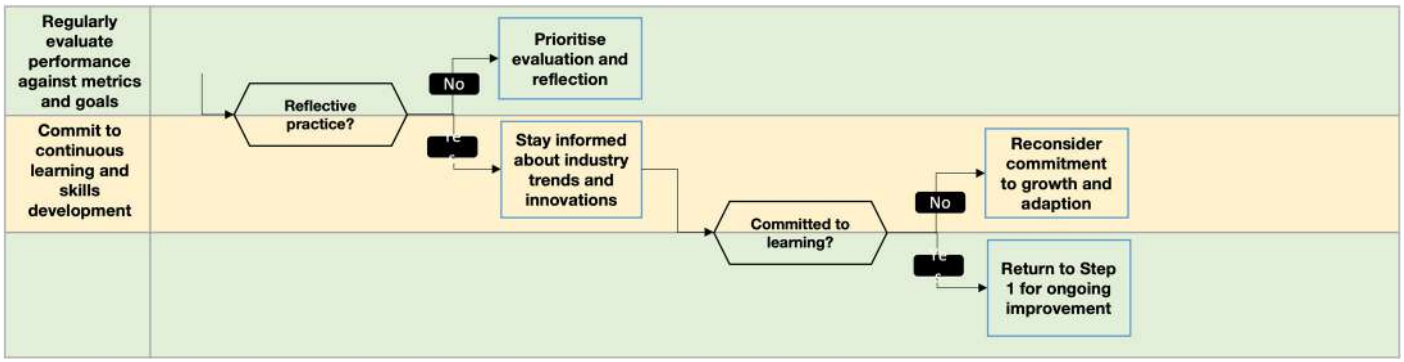

Figure 7. Decision-making process—part 5. Source: conceptualized by authors.

5. Discussion

The scientific contribution that this study brings to the light of specialized literature gravitates around the growth theory for entrepreneurs. In the same manner as how Hunter (2005) addressed the factors that influenced the course of entrepreneurial development, the authors intended to enrich the current state of knowledge with fresh perspectives on characteristics of healthcare entrepreneurs. In this sense, the current study provides valuable insights by elucidating the entrepreneurial behavior within the healthcare sector. By analyzing a diverse range of factors, including age, gender, education, family dynamics, motivation, and property ownership, the authors have uncovered nuanced patterns that shed light on entrepreneurial decision-making within the healthcare sector.

Specifically in this section, the researchers present the cohesive narrative flow to explicitly link the hypotheses to the findings, as presented in Figure 8.

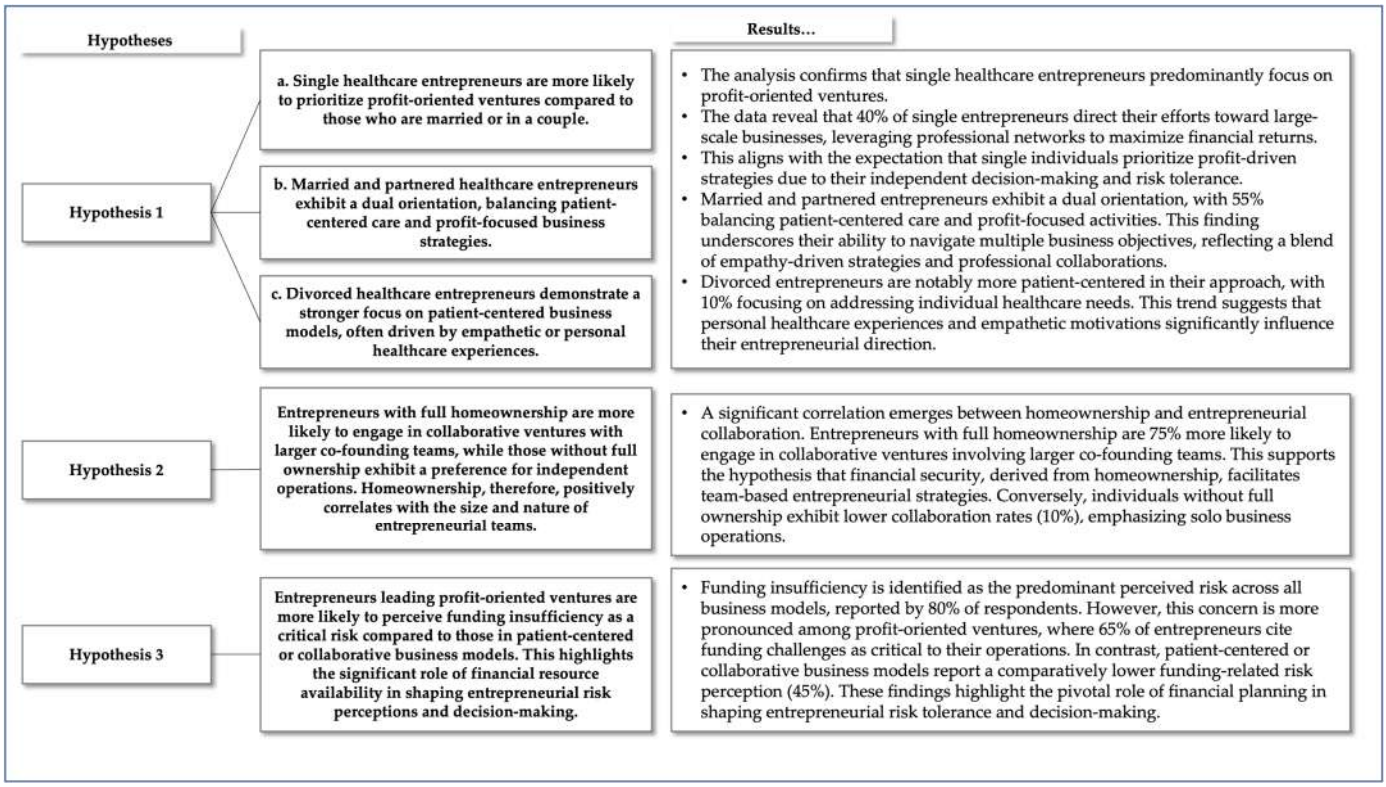

Figure 8. Narrative flow linking the hypotheses to results. Source: conceptualized by authors.

One of the key findings of this study pertains to the influence of marital status on business orientation. The analysis revealed distinct preferences among single, divorced, and married entrepreneurs. This result unveils marital status as the most relevant variable to define the orientation towards a certain type of business, refuting the hypothesis linked to gender as an influential factor for a specific type of business. This outcome completes the theory about the entrepreneurial journey from the point of view of the moment in which the person with whom the entrepreneur lives, influences behavior and entrepreneurial intentions. This study highlights the profit orientation of single individuals, and patient well-being orientation of couples or married entrepreneurs. Single individuals exhibited a strong inclination towards profit-oriented ventures, reflecting their desire for large-scale businesses and professional partnerships. In contrast, divorced entrepreneurs displayed a heightened focus on addressing healthcare concerns for individuals, perhaps driven by personal experiences or empathetic motivations. Married entrepreneurs, on the other hand, demonstrated a more diverse orientation, with preferences spanning businesses targeting both individuals and healthcare professionals. These findings underscore the importance of considering marital status as a determinant of entrepreneurial behavior within the healthcare industry.

Also, in the category of personal factors that the theory of entrepreneurial intention could consider, the sense of ownership is also counted. Strongly related with the number of co-founders and age, it can represent key-factors for business success. In this context, the managerial implications are various. Moreover, this study highlights the impact of property ownership on entrepreneurial decisions. While previous research has explored the relationship between homeownership and entrepreneurial activity, our findings provide additional insights specific to the healthcare sector. The authors observed that full

homeownership positively influenced entrepreneurial activity, suggesting that individuals with greater property ownership may feel more financially secure and, therefore, are more willing to undertake entrepreneurial ventures. However, the presence of housing loans exerted a negative impact on entrepreneurial intent, indicating that housing debt may act as a barrier to entrepreneurship by imposing financial constraints and risk aversion. Furthermore, the type of property ownership, whether acquired through inheritance or purchased below market price, also influenced entrepreneurial decisions, with implications for wealth accumulation and risk-taking behavior.

For instance, the age characteristic is a very important and influential factor in the literature (Petráková & Fialová, 2020); this study has strengthened its role in the entrepreneurial process. With high relevance in business orientation, it can be more relevant when it is considered as a determinant for the number of co-founders. As an explanatory factor, the age of the entrepreneurs can represent a real competitive advantage when young individuals choose to create teams and run businesses together. Regardless of the years an entrepreneur has, the perceived failure generated by risks can destabilize the mindset of entrepreneurs, especially when the risk is associated with the goal they have proposed. Surprisingly, gender, education, and motivation have not been discovered as defining factors for businesses, as the literature presents in some studies. Contrary to the mainstream view, and in line with the authors' findings, it was shown that there is no gender inequality related to entrepreneurship. At the same time, age is not a differentiator when it comes to risks, an aspect unintentionally identified as an influential factor. While Cacciotti (2016) studied the factors that led to the failure of a venture, including lack of funding, team management issues, lack of sufficient business knowledge, and technology delay, the analysis captured the characteristics that influence the orientation towards a certain type of business and the failure in relation to the perceived risks and goals to achieve. The unexpected finding that personal perceptions of failure are closely linked to the availability of funding and investments underscores the significance of the financial considerations in entrepreneurial ventures. Entrepreneurs who perceive a lack of funds as the greatest risk are more likely to prioritize hiring the right people and delegate responsibilities, reflecting their strategic approach to mitigating financial challenges. Additionally, the analysis revealed that entrepreneurs working with co-founders are more attuned to funding risks, suggesting that collaborative ventures may offer greater resilience in the face of financial constraints. These results support previous research confirming that entrepreneurs perceive failure to access to financial support as a major barrier.

Overall, the findings of this study contribute to a deeper understanding of the complex interplay between personal characteristics and business orientation among healthcare entrepreneurs. By elucidating the diverse motivations, preferences, and risk perceptions driving entrepreneurial behavior, this research informs policy initiatives and supports mechanisms aimed at enhancing entrepreneurship within the healthcare sector. Moving forward, interventions that address the specific needs and aspirations of healthcare entrepreneurs can empower individuals to pursue innovative ventures that drive positive change in healthcare delivery and outcomes. Also, the outcomes suggest that personal attributes, such as marital status, education, and homeownership, significantly shape entrepreneurial decision-making processes. These attributes were operationalized through survey questions and regression models, where variables such as age, gender, education level, and homeownership status were coded and analyzed to identify their influence on the type of business orientation chosen by healthcare entrepreneurs. These insights can guide policy makers, educators, and healthcare professionals in fostering an environment that supports sustainable and impactful healthcare entrepreneurship.

6. Conclusions

The scientific contribution of this study lies in its comprehensive examination of the factors influencing entrepreneurial behavior within the healthcare sector. By offering valuable insights into the existing literature on entrepreneurial development and decision-making, this research adds a significant dimension to the existing literature. The findings have important implications for policy makers and support organizations aiming to cultivate entrepreneurship within the healthcare domain. Additionally, the outcomes empower entrepreneurs to embark on innovative ventures that catalyze positive transformations in healthcare delivery and outcomes.

The relationship between business orientation and economic growth is crucial for understanding how economies prosper. A strong business orientation promotes innovation and competitiveness, enabling companies to adapt to market changes and consumer demands. This adaptability does not only lead to increased productivity but also encourages investment and job creation, which are essential components of economic expansion. Moreover, businesses play a vital role in driving technological advances and improving overall efficiency within various sectors. As companies grow and succeed, they contribute to the wider economy through higher tax revenues and improved living standards for individuals and communities. Ultimately, a vibrant business environment acts as a catalyst for sustainable economic growth, benefiting society as a whole.

From a theoretical perspective, this study provides a compelling rationale for further exploration of the factors influencing orientation in the healthcare sector. The academic community stands to benefit greatly from the insights, as they offer valuable guidance for the development of policies and strategies that better prepare young entrepreneurs for the challenges of starting and running a start-up in the medical field. Furthermore, understanding the challenges inherent in healthcare entrepreneurship can inform efforts to provide ongoing support and mentorship to young entrepreneurs. By empowering a culture of continuous learning and providing resources for networking, risk management, and conflict resolution, the academic environment can play a pivotal role in equipping young entrepreneurs with the skills and knowledge needed to navigate the complexities of business management and secure financing for their ventures.

The managerial implications are equally significant. Institutions can address financing barriers through the implementation of specialized programs that equip entrepreneurs with the tools and knowledge needed to combat such challenges. The decision-making model, depicted in Figures 3–7, synthesizes the key findings of the study, and offers a structured framework for understanding how personal characteristics influence entrepreneurial decisions within the healthcare sector. The model comprises five main components: age, gender, education, motivation, and property ownership, each of which plays a distinct role in shaping entrepreneurial behavior. This could help both trainers and managers to keep an eye on their actions and reactions in the moment of making decisions, considering personal characteristics, business orientation, and the attitude towards failure. This visual representation could represent a guideline for them to optimize and develop sustainable businesses.

Despite its contribution, the study acknowledges several limitations that warrant attention in future research. One key limitation is the methodological approach, where reliance on semi-structured interviews introduces the possibility of response bias and the absence of data triangulation. To address this, future studies could incorporate additional qualitative techniques, such as peer debriefing or investigator triangulation, to enhance the robustness of findings. Additionally, the sample size may not be fully representative of the broader population, highlighting the need for a more extensive data collection to ensure generalizability. Future research should also explore a broader range of factors

influencing entrepreneurial motivation to develop a more comprehensive understanding of this phenomenon.

To overcome these limitations, future research can employ a combination of quantitative and qualitative methods to analyze each attribute and explore the correlation between personal characteristics and entrepreneurial intention in greater depth. Additionally, interdisciplinary research involving authors and scientists from various fields can provide a more holistic understanding of entrepreneurship development. Collaborative efforts between academia and industry can also facilitate knowledge transfer and partnership, enabling the exploration of complex and contentious issues in entrepreneurship.

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How Do Visitors to Mountain Museums Think? A Cross-Country Perspective on the Sentiments Decoded from TripAdvisor Reviews

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Abstract: In the digital era, user-generated online reviews serve as a valuable resource for understanding visitor experiences in cultural institutions. This study analyses sentiments and thematic trends in TripAdvisor reviews of mountain museums, using Latent Dirichlet Allocation topic modelling and sentiment analysis. A dataset of 2157 reviews from ten museums was classified into local and non-local perspectives, revealing significant differences in visitor expectations. Findings indicate that local visitors prioritize historical authenticity and educational value, whereas non-local visitors emphasize aesthetic appeal, interactivity, and cultural immersion. Sentiment analysis highlights generally positive perceptions, with business travellers and groups of friends reporting the highest satisfaction levels. Comparative analysis across visitor types reveals distinct engagement patterns, with families valuing child-friendly exhibits, couples seeking cultural enrichment, and solo travellers focusing on intellectual depth. These insights inform strategic recommendations for museum management, including multilingual content, interactive elements, and guided tours dedicated to specific visitor profiles. Despite limitations related to lack of real-time feedback, this research demonstrates the potential of sentiment analysis in enhancing museum experiences. Future studies should integrate multimodal analysis and real-time tracking to further refine visitor experience evaluation.

Keywords: online reviews; sentiment analysis; topic modelling; mountain museum experience; TripAdvisor; human–computer interaction

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1. Introduction

In today's competitive environment, museums should determine specific goals and develop strategies to enhance their attractiveness and increase numbers of visitors along with their revenue [1]. The museum experience is a combination of cognitive and affective factors [2] and it correlates with visitors' unique personal context (e.g., motivations, attitudes, emotions, prior knowledge) and the museums' collections, services, practices, spatial context, and staff [3]. Assessing visitors' experiences helps museum managers and curators to design and redesign exhibits [4] and to improve the overall attractiveness of

the museum [5,6]. To improve and develop the quality of visitor experiences, museums must systematically collect and analyze customer satisfaction data from exhibitions and programs, providing valuable insights for making decisions and enhancing management practices [7,8].

During a museum visit, the experience unfolds through encounters with objects, interpretive texts, staff, other visitors, and additional services like souvenir shops and cafés [9]. This experience extends into the post-visit phase, where memories and online activities, such as social media posts and visitor online reviews on platforms, influence future visitors' pre-visit perceptions [9]. Improving museum offerings and visitor experiences requires systematic evaluation of satisfaction indicators, as visitor impressions are shaped by staff interaction, ambiance, complementary services, and a high tendency to capture and share experiences on social media during or after visits [8].

Traditionally, museum visit experience has been assessed using direct surveys of visitors focusing on a predefined set of dimensions [10,11]. However, digital and online technologies and data offer new opportunities for analyzing the visit experience [12,13]. In today's digitized and social media-dominated era, museums need to pay close attention to details at the micro-level, ensuring an impeccable visitor experience [14] as these experiences are increasingly being disseminated and discussed on digital platforms. Interpretation of visitors' reviews may contribute valuable information to understanding visitors' experience [9] and may have a significant impact on the decisions of other potential visitors [14].

Online museum reviews have become a crucial indicator of museum service quality, visitor experience, and public feedback in the digital age [15,16]. Analyzing online reviews on social media platforms can assist museums in developing appropriate management strategies [12,15]. TripAdvisor is one of the most popular travel and tourism sites worldwide [17–20]; it serves as an online platform for digital reviews, with over 1 billion reviews and 900 million registered users [21]. TripAdvisor comments can serve as an authentic and valuable tool for evaluating museum experiences [22,23], as the content extracted from this platform may capture visitor satisfaction and cultural perceptions, offering valuable and actionable insights for museum managers [24–26]. The platform can provide valuable insights into museum visitor experiences, helping potential visitors make informed decisions before their visit by relying on authentic perspectives rather than official narratives. Framed within a wider travel context [27] highlighted TripAdvisor's role as a trusted intermediary for independent travelers, offering user-generated reviews and rankings that often challenge traditional expertise.

Given its vast repository of user-generated content, TripAdvisor serves as a powerful tool for extracting data-driven insights into visitor sentiments and cultural perceptions, making it an essential resource for studying museum experiences in the digital era [15,28]. Within this context, the current study aims to explore the sentiments of visitors to mountain museums by analyzing online reviews from TripAdvisor.

Mountain museums constitute a distinctive segment within cultural tourism, shaped by their geographical context, alpine heritage, and integration into natural landscapes. Unlike urban museums, which often benefit from high visitor flows and broad cultural programming, mountain museums are typically situated in remote or seasonal destinations and serve as gateways to localized identities, ecological narratives, and historical memory tied to highland environments. Their dual role as cultural institutions and place-based heritage ambassadors demands a visitor experience model that accommodates diverse expectations across both local and international audiences [29–32].

Mountain museums were selected as the focus of this study because they represent a distinctive yet underexplored segment within heritage tourism, shaped by remote geogra-

phies, alpine cultures, and seasonally driven visitor flows. These institutions often integrate natural and cultural storytelling, serving as both educational and place-based interpretive centres. While user-generated content (UGC) is increasingly being used to study museum experiences, a review of Web of Science revealed that very few studies ($n = 6$) have applied TripAdvisor data in their research on museums, and none of these have addressed mountain museums specifically. This gap is particularly relevant considering the existence of the International Mountain Museums Alliance (IMMA), which connects institutions sharing similar interpretive missions in mountainous regions worldwide. The authors' attention turned to this network when the newest IMMA member, the Olimpia Museum in Brașov (Romania), opened in early 2024. The authors' proximity to this development, along with direct contact with IMMA's founding members (such as Museo Nazionale della Montagna in Turin), allowed researchers to construct a cross-national comparative dataset. Much like Baleiro [3]'s focus on literary museums, this study investigates a coherent group of specialized institutions with shared thematic identities, offering both geographic diversity and interpretive consistency.

In the context of digital transformation and human–computer interaction, visitor-generated content has become a valuable resource for understanding museum experiences, visitor satisfaction, and intercultural communication in the tourism sector [33–36]. This study identifies key themes and emotions expressed in mountain museum reviews, offering insights for management, cultural experience enhancement, and tourism development strategies. Despite the ongoing academic discourse on the role of TripAdvisor for evaluating museum experiences [37–41], there is limited focus in the specific literature on differences in the latent dimensions perceived by local and non-local visitors, as identified through the language of their reviews. Therefore, this paper aims to fill this gap and investigates the differences in perceptions between local and non-local visitors, examining how cultural and linguistic diversity influences visitors' experiences in mountain museums. The findings contribute to a deeper understanding of the role of digital platforms in shaping visitor expectations, decision-making, and post-visit reflections. In this context, the following research questions were formulated:

RQ1: *What are the latent dimensions of the museum visitor experience perceived by visitors who write reviews in the local language?*
RQ2: *What are the key themes of museum visitor experience perceived by visitors who write reviews in non-local languages?*
RQ3: *What are (if any) the differences in latent dimensions of museum visitor experience perceived by visitors who write reviews in the local language compared to those who write in non-local languages?*
RQ4: *How do visitor profile (solo traveller, couples, families, and group of friends) influence perceptions regarding museum visitor experience?*

To address these questions, this study aims to achieve the following objectives: (O1) identify and analyze the latent dimensions of visitors' perceptions expressed through reviews written in local languages; (O2) identify and analyze the latent dimensions of visitors' perceptions expressed through reviews written in non-local languages; (O3) compare the key themes and differences in visitor experiences between those who write reviews in the local language and those who write in non-local languages; and (O4) examine the impact of visitors' profiles on their perceptions of the museum experience. To answer to these questions, the research followed the workflow pictured in Figure 1.

Based on the findings, strategic recommendations for museum management to enhance visitor experiences are formulated in the Discussion Section. These recommendations are formulated in relation to visitor expectations, suggesting ways to improve engagement for different visitor types. Specific improvements are proposed, such as enhancing interactive elements for families, refining historical content for solo travelers, and optimizing

museum logistics for business visitors. With reference to these insights in the specialized literature, museums can make data-driven decisions to improve their services, attract more visitors, and ensure a high-quality, memorable experience for all guests.

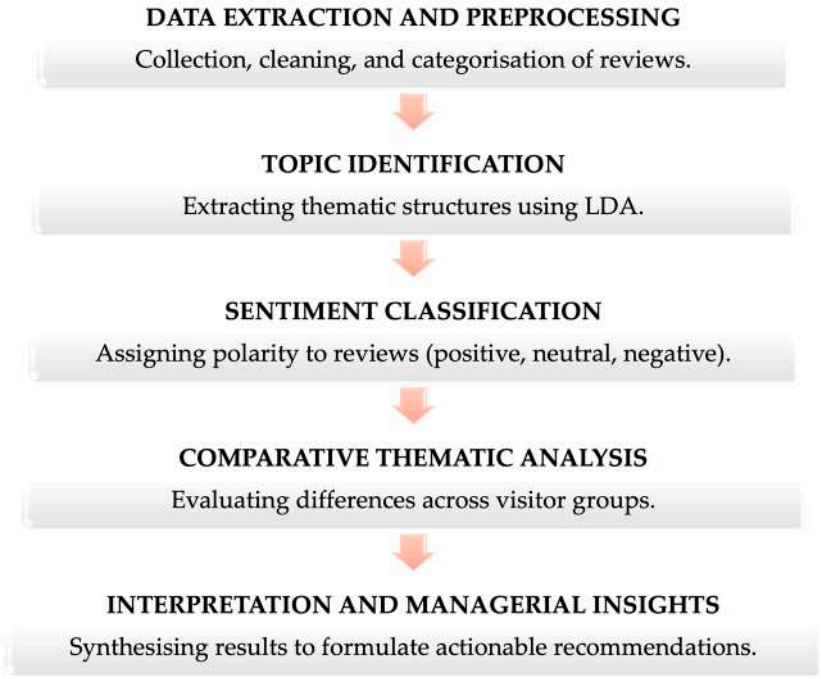

Figure 1. The research workflow. Conceptualized by authors.

2. Literature Review

The latest definition of museums, approved on 24 August 2022 during the 26th ICOM General Conference held in Prague [42], includes the concept of "experience", stating that museums offer varied experiences for education, enjoyment, reflection, and knowledge sharing [43]. Currently, museums are transforming from object-centred institutions to visitor-focused, interactive spaces, emphasizing engagement, community impact, and experiential value. Modern museum experiences blend cognitive and affective elements, intertwining with visitors' personal and sociocultural contexts while fostering adventure, learning, and social connections, redefining the museum–visitor relationship with a client-centered approach [44,45]. Drawing on Pine and Gilmore's (1998) [46] framework, modern museums deliver diverse values—education, entertainment, escapism, and aesthetics—that enhance perceived visitor benefits through engagement with their personal, sociocultural, and physical contexts. Recent studies have revealed that museums are perceived as unique, multidimensional spaces with exceptional qualities that captivate visitors [47].

2.1. The Museum Experience

Packer and Ballantyne [48] define the museum visitor experience as an individual's personal and immediate response to activities or settings outside their usual environment, characterized by ten facets: physical, sensory, restorative, introspective, transformative, hedonic, emotional, relational, spiritual, and cognitive. The museum experience now extends beyond the visit itself [49,50], beginning with pre-visit activities like online research for hours, location, ticket prices, and reviews from other travelers, and continuing afterward [9,44].

Godovykh and Tasci [51] define the museum experience as the totality of cognitive, affective, sensory, and conative responses across pre-visit, on-site, and post-visit stages, influenced by situational and personal factors, providing a comprehensive framework for

explaining and measuring visitor experiences. Conti, Pencarelli, and Vesci [52], building on prior research by Falk and Dierking [44], Sheng and Chen [53], and Pine and Gilmore [46], introduced socialization as a fifth experiential dimension, emphasizing interaction between visitors and staff or among visitors. Guo et al. [54] highlight that visual and auditory cues are the most impactful in enhancing visitor experiences, mediated by emotional state and sense of presence. Joviality, personal escapism, and localness are identified as key evaluative dimensions, providing insights for designing immersive, hedonic experiences that cater to visitors' emotional and physiological needs. Understanding which of these dimensions are important for visitors helps museum managers tailor their offerings effectively. Ducros and Euzéby [55] explored how visitors perceived and experienced hybrid museums, emphasizing the dual cognitive and sensory stimulation offered, and found that while these venues provided edutainment value, they often fell short of delivering the promised immersive and memorable experiences due to design elements such as spatial freedom, digital scenarization, and reliance on passive individual engagement, which limit active participation and social interaction.

Antón, Camarero, and Garrido [56] argue that museum visitors actively co-create their experiences across three stages: before the visit, through knowledge, planning, and involvement; during the visit, through participation and interaction; and after the visit, by engaging with social networks and sharing opinions, which intensifies their connection with the museum. These active experiences foster a stronger intention to revisit, seek additional information, and recommend the museum to others [57–60]. Moreover, Yin, Chen, and Ni [61] concluded that museum experiences significantly influence word-of-mouth (WOM) recommendations in relation to brand image and museum attractiveness, with temporary experiences amplifying this effect.

2.2. The Role of Visitor Online Reviews in Decoding the Museum Experience

Visitor online review (VOR) platforms like TripAdvisor serve as judgment devices, enabling visitors to widely share experiences and foster new social interactions. Tourists often write reviews with an awareness of their audience, using various strategies to engage readers they may never meet [62]. VOR websites highlight user-generated content as a public voice for visitors, but accessing this space requires technological literacy, registration, and acceptance of the platform's terms [63]. Notably, these platforms often assign badges and awards to prolific contributors, elevating their influence through visible markers and user feedback [64,65]. VOR sites not only facilitate visitor expression but also help establish collective perspectives on travel experiences.

Marques [39] considers that museum visitors use reviews to share personal experiences that guide and inform future visitors, establishing a bridge across time. Despite the increase in research on online reviews, studies focusing specifically on museums and cultural sites remain limited. Research has identified key themes in these reviews, such as practical advice, exhibits, the overall experience, and logistical aspects like buildings, shopping experience, and ticketing [3,41,66]. Emotional engagement has become central to museum experiences, shifting the focus from simply conveying historical knowledge to fostering empathy [67]. For example, Lee et al. [40] categorized emotions in museum reviews and found a strong alignment between positive emotions and TripAdvisor ratings, though some nuanced feelings defied standard classification.

Shao et al. [41] found that analyzing user-generated reviews of the National Gallery in London using topic modeling and sentiment analysis provided valuable insights into improving museum shopping experiences, emphasizing the importance of addressing visitors' specific needs to enhance satisfaction and support museum tourism development. Furthermore, Riva and Agostino's [68] study highlights the value of user-generated data in

assessing museum experiences and offers actionable insights for museum management. By analyzing 36,460 TripAdvisor reviews of 30 popular Italian museums using latent Dirichlet allocation, they explored differences between local and non-local visitors. The results revealed three shared dimensions of museum experience (cultural heritage, personal experience, and services) and unique dimensions for locals (e.g., 'wow effect') and non-locals (e.g., time management). Su and Teng [46] used content analysis of negative TripAdvisor reviews and document analysis of related studies to identify categories of service failure in museums. They extracted 12 dimensions of museum service quality, incorporating SERVQUAL dimensions (reliability, tangibles, communication, empathy) and HISTOQUAL dimensions (responsiveness, communication, consumables) tailored for cultural heritage tourism.

Alexander et al. [9] noted that reviews of cultural sites in London tended to focus on practical aspects and personal experiences rather than deep engagement with cultural content. Ramírez-Gutiérrez et al. [69] similarly found that reviews blended emotional reactions with practical insights, often advising future visitors while occasionally critiquing management. Huo et al. [15] propose a comprehensive model linking museum attributes, visitor experience, and satisfaction; they analyzed TripAdvisor reviews of four UK museums using structural topic modelling, identifying 19 topics. Their findings reveal that core offerings, peripheral services, and ambiance positively influence visitor experience and satisfaction, with experience strongly impacting satisfaction.

Gerrard, Sykora, and Jackson [70] concluded that the gap between real and expressed experiences on Twitter requires further exploration. Analyzing data extracted from Instagram, Rhee, Pianzola, and Choi [71] concluded that hashtags, particularly geo-related and city-specific tags, highlight the cultural and touristic influence of museum locations and help identify spaces that attract the most visitor attention. Baniya, Dogru-Dastan, and Thapa [72] analyzed TripAdvisor reviews by separating one-to-three-star ratings from four-and-five-star ones, revealing that 96% gave high ratings, while low ratings primarily cited issues with ticket prices, crowding, and persistent selling. Catir [73] used text mining on TripAdvisor reviews to reveal five key themes of the Topkapı Palace Museum experience: easiness and fun, cultural entertainment, personal identification, historical reminiscences, and escapism. The results show that visitors appreciate the museum's convenience, cultural insights, immersive storytelling, and unique atmosphere, while fostering both personal connections and a sense of escape.

Agostino et al. [74] analysed 47,993 TripAdvisor reviews of 100 Italian museums, comparing 'top-down' (policy-driven) and 'bottom-up' (user-driven) approaches to identifying quality dimensions. They found significant differences, with visitors prioritizing cultural heritage and personal experiences over museum services. That study highlights the limitations of predefined quality assessments, emphasizing the importance of user-generated content in identifying emergent, visitor-centric dimensions and contributing to data-driven decision-making and the cultural tourism literature.

2.3. Cultural Differences in the Museum Visitor Experience

Numerous studies on cultural tourism indicate that the experiences of tourists are influenced by their cultural backgrounds [75,76]. In the context of museums, this is especially relevant, as visitors' cultural backgrounds influence how they view, understand, and filter their sociocultural distance from the location [68]. While demographic characteristics have been used to identify inter-group specificities in visitor motivations, behaviors, and expectations [39] other traits can also be attributed to differences (e.g., local versus non-local visitors) [77].

Museums attract both local and non-local domestic visitors and face distinct challenges [77]. The different backgrounds and experiences of local and non-local visitors shape how they assess museums. For example, the extent to which local visitors 'own' indigenous heritage assets at sites of national significance is challenged when non-local domestic visitors also consider them an important part of their heritage [78]. Non-local visitors are often partly or wholly unfamiliar with indigenous culture, and the knowledge they do possess may be based on inaccurate cultural stereotypes regarding locals' attitudes, service quality expectations, and safety [79]. Furthermore, local visitors typically have a unique viewpoint on the traditions and expectations of the places they visit, which could lead to more enjoyable, memorable, and relaxing experiences [80].

Despite the relevance of differences in the latent perceptions on the parts of local and non-local visitors, as identified through the language of their reviews, there is very limited empirical research that investigates the importance of language as a proxy for cultural background. Focusing on Italian museums, [68] used the language of museum visitors in their online reviews to indicate cultural background and compared the latent dimensions of the experience between those writing in the local language and visitors writing in non-local languages.

The present study takes a further step in the analysis of latent dimensions within the perceptions held by local and non-local visitors from different countries to 10 mountain museums, revealing significant differences in visitor evaluations of the museum experience.

3. Materials and Methods

This study employed a computational text analysis approach to examine visitor experiences, utilizing user-generated content from TripAdvisor. The International Mountain Museums Alliance (IMMA) provides an ideal case for computational text analysis of visitor experiences due to its unique combination of thematic homogeneity and geographic diversity. Museums that are members of IMMA are all specialized in mountain culture and present similar content, yet they are situated in distinct cultural and touristic contexts. This enables comparative analysis of how visitors sharing common interests perceive and engage with mountain heritage across different locations [81].

To decode visitor sentiments, identify key experiential themes, and compare the perceptions of local and non-local visitors, as well as different visitor profiles, the methodology of the analysis comprised five steps, as shown in Figure 2. This approach enables a data-driven understanding of how a specialized yet internationally dispersed museum network shapes visitor engagement, offering insights into experiences within a shared curatorial framework.

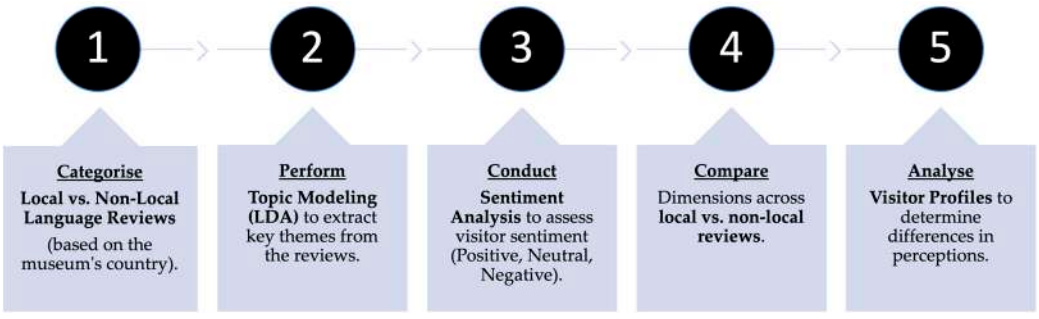

Figure 2. Data analysis flow. Conceptualized by authors.

The dataset comprised 2157 reviews of 10 mountain museums (Table 1), ensuring the inclusion of a diverse range of visitor experiences. The data were collected between 15 and 20 September 2024.

Table 1. Number of reviews for each mountain museum.

Museum Name	No. of Reviews
Museo Nazionale della Montagna	164
Musee Alpin Chamonix	91
Whyte Museum of the Canadian Rockies	595
Tatra Museum in Zakopane	11
Alps Swiss Alpine Museum	102
Museo degli Usi e Costumi della Gente Trentina	80
International Mountain Museum	972
Musée Savoisien	55
Museo Valtellinese di Storia e Arte (Valtellina Museum of History and Art)	41
Olimpia—Muzeul Sportului și Turismului Montan	46

Source: Data retrieved from public TripAdvisor accounts of the museums. Table created by the authors.

Reviews were extracted using a web-scraping method via the console.apify.com application, generating ten separate files corresponding to each observation. All reviews analyzed in this study were publicly available on TripAdvisor and were accessed in accordance with the platform's terms of use at the time of data collection. No personally identifiable information was collected or stored, and all user identifiers were excluded from the dataset. Data were extracted using Apify's public scraping interface, and the dataset was anonymized during pre-processing to ensure compliance with ethical standards for user-generated content analysis.

These files were subsequently merged into a unified dataset to facilitate comprehensive analysis. To ensure data accuracy and reliability, a systematic extraction process was implemented, incorporating criteria such as relevance, linguistic categorization, length threshold, and potential applicability for sentiment analysis. Reviews were required to explicitly reference aspects of the museum experience to qualify for classification into local and non-local language categories, thereby ensuring the inclusion of meaningful content. To ensure data accuracy and analytical relevance, a character length threshold of $\geq$50 was established to filter out excessively brief or generic reviews, which typically lack substantive insights. This approach aligns with prior research that similarly applied length-based filters to exclude non-informative or low-quality content from sentiment and topic modelling analysis [41,72,73]. This 50-character minimum was chosen as a balanced threshold that retains meaningful feedback while minimizing noise, in accordance with common practices in tourism and museum-related text mining studies.

The dataset underwent preliminary pre-processing, including the removal of stop words, punctuation, and special characters. Additionally, lemmatization was performed to standardise textual content, improving consistency for subsequent linguistic and sentiment analysis.

To classify visitor types (solo travelers, couples, families with children, groups of friends, and business travelers), rule-based textual analysis was applied to the review content. Specific keywords and linguistic patterns were used to infer the profile of the reviewer. For example, phrases such as "I visited alone", "went with my partner", "our children enjoyed", "we were a group of friends", or "visited during a business trip" were extracted to determine the visitor category. Each review was manually or semi-automatically labelled based on these indicators. This approach is in line with methods applied in previous studies that have used self-reported information in online reviews to infer demographic or behavioral profiles [68].

Lemmatization is a fundamental process in Natural Language Processing (NLP) that converts words into their base forms or lemmas. This text-processing technique reduces words to their root forms, thereby enhancing linguistic analysis. For better conceptualization, an illustrative example is the transformation of "running" to "run" or "better"

to "good". This standardization ensures that variations of the same word are analyzed collectively, improving the accuracy of sentiment analysis and topic modelling.

In this study, lemmatization facilitated the grouping of related words such as museum and museums, mitigating redundancy within the dataset. By consolidating different inflected forms of a word into a single reference point, lemmatization enhances the efficiency and accuracy of computational linguistic tasks. Lemmatization [82,83] is a crucial post-tokenization technique that refines textual data by converting words into their morphological roots. This process optimizes word classification, thereby facilitating the analysis of meanings, synonyms, and contextual relationships in textual data [84,85].

To determine the optimal number of topics, researchers tested multiple LDA models with topic numbers ranging from 5 to 20. Each configuration was evaluated using the C_v coherence metric, a standard measure for assessing semantic interpretability in topic modelling. Based on these scores and qualitative evaluation of topic coherence, they selected five topics as the most balanced configuration, providing clear thematic structure while avoiding fragmentation. The models were implemented in Python using the Gensim library with default variational Bayes settings (alpha = 'auto', eta = 'auto', 1000 iterations).

LDA operates by clustering words that frequently co-occur, facilitating the extraction of dominant themes from extensive textual corpora. In this study, LDA was utilized to categorize key visitor concerns based on their reviews, enabling the identification of primary thematic structures within local-language reviews. Consequently, distinct thematic patterns emerged in reviews provided by local and non-local visitors, offering insights into variations in visitor perceptions.

The rationale for employing this method in the study's methodology was based on the following three key considerations:

(i) Identification of latent dimensions of visitor experience through clustering words into coherent topics, as LDA facilitates the extraction of dominant themes from extensive textual data;

(ii) The ability to compare local and non-local visitors within diverse audiences while ensuring an unbiased identification of key aspects valued by different cultural groups;

(iii) The objective of understanding variations in experience across visitor types, thereby enabling the differentiation of visitor categories and their respective interests.

Sentiment analysis was conducted to classify visitor reviews into positive, neutral, or negative categories. Sentiment analysis is a Natural Language Processing (NLP) technique used to determine the emotional tone of content. In this study, sentiment analysis was employed to categorize reviews based on the words and phrases present in visitor feedback, with sentiment polarity indicating the direction of emotions within the text. This classification enabled objective assessment of overall visitor satisfaction across various demographic groups. Widely applied in consumer behavior research, sentiment analysis systematically extracts subjective opinions from textual data. Given that museum visitor experiences are inherently affective and evaluative, this technique provides a structured approach to categorizing visitor feedback. Specifically, this method facilitated the following:

(i) Quantification of visitor satisfaction by aggregating sentiment scores to assess overall perceptions of the museum experience;

(ii) Comparison of perceptions across visitor groups, identifying variations in sentiment polarity based on language (local vs. non-local) and visitor type (solo travelers, families, couples, groups, business visitors);

(iii) Detection of potential service gaps, as a higher proportion of neutral or negative sentiments within a specific visitor segment may indicate areas requiring improvement.

Sentiment analysis of user-generated content offers an efficient and objective tool for decoding visitor experiences in museums, enabling the identification of key museum

attributes. Gómez Punzón and Recuero Virto [58] used sentiment analysis with a Support Vector Machine (SVM) algorithm to classify user-generated content about museums into positive, negative, and neutral sentiments, revealing visitors' emotional responses to their experiences. Text mining with Atlas.ti and weighted percentage metrics identified frequently repeated words, providing actionable insights into visitor perceptions and feedback.

Sentiment analysis was conducted using TextBlob, a Python 3.11. library for processing textual data, assigning a sentiment score to text based on word associations. TextBlob automatically classified reviews as positive, neutral, or negative by identifying key sentiment-carrying words. To analyze sentiment polarity, reviews were categorized as follows:

- Positive sentiment: reviews containing expressions of satisfaction, enjoyment, or appreciation;
- Neutral sentiment: reviews exhibiting a balanced perspective, neither overtly positive nor negative;
- Negative sentiment: reviews highlighting dissatisfaction, service issues, or unmet expectations.

To enhance analytical depth, comparative analysis was conducted across different visitor profiles. Sentiment trends were examined for solo traveers, couples, families, groups, and business travelers, providing insights into how each group experienced and evaluated their mountain museum visit. Additionally, key themes mentioned by different visitor types were analyzed, identifying dominant topics such as education, interactivity, history, and social experience. This study also investigated variations between local and non-local visitors, assessing how cultural and linguistic factors influenced visitor expectations and satisfaction levels.

4. Results

This study included analysis exploring visitor engagement patterns based on review data. By examining diverse visitor perspectives, it uncovers key aspects that shape museum experiences. The analysis identifies distinct themes and variations in visitor feedback, offering insights into how different audience segments perceive and interact with museum offerings. This exploration provides a structured approach to understanding visitor satisfaction, preferences, and overall engagement.

4.1. Reviews Categorisation

Understanding the composition of visitor reviews is essential for analysing museum engagement and visitor perceptions. The dataset consisted of 2157 reviews collected from 10 mountain museums, written in multiple languages. To distinguish between local and international perspectives, reviews were categorized based on language: those written in the local language were considered local, while those in any other language were classified as non-local. The analysis reveals that a significant majority (87.44%) of reviews come from non-local visitors, while only 12.56% originated from local visitors. This distribution highlights the strong international appeal of these museums, indicating that they attract a diverse audience beyond their immediate geographical region. The difference in representation suggests potential variations in visitor expectations, satisfaction levels, and review characteristics, which will be explored in subsequent analyses.

A visual representation of this distribution is provided in Figure 3, illustrating the dominance of non-local reviews in the dataset. Subsequent sections present the differences between local and non-local reviews in terms of sentiment and thematic content.

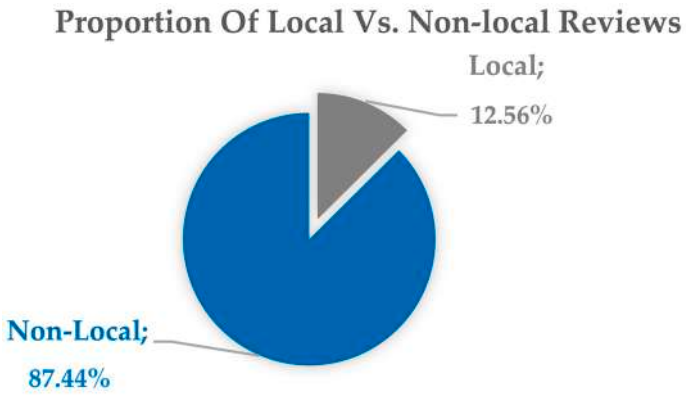

Figure 3. Proportion of Local vs. Non-Local reviews. Conceptualized by authors.

4.2. Latent Dirichlet Allocation Topic Modelling

By applying topic modeling to the reviews, the researchers identified the common themes and topics that each visitor segment emphasized in their feedback. Each group tended to highlight slightly different aspects of the museum experience. Based on these findings, researchers determined distinct thematic patterns in visitor feedback, focusing on differences in priorities and experiences between local and non-local visitors (Figures 4 and 5).

Figure 4. Five latent dimensions in local reviews of mountain museums. Authors' conceptualization.

Figure 5. Five latent dimensions in non-local reviews about mountain museums. Authors' conceptualisation.

These findings indicate that local visitors engage deeply with the cultural and educational dimensions of the museums, emphasising the role of museums in preserving and promoting local and national identity.

These insights suggest that non-local visitors primarily perceive the museums as part of their travel experience, with greater emphasis on interactivity, convenience, and overall ambiance.

Table 2 provides a better understanding of the perceptions of each visitor type.

Table 2. LDA topic modelling results.

Type of Visitors	Content Category	Perceptions
Solo travelers (Often appreciate the depth and detail of the museum content)	Historical and informative exhibitions	Many solo reviewers mention the rich history on display and detailed exhibits, valuing how informative and "interesting" the collections are. They often dive deep into museum content, indicating that they enjoy absorbing information at their own pace.
	Personal experience	They frequently comment that the visit was "worth the time" and "worth the money", suggesting a strong focus on the value of the experience. They typically spend substantial time (often a few hours) and note that the visit met their personal expectations for learning or enjoyment.
	Photography and reflection	There are mentions of photos and taking the time to observe. This implies solo travelers may engage in photography and quiet reflection. They enjoy being able to linger and truly take in the exhibits (appreciating art or artifacts without rush).
Couples (Tend to enjoy a leisure experience)	Cultural and historical enrichment	Like solo travelers, couples frequently highlight history and interesting information. They also often note art displays or local culture (regional art, heritage exhibits), indicating that a blend of history and art appeals to them.
	Contextual elements	They mention the area or context of the museum (such as a museum's setting or theme like mountaineering in the Himalayas or Rockies). They appreciate it when the museum visit complements their travel itinerary, such as learning about the local history of a place they are vacationing in.
	Overall enjoyment and value	Couples use words like "nice", "great", and "worth it" to describe their experience. They often recommend a visit as a good way to spend part of the day. Some mention going early in the day, suggesting they plan visits to avoid crowds or to fit into a day's schedule conveniently.
Families with children (Focus on engagement and educational value)	Child-friendly exhibitions	One of the key themes is how well the museums cater to children Families frequently mention interactive displays and exhibitions that can hold children's attention. Reviews from this category highlight when children have enjoyed specific sections or activities. When a museum offers hands-on multimedia resources, families' notes reflect this positively
	Educational experience	Parents appreciate it when the museum is informative and engaging. Topics like mountaineering history or natural history are mentioned alongside comments about learning. Families often value that the visit was "educational for children and adults alike", indicating that they seek a learning experience that is also fun.
	Practical aspects	Families often plan their visit length and logistics. Reviews mention spending a couple of hours and sometimes note facilities (such as availability of coffee shops or rest areas). Keeping kids engaged for the whole visit is a common concern. When a museum succeeds in this (through child-friendly content or play areas), it is highlighted as a positive. Conversely, any lack of amenities for children or exhibits that are not engaging might be pointed out by this group.

Table 2. *Cont.*

Type of Visitors	Content Category	Perceptions
Groups of friends (Emphasize fun and social activities)	Variety and "must-see" highlights	Groups of friends often talk about specific exhibits or exhibitions that stand out, using terms like "worth the visit" or even naming unique displays. They seem to enjoy a broad variety of content, possibly because each person in the group finds something of interest. A common theme is that visiting together is "fun and interesting" for everyone.
	Social experiences	These visitors sometimes mention the museum shop or coffee shops. For example, a group might note enjoying the gift shop or grabbing a snack together. This suggests that for groups of friends, the museum visit is a social outing, and things like cafes, rest areas, and souvenir shops add to their experience.
	Guided tours and explorations	Some groups of friends take tours. They mention guided tours' availability and how these have added to their understanding (such as learning a lot from a tour guide). In general, friends appreciate an experience that is easy to navigate as a group (clear information and engaging guides help keep everyone in the group interested).
Business travelers (Values efficiency)	Guided experiences	These groups often mention taking a "tour" or having a limited time frame. Business reviewers frequently praise guided tours or well-organized exhibits that allow them to experience the museum in a short visit. They appreciate when the museum offers a quick yet enriching overview. For instance, a guided walk through key exhibits or an informative highlight the museum's best feature.
	Unique local highlights	Even on business, these visitors notice standout aspects like historic houses or special exhibits. For example, if the museum includes a tour of a historical building or a famous artifact, business travelers point it out as a high point. They often use words like "amazing" or note something memorable they can share when they get back home. Since their time is limited, impactful displays that leave an impression (an iconic mountain climbing exhibit or a life-size model) are particularly appreciated.
	High satisfaction	It is worth noting that despite shorter visits, business travelers give very positive reviews. This suggests that when museums provide convenient options (like luggage storage, flexible hours, or quick tours), business visitors can comfortably fit a museum visit into their trip and end up very satisfied.

Source: Conceptualized by authors.

4.3. Sentiment Analysis

The sentiment analysis revealed that overall visitor satisfaction was high, with the majority of reviews exhibiting positive sentiment (Table 3).

Table 3. The overall sentiment of the reviewers by visitors' type.

Visitor Type	Negative Reviews	Neutral Reviews	Positive Reviews
Solo	12	98	144
Couples	48	172	571
Families	20	93	221
Groups of friends	22	111	292
Business	1	98	144

Authors' computation based on TripAdvisor reviews dataset.

Groups of friends and business travellers were especially positive, with nearly nine out of ten giving a favourable review. Solo travelers, couples, and families also showed strong positivity (around four in five were positive). Neutral sentiments (mixed or average experiences) made up roughly 8–14% of reviews depending on the group. Negative

experiences were uncommon across the board (under 7% for leisure travellers, and only ~3–4% for friends and business visitors). This suggests that museums in the dataset are generally meeting or exceeding visitor expectations regardless of who is visiting. Most reviewers in every group gave positive feedback, while negative opinions were relatively rare (Figure 6).

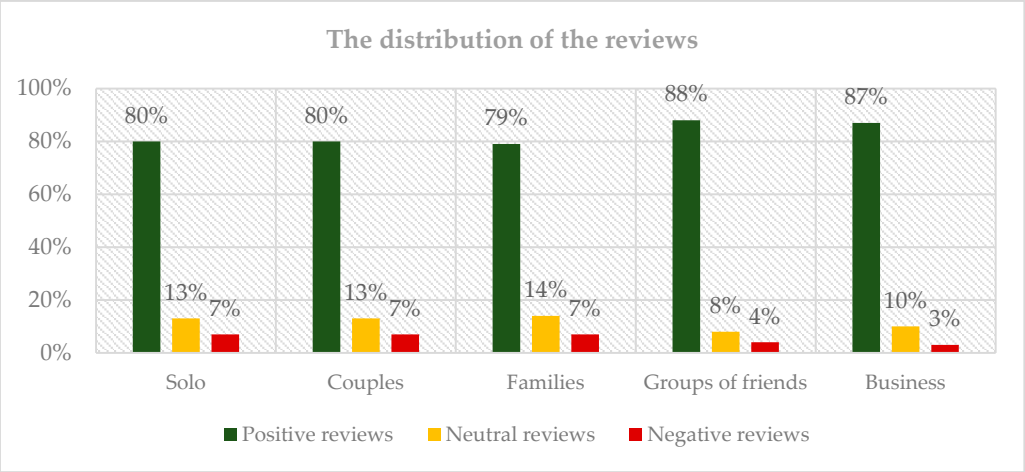

Figure 6. The distribution of the reviews—sentiment analysis by visitor type. Conceptualized by authors.

The sentiment analysis of museum visitor reviews revealed distinct patterns among different visitor types. Couples and groups of friends exhibited the highest levels of positive sentiment, primarily due to their enjoyment of the social aspects of the museum experience. They were likely to view the visit as an opportunity for shared exploration, which enhanced their overall satisfaction. Families, on the other hand, tended to leave more neutral reviews, which may be attributed to the challenges of keeping children engaged and managing logistical concerns such as facilities, accessibility, and exhibit interactivity. Their experience is shaped not only by the museum's offerings but also by practical factors that influence the ease and comfort of their visit. Business travellers generally provide neutral feedback, reflecting the fact that their visits are often brief and more observational rather than immersive. While business travellers typically spend less time in museums, the data show surprisingly high levels of satisfaction. This may appear contradictory at first glance, but their needs and expectations differ significantly from other visitor groups. This paradox is explained by the type of museum experiences they seek: efficient, focused, and high-impact. Reviews often praised well-structured guided tours, curated highlights, and clear wayfinding that allowed them to enjoy a meaningful visit within a limited time window. These visitors appreciate "just enough" storytelling, minimal cognitive load, and visual summaries that offer a "TL;DR" (too long; didn't read) version of the museum narrative. Since they typically visit museums within tight schedules, their engagement is likely to be limited, leading to less emotional investment in the experience. Finally, solo travelers demonstrate a more analytical approach, resulting in a higher proportion of neutral reviews. Their feedback suggests that they critically assess the depth and quality of exhibits, focusing on educational value and self-paced exploration rather than the social or logistical aspects that influence other visitor groups. Their high satisfaction suggests that mountain museums offering condensed, high-quality experiences like top-exhibit routes or thematic overviews effective meet the needs of this segment. Such findings underline the value of efficiency-driven design for time-sensitive visitors.

4.4. Comparative Analysis of Visitors' Perceptions

Bringing all these findings together, a comparison reveals how each visitor profile's experience converges or diverges. Firstly, all groups generally enjoyed the museums, with positive sentiment around 80% or higher for each. Groups of friends and business travelers were most satisfied, possibly because they self-selected into visiting only if they were truly interested or because they had limited time and thus appreciated the opportunity. Solo travelers, couples, and family visitors, while still largely happy, had slightly more mixed feelings as indicated by higher proportions of neutral/negative reviews, indicating a few more critiques or unmet expectations in those groups.

Secondly, focusing on the content confronting the amenities, solo travelers and couples put a lot of emphasis on the content (history, art, or information). They rarely mentioned practical details; their satisfaction resulted from the depth of the exhibits and intellectual or cultural fulfilment. Families and friends also valued the content but were more likely to mention amenities (places to rest, eat, shop) and interactive or social aspects. For example, families care about children-friendly facilities and friends enjoy coffee shops or the gift shop as part of the outing. Business travelers are an interesting mix. They focus on efficiently delivered content because they want the highlights without the clamour.

Thirdly, specific interests differentiate the categories; families stand out by frequently discussing children's engagement. If exhibits are too static or scholarly, families might be less satisfied, whereas other groups might not mind. Otherwise, friends sometimes mentioned enjoying specific special exhibits or the fact that a visit was a fun group activity, which solo travelers might not have experienced in the same way. Business travelers often explicitly mentioned being on a tight schedule, so they appreciated elements that others might not have mentioned, like concise tours or easy access.

Regarding complaints or neutral tones, these differed by group. For instance, a couple or a solo traveler might say an exhibit was not detailed enough or the museum was smaller than expected, determining content-focused critique, whereas a family might comment that their toddler was bored or there was not enough interactivity, generating engagement-focused critique. A group of friends might be disappointed if the outing wasn't as exciting as hoped or if a key exhibit was closed (experience-focused), and a business traveler might note if the visit felt like wasted time in a packed schedule (efficiency-focused). These nuances show that the satisfaction of each visitor type is dependent on different aspects of the museum experience.

Lastly, in addition to sentiment analysis, a keyword cloud was generated to visualize the most frequently occurring terms in the reviews. The word cloud was created using WordCloud and Matplotlib Python 3.11. libraries, which extracted and displayed key terms based on their prominence in the dataset. The size of each word in the cloud correlates with its frequency in the reviews, making it easier to identify common themes and repeated discussions among visitors. Key terms such as "museum", "exhibits", "interesting", and "history" suggest that visitors frequently discussed the nature of the collections and their overall experiences. Additionally, some sentiment-driven words like "amazing", "beautiful", and "small" provided an initial impression of how visitors perceive the museums. The visualization revealed that "Banff" was one of the most dominant words, reinforcing the strong geographical association with the Whyte Museum of the Canadian Rockies, located in Banff National Park, Canada.

In addition to sentiment and topic modelling analysis, a keyword cloud (Figure 7), was generated to visually indicate the most frequently used content-bearing words in the visitor reviews. The word cloud was created using Python 3.11 (WordCloud and Matplotlib libraries), following standard text preprocessing steps such as lowercasing, lemmatization, and removal of stopwords and punctuation. High-frequency function words and generic

terms were excluded where possible to enhance interpretability. However, due to the strong presence of certain terms like "museum" and "Banff" in the original dataset, these still appear prominently. The visualization reflects recurrent concepts in the reviews, with common keywords including "history", "exhibit", "visit", "interesting", "area", and "painting". These terms illustrate the emphasis visitors place on the cultural and educational dimensions of the museum experience.

Figure 7. The keyword cloud. Computed by authors in Python 3.11.

This visualization complements the LDA analysis by offering an intuitive representation of lexical salience within the dataset and helps identify recurring topics that resonate with visitors. By utilizing this keyword cloud, we were able to gain a broad thematic overview of what matters most to museum visitors. It serves as a complementary tool to the sentiment analysis, offering a quick and visual representation of dominant topics in visitors' museum experiences.

5. Discussion

By applying LDA across multilingual TripAdvisor reviews, this study contributes to the methodological advancement of cross-cultural tourism research. While LDA has been used in tourism contexts, its application in decoding visitor narratives across national, linguistic, and motivational contexts in a single comparative framework remains underexplored. The approach followed in this study demonstrates how computational linguistics can uncover latent experiential dimensions that are not always visible through traditional survey instruments. In doing so, this study offers a scalable, reproducible model for analyzing user-generated content in niche tourism contexts, providing a template for future cross-cultural visitor research that transcends language and location boundaries.

Building upon previous work focused on museum experiences from a general perspective [39] this study presents a cross-country, visitor-profile-based exploration of a specialized museum typology. By analyzing reviews of ten mountain museums through topic modeling and sentiment analysis, this study reveals how different visitor types, including solo travelers, families, business tourists, and others, engage with mountain heritage in ways that reflect not only personal motivations but also spatial and cultural contexts. The findings demonstrate that visitor satisfaction and thematic engagement vary not only by visitor identity but also with the unique characteristics of mountain museums, including their educational framing, immersive environments, and the strong presence of cultural narratives rooted in place. In doing so, this research contributes to museum studies and niche tourism scholarship by highlighting how mountain museums act as cultural mediators within the broader experience of alpine destinations.

Therefore, the findings of this study highlight distinct patterns in how different visitor profiles experience and engage with museums. By analyzing visitor reviews in both local

and non-local languages, researchers identified key themes reflecting varying expectations and preferences. For a better understanding of the overall context, the authors created Figure 8 to logically present the aims of the study and the results of the research questions.

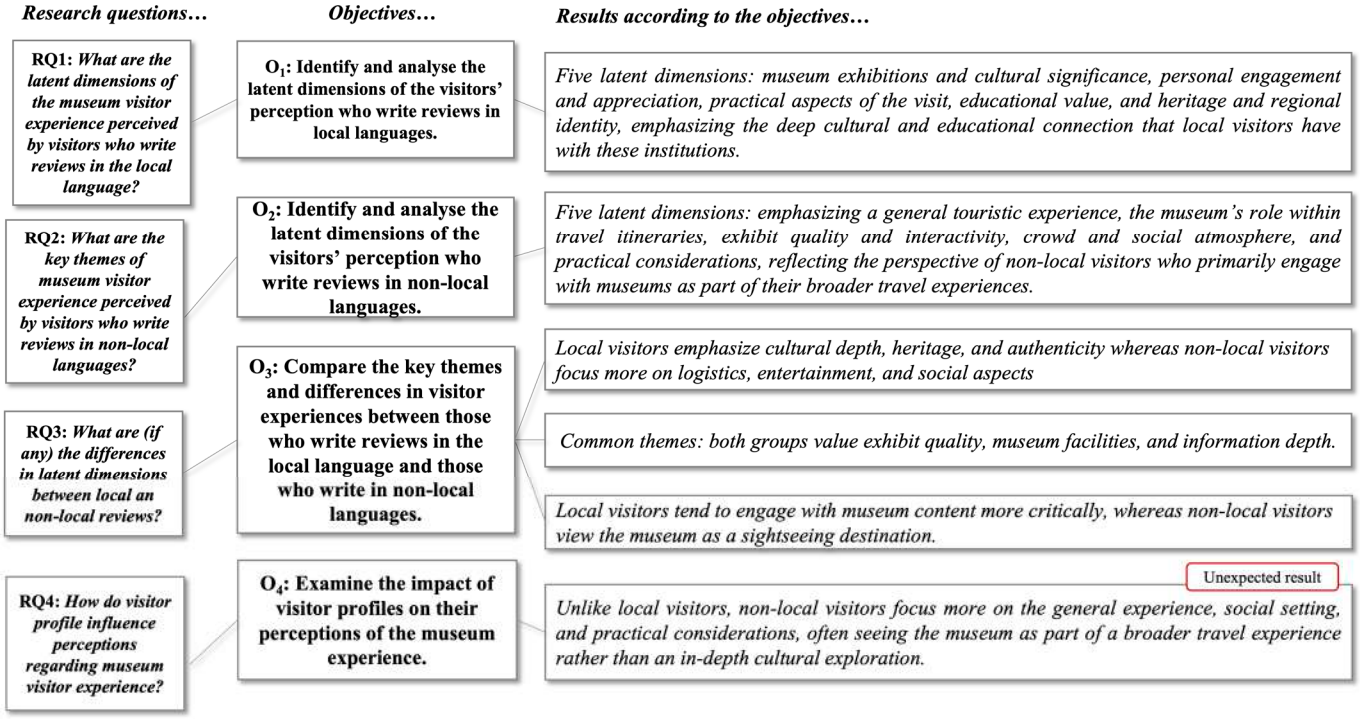

Figure 8. The research questions of the study, objectives, and results. Authors' conceptualization.

The Discussion Section explores how these insights can inform museum strategies to create more inclusive, engaging, and enhanced experiences for diverse visitor segments. The thematic differences between local and non-local reviews reflect distinct visitor motivations. Local visitors engage with museums as cultural and educational institutions, valuing their contribution to heritage and knowledge. In contrast, non-local visitors experience museums more as tourist attractions, prioritizing factors such as exhibit interactivity, itinerary fit, and atmosphere. These findings provide valuable insights for museum management, allowing the development of enhanced strategies to improve visitor experiences based on audience type. Local visitors may benefit from more in-depth cultural programs, while non-local tourists might appreciate improved accessibility, multilingual guides, and interactive exhibits.

Local visitors primarily engage with mountain museums as cultural institutions, placing strong emphasis on historical significance, personal appreciation, educational value, and heritage preservation, according to responses relating to the first research question (RQ1). Reviews written by local visitors reflect a deep interest in authenticity, knowledge acquisition, and national identity, suggesting that they perceive museums as repositories of cultural heritage rather than mere attractions, which strengthens the existing literature.

In contrast, exploring the second research question (RQ2) reveals that non-local visitors approach museums through a touristic lens, focusing on their role within travel itineraries, exhibits' interactivity, social atmosphere, and practical considerations. Their experiences are shaped by factors such as ease of access, entertainment value, and logistical convenience, reflecting an engagement style that aligns with sightseeing priorities rather than cultural immersion.

As outlined by addressing the third research question (RQ3), researchers state that clear distinctions exist between local and non-local visitor expectations. Despite these

differences, both local and non-local visitors share a common appreciation for high-quality museum exhibits, well-maintained facilities, and comprehensive information delivery. Regardless of their background, visitors value engaging displays, clear and accessible interpretive materials, and a well-curated museum environment overall. This suggests that exhibit quality, infrastructure, and visitor support services are key determinants of visitor satisfaction across all audience types. Museums that prioritize these aspects can effectively cater to a diverse audience, ensuring that both culturally invested locals and experience-driven tourists find meaningful engagement in their visits.

Analyzing how visitor profiles shape museum experiences (RQ4) reveals distinct engagement styles. Solo travelers seek in-depth learning, valuing immersive storytelling, quiet reflection, and taking photos. Couples integrate museum visits into their broader travel experiences, appreciating history, regional identity, and convenience. Families prioritize interactive, child-friendly exhibits, emphasizing education and amenities that enhance engagement. Groups of friends experience museums as social outings, enjoying diverse exhibits, cafes, and guided tours that enrich shared visits. These variations highlight how visitor expectations influence satisfaction, providing museums with insights for tailoring their content and designing engagement strategies to enhance experiences for different audience types.

Analysis of visitor-generated reviews also contributes to ongoing debates in museology regarding the shifting boundaries of cultural authority. Traditionally, museum narratives have been curated and controlled by experts, with limited input from audiences. However, platforms like TripAdvisor enable visitors to publicly evaluate, interpret, and reframe cultural experiences based on personal perceptions. The fact that these reviews can be mined for sentiment and thematic structure through tools like LDA gives voice to audiences that have historically been passive recipients. The outcomes of this study, which reveal nuanced, experience-driven patterns in feedback, suggest that online reviews are increasingly shaping the public meaning of museum content, thereby challenging top-down curatorial hierarchies and contributing to a more participatory, decentralized model of meaning-making in heritage spaces.

Based on these findings, the authors propose actionable insights for museum management to optimize offerings for each type of visitor by considering five dimensions comprised in the model pictured in Figure 9.

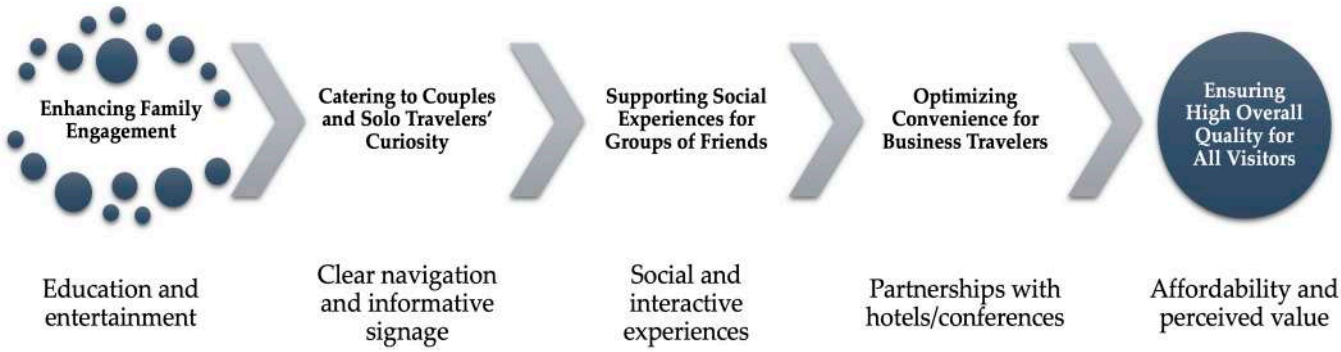

Figure 9. The dimensions for optimisation. Authors' conceptualization.

5.1. Enhancing Family Engagement

Families' prioritize both education and entertainment for their children when visiting museums. To meet these needs, museums should implement interactive exhibits, hands-on activities, and family-oriented guides. Offering family-friendly ticket options, dedicated learning areas for kids, and seating areas for parents can enhance the overall experience. Additionally, clear signage highlighting exhibits that appeal to younger visitors

can ensure a more structured and enjoyable visit. These efforts will keep children engaged, leading to a positive experience for the whole family and encouraging word-of-mouth recommendations among parents.

5.2. Catering to Couples and Solo Travelers

Adult leisure travellers, including both couples and solo visitors, tend to be drawn to rich content and immersive storytelling. Museums should invest in high-quality exhibits featuring detailed information panels, multilingual audio guides, and well-curated collections. Couples particularly enjoy cultural and artistic elements, making it beneficial to integrate local art, history, and thematic storytelling into exhibitions. For solo travelers, creating quiet corners with reading materials and ensuring an intuitive layout for self-paced exploration will enhance their engagement. These strategies cater to inquisitive visitors seeking a deeper understanding of the exhibits.

5.3. Facilitating Social Experiences for Groups of Friends

For groups of friends, museum visits often serve as a social outing rather than just an educational experience. Museums can cater to these groups by creating spaces for social interactions, such as cosy coffee shops, scenic courtyards, or communal seating areas. Offering group discounts and visually engaging, Instagrammable exhibits may encourage social sharing and word-of-mouth promotion. Additionally, museums can host special events, scavenger hunts, or trivia nights to make visits more interactive and appealing to groups looking for a fun and engaging experience.

5.4. Optimizing the Efficiency for Business Travelers

Business travelers, often on tight schedules, value efficiency and convenience. Museums can accommodate these visitors by introducing short, structured guided tours (30 min highlight tours at predictable times) that allow visitors to experience key exhibits efficiently. Providing lockers for briefcases/luggage and ensuring strong wi-fi connectivity can further enhance the convenience of a visit. Additionally, forming partnerships with conference organizers and hotels could introduce unique opportunities such as after-hours networking events or discounted entry for conference attendees. These initiatives can turn business travellers into enthusiastic advocates for the museum.

5.5. Maintaining High Overall Quality Standards

Across all visitor categories, several universal expectations emerged from the analysis, including cleanliness, knowledgeable and friendly staff, and clear visitor information. Museums should continue to train staff to provide excellent customer service and maintain an environment that meets high-quality standards. Pricing should remain transparent and reasonable, with clear communication of the value offered. Where feedback suggests areas for improvement (families desiring more interactive exhibits or solo travelers seeking more in-depth content), targeted refinements can enhance the visitor experience. Even small adjustments dedicated to each visitor segment can contribute to greater overall satisfaction.

5.6. Aligning Museum Offerings with Visitor Expectations

By aligning museum services and exhibits with these visitor-specific insights, mountain museums can provide a more personalized and memorable experience. This means delivering core museum content via multiple modes, such as hands-on and immersive for families, in-depth and research-focused for history enthusiasts, socially engaging for groups of friends, and time-efficient for business travellers. Such improvements will not only enhance visitor satisfaction but also determine repeat visits and positive online reviews, creating a cycle of continuous engagement and growth for the mountain museum sector.

6. Conclusions

This study provides valuable insights into how visitor experiences vary by language and visitor type, highlighting the importance of customized museum offerings. By adapting museum services and exhibits to different visitor segments, mountain museums can enhance engagement, improve satisfaction, and create multiple memorable experiences for all guests. This research contributes to the knowledge on mountain museum visitor experiences, sentiment analysis, and intercultural communication. By deploying human-computer interaction techniques and text mining, the study provides a data-driven approach to understanding visitor perceptions, bridging the gap between digital analytics and mountain museum management. The findings highlight the role of TripAdvisor reviews as an alternative data source for visitor experience evaluation, contributing to advancements in tourism and cultural studies.

From a theoretical perspective, this study reinforces the importance of user-generated content in tourism research. The application of latent Dirichlet allocation topic modelling and sentiment analysis demonstrates how natural language processing can decode visitor emotions and preferences in a cross-cultural context. The results contribute to the understanding of how language and cultural background shape visitor satisfaction and expectations, offering new insights for researchers in the fields of tourism, communication, and museum studies.

The findings provide practical recommendations for mountain museum managers aiming to optimise visitor experiences. Museums should invest in interactive exhibits and child-friendly spaces to improve family satisfaction. By creating engaging, hands-on experiences, museums can better cater to families, ensuring that both children and adults enjoy their visit. Providing designated play areas and structured learning activities can significantly enhance family engagement and increase repeat visits. Museums can meet the needs of solo travelers by offering short, guided tours, self-guided digital experiences, and quiet study areas where visitors can explore at their own pace. Creating flexible visiting options ensures that these visitor segments can engage with museum content efficiently, even on limited time. For couples and groups of friends, a mountain museum visit is often a social activity. Museums can enhance this experience by providing photo opportunities, themed tours, and interactive engagement activities. Incorporating elements that encourage social interactions, such as shared activities, group challenges, or social media-friendly installations, can increase visitor engagement and create lasting memories.

To communicate to local and international audiences, museums should develop multilingual and culturally immersive exhibits. Providing translated materials, multilingual guides, and digital resources can make exhibits more accessible and enjoyable for diverse audiences. Culturally contextualized storytelling, featuring both local and global perspectives, can help bridge the gap between different visitor expectations, providing a more inclusive museum experience. By deploying these strategies, mountain museums can increase engagement, visitor satisfaction, and overall attendance rates, while also using insights gained from human–computer interaction to support continuous improvement.

While this study provides valuable insights, it has some limitations. One acknowledged limitation is the exclusive reliance on TripAdvisor as the sole source of user-generated reviews. While TripAdvisor is not a museum-specific platform and covers a wide range of tourism and hospitality experiences, its extensive user base and broad geographic coverage provide a valuable source of authentic visitor feedback. Prior research has also validated TripAdvisor as a meaningful source of insights for museum and cultural tourism analysis [9,20,39].

Nonetheless, future research could enhance robustness by incorporating data from other specialized review platforms, museum websites, or real-time feedback tools to tri-

angulate findings and explore deeper qualitative dimensions. Meanwhile, TripAdvisor review may not capture the perspectives of visitors who do not engage with online review platforms. This may result in sample bias, where only digitally active visitors' opinions are reflected in the findings. As with all studies relying on user-generated content, TripAdvisor users do not represent the full spectrum of museum visitors; individuals who post reviews tend to be more digitally engaged, vocal, and motivated to share their opinions, while families with toddlers, elderly visitors, or those less comfortable with online platforms may be underrepresented. This introduces a potential sampling bias, skewing the data toward particular demographic and behavioral profiles. Furthermore, the multilingual nature of the dataset presents additional challenges. Cultural and linguistic norms influence how emotions and experiences are articulated; what is framed as neutral in German may imply satisfaction, while Spanish reviews may express enthusiasm more vividly due to cultural conventions. Even with translation and manual validation, these nuances are difficult to fully capture with standard NLP tools. Future research could mitigate these limitations by incorporating in-person surveys, multilingual sentiment models, or native-language analysis to ensure broader inclusivity and cultural sensitivity.

Thus, where language-based segmentation was applied, some nuances in sentiment and cultural expression may not have been fully captured. Differences in linguistic structures and tone may influence how sentiment is interpreted across languages. Also, the current findings are based on mountain museums, which may limit the generalizability of the results to other types of museums or cultural institutions. Future studies could expand the research scope to include a variety of museum types in order to compare findings. Moreover, this study used historical reviews, meaning that the findings do not account for real-time changes in visitor sentiment or immediate reactions to exhibits. The incorporation of real-time feedback mechanisms could further enhance the accuracy and applicability of insights. The dataset included reviews written in multiple languages, reflecting the international reach of the museums. To ensure the reliability of sentiment analysis, the authors restricted this step to reviews originally written in English, as the TextBlob classifier is designed and optimized for English-language input. For non-English reviews, initial translation was performed using the Google Translate API to support thematic comparison in the topic modeling and cross-segment analysis. During preprocessing, the researchers removed or standardized non-standard characters, emojis, and informal expressions, though they acknowledge that linguistic nuances may have been lost or distorted in translation. To assess the accuracy of the sentiment classification process, the authors manually validated a random sample of 100 reviews (including both English and translated non-English entries). In over 85% of cases, TextBlob's automated sentiment classification aligned with human-coded judgments, suggesting that, despite limitations, the tool provided a reasonable approximation of visitor sentiment for the purpose of this study. Other options could be determined from multilingual sentiment models or native-language classifiers to capture cultural and emotional subtleties more accurately.

Future research can explore several promising directions. Firstly, investigating how machine learning and artificial intelligence can track sentiment changes in real time may provide dynamic insights into visitor experiences. Through analyzing trends over time, mountain museums can adapt more proactively to visitor feedback. Secondly, implementing interactive digital feedback mechanisms within museums should allow visitors to provide immediate feedback, enabling real-time adjustments to improve engagement and satisfaction. Furthermore, refinements could include categorising words by sentiment, filtering out common location names, or grouping words by contextual themes, such as positive experiences, criticisms, or exhibit-related discussions. Also, expanding the analysis

to art museums, science museums, and historical sites would help determine whether the findings of this study are applicable across different types of cultural institutions.

Moreover, by integrating direct survey data with online review analysis, future research can overcome the current study's limitations. Demographic data can enable refined analysis of sentiment and experience, revealing, for instance, whether certain age groups consistently report more positive sentiments about educational exhibits or whether family visitors emphasize different aspects of satisfaction than solo travelers. In sum, survey platforms (such as Qualtrics, Google Forms) and distribution channels (museum websites, email invitations, on-site QR codes) to collect visitor demographics and feedback can greatly enhance the depth of sentiment analysis. This approach should allow researchers and museum managers to identify segment-specific trends and employ interpretive strategies or services accordingly, ultimately providing a richer, evidence-based understanding of the mountain museum visitor experience. Also, incorporating visual and audio reviews (social media videos, voice reviews) can offer a more comprehensive understanding of visitor feedback. This approach can capture non-verbal cues and emotional expressions that are not always evident in written reviews. Finally, location-based tracking and digital engagement metrics may help museums understand visitor movement patterns, dwell times, and levels of interaction with different exhibits. These insights could be used to optimize exhibit layouts and improve visitor flow within museums. By pursuing these future directions, researchers can further enhance understanding of museum visitor behavior, helping institutions adapt to evolving digital trends and cultural expectations.

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Using Chatbots to Enhance Integrated Reporting: Insights from Accounting and Consultancy Companies from Romania

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Abstract: Integrated reporting is essential for businesses to communicate long-term value creation. Despite growing interest, little research has examined AI technologies like chatbots in sustainable reporting practices. This study addresses this gap, exploring chatbot adoption within 11,113 Romanian accounting and consultancy firms in Romania's emerging digital landscape. Researchers used Python's Seaborn library to analyze financial data from 2018 to 2022, finding that companies with higher revenue and liquidity were more likely to make their mark on how to achieve integrated reporting. Additionally, this study revealed the potential of chatbot technology adoption to enhance financial reporting and management, significantly improving financial reporting efficiency, accuracy, and accessibility. By automating data collection and analysis, generating real-time reports, and improving communication with stakeholders, chatbots can significantly improve efficiency and accuracy in financial processes. By addressing the challenges and capitalizing on the opportunities, firms can use chatbot technology to create more efficient, effective, and sustainable reporting practices. The findings contribute to this field of knowledge on sustainable reporting by examining the potential of technology and artificial intelligence (virtual assistants) to improve stakeholder communication. This study provides a case study from Romania, with implications for other regions.

Keywords: sustainable accounting; integrated reporting; chatbots; artificial intelligence; digital technologies; financial performance; communication; management optimization

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1. Introduction

Sustainability accounting plays a critical role in addressing Environmental, Social, and Governance (ESG) objectives by enabling organizations to quantify and disclose their impact on stakeholders and the environment. It is the process by which companies must assume responsibilities, become aware, and act for the well-being of all stakeholders. An active contribution to this global movement is represented by the multitude of organizations that target objectives concerning environmental issues, social responsibility, and corporate governance (ESG). Institutions with responsibilities in the accounting field such as the International Accounting Standards Board (IASB) (an independent body within the IFRS Foundation) and the International Sustainability Standards Board (ISSB) (an independent standard-setting body within the same foundation) are responsible for the development of the IFRS Accounting Standards and the IFRS Sustainability Disclosure Standards, respectively [1]. Although, in most of them, the companies do not make a complete disclosure of the internal and external sustainability strategies, the expectations

and the need to inform clients about the environmental and social performances attract the development of sustainability accounting [2]. While prior research emphasized the use of digital tools for sustainability reporting, limited attention has been given to AI-driven solutions like chatbots. These tools offer transformative potential by automating data collection, generating real-time reports, and enhancing communication with stakeholders. Previous studies on sustainability accounting have largely focused on reporting processes using traditional digital tools, often overlooking AI-based interactive technologies. This lack of empirical data on AI-driven automation and engagement tools in sustainability contexts highlights the need for research on chatbot applications in integrated reporting. The existing literature on AI applications in sustainability reporting primarily focuses on analytics and predictive capabilities, with little attention given to the role of interactive tools like chatbots. Moreover, the potential of chatbots to improve real-time communication and automate data-driven reporting in sustainability contexts remains largely unexplored. As an emerging market in the European Union, Romania provides a compelling context for exploring digital transformation in sustainability reporting. Despite growing interest, challenges such as limited infrastructure and varying digital literacy levels create opportunities for innovative solutions like chatbots to address gaps in reporting practices. Studying chatbot adoption in Romania provides insights into the potential for digital tools to enhance sustainability practices in similar emerging markets, where the dynamics of digital adoption may differ significantly from those in more developed countries.

Sustainability accounting must emphasize environmental performance reporting so that management decisions on resource consumption operations optimize and pursue sustainability goals. It also contributes to the assessment of the impact of the activity on the environment [3–5] and assesses the sustainability efforts that companies are making to meet regulations. In this context, the accounting profession actively participates in delivering quality information related to sustainability to all stakeholders [6]. Professional entities identify the existing stage in the professional training of specialists and establish key areas for developing new skills and updating the knowledge they possess so that the data they produce on sustainability issues conveys confidence to users. The significant changes in stakeholder expectations regarding sustainability, as communicated through reports prepared by companies, require the accounting profession to prepare for sustainability reporting and a certain alignment at a global level regarding mandatory disclosure. So, entities like the International Sustainability Standards Board (ISSB) and the International Auditing and Assurance Standards Board (IAASB) work together to provide direction for aligning sustainability standards.

In this complex sustainability reporting process, accounting firms are interested in working with professional accountants whose skills are in the following areas: analysis and systemic thinking, critical thinking and solving problems, working in teams interdisciplinary, communication skills, ease of adaptation and flexibility, etc. [7,8]. To achieve such qualities, the existence of strategies aimed at training professional accountants in an adequate way, starting in the academic framework, to provide services related to sustainability, is required.

While studies by PwC US [9] and Deloitte [10] underscore the importance of integrating sustainability into education programs, promoting innovation, and the role of technology in achieving business goals. The existing literature on AI applications in sustainability reporting [11] primarily focuses on analytics and predictive capabilities, with little attention given to interactive tools like chatbots [12].

The integration of sustainability in the accounting curriculum appears as a necessity in the context where issues such as social and environmental responsibility, environmental and social accounting, and, currently, sustainability are topics that concern the business world, the academic world, governments, and all other stakeholders [13]. According to a study, the traditional accounting curriculum focuses more on the technical side of training future professionals, while the sustainability curriculum aims to contribute to the development of independent and holistic thinking regarding economic phenomena. Curriculums

must quickly adapt to the implementation process of sustainability standards and actively participate in supporting companies that prepare sustainability disclosure reports.

Moreover, while artificial intelligence is increasingly implemented across various sectors to enhance efficiency and support data-driven decision-making, limited research by refs. [14–16] has explored its specific application within sustainability management and financial reporting [17–19]. Most studies on AI in business contexts have focused on predictive analysis [20], data processing [21,22], or customer engagement, with few examining the potential role of virtual assistants [23,24], such as chatbots, in supporting reporting on sustainability standards. A systematic review of a recent literature review revealed a gap in understanding how chatbots might contribute to sustainable business operations by optimizing financial management and reporting. In this context, the study examines how the use of artificial intelligence can improve the dissemination of information related to the fulfillment of sustainability standards. The study addresses the central research question, namely, *how can digital technologies, such as chatbots, enhance sustainability-focused reporting and value creation for stakeholders?* To explore this, this study examines the following subquestions: (1) How can chatbot technology enhance the accuracy and timeliness of financial reporting? (2) In what ways can chatbots optimize financial management and operational efficiency? (3) How can chatbots support effective communication with stakeholders in sustainability reporting? All these questions represent the basis of the objectives of this study, which, for greater specificity, are represented by the following: (1) to assess the potential of chatbots in improving the timeliness, accuracy, and efficiency of sustainability reporting; (2) to explore how chatbot technology can optimize financial management and operational processes in sustainability contexts; and (3) to evaluate the role of chatbots in facilitating effective communication and engagement with stakeholders.

This study employs a mixed-method approach, combining exploratory data analysis and cost amortization analysis to assess chatbot adoption and its financial impact. These methods allow the capturing of early-stage adoption patterns in emerging digital landscape markets, providing insights distinct from those in the existing literature.

This study demonstrates the potential of chatbot technology to enhance financial reporting and management, and it focuses on the economic dimension of sustainable development, specifically examining how chatbots may enhance financial reporting and management efficiency. Although sustainable development encompasses economic, social, and environmental aspects [25], the scope of this paper is limited to economic impacts, with a goal to establish how AI-driven technologies can support economically sustainable practices within organizations. By automating data collection and analysis, generating real-time reports, and improving communication with stakeholders, chatbots can significantly improve efficiency and accuracy in financial processes.

To introduce the outcomes of this study, this paper presents five sections. After introducing the literature review about the topic of interest, namely, sustainability in accounting, integrated reporting, and virtual assistants' implications in sustainable accounting, the third section draws attention to the materials and methods used for this study.

Therefore, the results and discussions present the contributions to the specialized literature, followed by the final section, where the conclusions highlight the theoretical and managerial implications, limitations, and potential for further research.

2. Literature Review

2.1. Sustainability in Accounting

At the European level, the private association European Financial Reporting Advisory Group (EFRAG)—established in 2001—was involved in the development of the International Financial Reporting Standards, and currently contributes through the consultancy offered to the development of directives regarding EU sustainability reporting standards.

The professional entities, in turn, are engaged in the development, adoption, and implementation of international standards for accounting, ethics, and deontology education in the public sector, as well as auditing and assurance. They participate through collective

actions at the global, regional, and local level in the training of members in order to deepen existing knowledge, but also to accumulate new knowledge to adapt to the requirements regarding the implementation of sustainability reporting standards [26].

The process regarding the adoption and implementation of sustainability reporting standards aims at the direct and responsible participation of accounting in the sense of expressing sustainability in quantitative indicators, such as the analysis and reporting of the social and environmental impact of a company [27–29].

Along with the professional bodies, the companies that offer accounting, taxation, audits, and insurance services in the process regarding the sustainable reporting standards, through the activity carried out, claim the need for digitization and the use of advanced technologies in carrying out their actions [30]. Research indicates that AI adoption in sustainability and integrated reporting varies significantly between developed and developing countries. Developed countries, with advanced digital infrastructures and greater regulatory support, have seen a more widespread integration of AI technologies, including chatbots, in corporate reporting [31]. In contrast, developing countries face challenges such as limited technological infrastructure, lower levels of digital literacy, and budget constraints, which can hinder AI adoption in reporting practices [32,33]. This disparity highlights the need for context-specific studies, such as this study on Romania, to understand the unique opportunities and barriers in emerging markets.

Digital transformation has required the development of skills and competencies to help develop accounting and finance work in a digital economy. In this sense, some of necessary the skills are as follows: learning and applying transformative technologies, ease in analyzing and presenting data, critical thinking and communication with partners, openness to learning new things, etc. [19,34].

The existence of a wide range of stakeholders with multiple and varied concerns gives rise to the need to find solutions that combine all environmental, social, and governance aspects of an organization with common interests and future well-being. The intervention of sustainability accounting can help companies develop businesses that differentiate them in the market, are competitive, and achieve financial and environmental performance. The issue of sustainability and stakeholder engagement formed the premise from which the Sustainability Accounting Standards Board (SASB) identified issues relevant to investors that vary by industry. At the same time, the analysis carried out by the Global Reporting Initiative (GRI) established a whole range of sustainability issues of importance to society. Joint research by the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB) explored the experiences of companies using the two sets of standards together to meet their reporting needs [35].

From investors to consumers and state institutions, a joint effort to change lifestyles and practices can support the development of a society where companies are interested in measuring and reporting their sustainability information.

According to the Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS), users interested in a certain company must be allowed to know not only the significant impacts it has on the environment and people but also the significant effects that environmental aspects have on the company's development and performance.

In the conditions of an ongoing digitization process, the business model, the sustainability management system, and its monitoring are easier to access, and transparency in the disclosure of sustainability information is increasing [36]. Accounting service companies are directly involved in the use of digital technologies, and communication with the users of financial accounting information tends to be performed in real time. For the preparation of integrated reports comprising financial and non-financial information, they offer consultancy in order to apply sustainability standards that are intended to allow investors and other users to evaluate the risks of the investment from the point of view of the impact on the environment and other aspects of sustainability and to increase the degree of transparency in communication [37]. In Europe, the most common accounting

services offered by specialized companies are as follows: external audits, accounting and financial reporting, accounting and auditing in the public sector, real estate valuation, and financial consulting [30].

The training accounting services to measure specific sustainability indicators are resource consumption (materials, water, energy) and the impact of the entity's activity on the natural environment (conditions of land use, emissions in the air, in water, in the soil that seriously affect the natural environment, waste, the number of indemnities paid by judicial decisions regarding the natural environment). The measures taken by the entity to reduce these impacts (Global Reporting Initiative (GRI) represent the stage of involvement of the field in the creation of value for sustainable businesses. Accounting must respond to the needs of the interested parties and find a balance in the creation of the value related to each party. According to Harrison, ref. [38], conducting business is the result of a set of relationships that contribute to the creation of value for stakeholders in the firm's activities and results and that influence the achievement of its objectives.

Effective stakeholder relationship management can bring competitive advantages to the company and impact the company's conduct of responsible business [39–41]. Sustainability accounting can provide information on different aspects of sustainability and help to compare ESG performance indicators considering the investment function developed in the company. The impact of each project and the business model can be reflected by cost accounting and measuring the benefits recorded [42–44]. In this sense, an important role belongs to management accounting, which must provide relevant data on the consumption of raw materials, energy, water, and the waste generated by the company's activity, as well as data on the costs of protecting and maintaining the environment in relation to performance financial because of the application of environmental policies and the reduction in the consumption of natural resources.

Sustainability accounting deals with tracking, aggregating, and reporting environmental and social information, often linked to economic information related to reducing sustainability problems or contributing to sustainable development [45–47]. In conventional accounting, thinking in relation to stakeholders registers a certain gap that is also maintained regarding sustainability accounting and stakeholder information. The results of a study on the level of reporting of value creation and distribution to stakeholders [48] shows that, in general, companies do not address the full variety of stakeholders when reporting on value creation. Sometimes, in the development of integrated reports, significant influences are found in some departments within the company.

With the help of sustainability accounting, the business model managed by the entity; the monitoring of the impact of the activity carried out on financial performance, the environment, and society; and the quality of the disclosure of non-financial information, are reflected in all interested parties [49].

Artificial intelligence can be implemented into this communication process, bringing with it opportunities and challenges that influence everything from data analysis to decision-making processes. AI intervenes in the accounting processes not only for the processing of transactions of purchases, payments, receipts, and closings of the month but also for the realization of a real-time analysis to substantiate business decisions. The integration of AI into the organization and management of companies allows professionals to focus more on strategic analysis to achieve performance goals and create value.

2.2. Integrated Reporting

Integrated reporting encompasses an entire process of developing a report based on the concept of integrative thinking (IT) [50], intended to convey information in a clear format and increase corporate transparency. According to a recent reference, ref. [51], an integrated report must contain information about all aspects of the company, conveying it accurately and in a balanced way to investors and other interested parties [52,53].

According to the study carried out by Nandram et al., company management is tempted to disclose information on performance indicators (KPI—Key Performance In-

dicator) emphasizing good performance and minimizing poor performance through the presentation in the form of the integrated report. Therefore, there are situations where management turns to positive presentation models, using impression management, to express a better picture of the result in their integrated reports for the purpose of transmission to users [54].

In this way, the concept of information asymmetry is present, but it can be ameliorated by considering the content elements of an integrated report. According to Ghofar, 2023, an integrated ratio presented with fidelity negatively influences the information asymmetry (IA) and cost of equity (COE) of companies [55].

Accounting also contributes to the reduction in information asymmetry, which reflects the process in which information flows are provided for managerial decision-making, becoming a tool for designing a company's relationship with its stakeholders [56].

The quality of integrated reporting has increased over time, a phenomenon also supported by the study conducted by Nada and Hassan [57]. This study uses a company disclosure index based on the balanced scorecard (BSC) relationship that reflects the information content of integrated reports. The transmission of financial information with fidelity supplemented with non-financial information about the objectives regarding the sustainability of the company's business model is a necessity under the conditions of the introduction of sustainable reporting standards. Their implementation directly involves the work of professional accountants and sustainability accounting.

Integrated reporting can be considered a derivative of sustainability accounting as long as sustainability accounting is analyzed as a part of financial accounting. It aims to convey non-financial information to stakeholders and focuses on issues such as social and environmental accounting along with social and corporate responsibility reporting [58].

Stakeholders aim to understand how companies manage and use resources to achieve their strategic goals while considering sustainable development goals.

Along with sustainability accounting, which highlights all the processes directly related to a company's external performance, sustainability audits examine the strategy for achieving sustainable development goals and their disclosure through integrated reports. Thus, sustainability audits and reports guarantee an oversight of how the organization complies with tax laws, environmental laws, and social protection laws and how stakeholders are involved in its processes [59]. The use of innovative management accounting tools (IMAT Innovative Management Accounting Tools) results in better financial and sustainable organizational performance [60]. The companies that used innovative management accounting tools performed significantly better and created the framework to measure and manage a sustainable approach. They provide more and more detailed information on company performance and business sustainability behavior. Integrated reporting is influenced by innovation performance, especially within companies that have a high level of sustainability performance—a factor with an impact on the tendency to publish integrated reports, along with innovation performance at the country level [61].

The managerial control system (MCS) has an important role in the qualitative process of integrated reporting [62]. Also, integrated reporting developed based on reporting data formation methodology that includes a basis for generating financial and non-financial information and a complex integrated accounting policy would lead to a qualitative increase in the flow of information [63] and could contribute to the sustainable accounting paradigm [64].

The increase in the quality of financial and non-financial information disclosures has also been influenced by the means of disseminating content through ICT that can transmit information in real time and at the right time for all interested parties. Thus, the eXtensible Business Reporting Language (XBRL) can be used for the unitary representation of the content of financial statements or other types of performance and business reports. However, studies conducted on industry reporting [5,65,66] show that factors such as online financial reporting, profitability, size, and stakeholder involvement have little significant effects on integrated reporting. However, a complex business system with performance results

requires the development of a sustainability report whose premise consists of a business model that contains the objectives of sustainable development, namely, performance, environment, and social responsibility. Through integrated reporting, it is conveyed how the merging of objectives related to governance, performance, and social responsibility leads to the creation of value in the short, medium, and long term. Measuring the achievement of sustainability objectives is facilitated with the help of integrated reports that analyze the integrated transmission of financial and non-financial information for the six types of capital ("financial capital, manufactured capital, intellectual capital, human capital, social and relationship capital, and natural capital") [67].

2.3. The Role of Digitalization in Increasing the Level of Sustainability in Accounting

The digitization of the process of accounting activities has reached the stage where the automatic recording of repetitive transactions in accounts is ensured, contributing to the dedication of accountants to the control activities of accounting operations and the financial management of the company. Digitization brings benefits in terms of time savings, lower costs, and an overview of the amount owed on invoices [68].

Using technical knowledge and developing skills specific to digital transformation, accounting professionals are challenged in thinking about accounting processes using digital technologies. In the development of the accounting field, the existence of a balance between the improvement of technological knowledge and communication, critical thinking, and creativity is affirmed. In this context, the accounting professional must relate to technology, adapt, accumulate digital knowledge and skills, and use analysis and synthesis for communication in client relations [69].

All economic entities are oriented towards the digitization of business and pursue the use of information technology (intelligence, software robots, and blockchain) to increase performance. The digitization of accounting is not left out of the process and is leaving its mark on the working style and role of accounting professionals [70]. The research by Coman et al. shows that the accounting digitalization process, in addition to the implementation stages, has a component related to the human factor (change in mentality) and a component related to the organizational culture of economic entities that must be oriented towards sustainable business models.

Digitization is associated with technologies such as artificial intelligence, process automation through robotics, blockchain, intelligent data analysis, and cyber security, which help change processes inside and outside the company. Digitization assimilated in the field of management accounting and control contributes to the creation of value by designing new forms of collaboration between all interested parties, including organizations, suppliers, customers, and employees [71].

The use of AI leads to the development of new skills and knowledge, such as data analysis, critical analysis, and creative thinking. In the study carried out by the Institute of Management Accountants (IMA), the development of the following skills is identified as a result of the impact of AI on accounting and finance: cognitive skills (analytical thinking, creative thinking), self-efficacy (resilience, flexibility and agility, motivation and self-awareness, curiosity and lifelong learning, reliability and attention to detail), managerial skills (quality control), technological skills (technological literacy), and skills for working with others (empathy and active listening, leadership and social influence). Digitization in all areas of business (The European Green Deal) encourages organizations to adopt the latest digital technologies; the accounting function of a company cannot be excluded from this process, highlighting the need to update university curricula [72].

The digitization of the accounting field brings opportunities and also risks, which can be expressed in the decrease in the importance of providing information related to the other functions of the organization (marketing, IT, etc.). Accounting professionals must engage in technological development, participate in training through education, and activate the role of the educational system in the evolution of digital technologies [73].

By emphasizing the usage of the virtual assistants (chatbots) in integrated reporting [74,75], the process of making the information about reporting becomes more easy to communicate and more transparent [76], with a particular impact on the company's image to users who access the organization's presentation platform in search engines. Increasing transparency, clients identify the organization as a reliable one, wanting to collaborate with it. In this sense, in the long term, it can be stated that the use of artificial intelligence through chatbots to operationalize integrated reporting will increase the degree of interest for the company's stakeholders, and, implicitly, the financial performance will also experience improvements [77,78]. It can thus be said that, by increasing the company's trust using chatbots, AI also helps in the long-term growth of organizations that apply the principles of integrated reporting, even with financial implications.

A relevant example is given by Manifest Climate, which supports the use of AI to report with confidence, arguing that chatbots offer several advantages for financial reporting, such as automating routine tasks, freeing up human resources for strategic work, and providing real-time insights to process and analyze data quickly for timely decision-making. Also, the potential to obtain improved communication with personalized financial information and 24/7 accessibility is another factor [79].

In this context, the accounting profession requires people qualified in information technology (IT) and accounting information systems (AISs) and who can quickly familiarize themselves with the software tools used to maximize accounting functions [80]. The changes that take place through the adoption of digital technology influence the company's business model, its strategic and competitive objectives, and also the demands of consumers in the market [81].

Under these conditions, business management is more creative, and the training of the accounting function and its tasks contributes to the ability to access information much faster, from anywhere, and with impact in terms of corporate reporting [82]. The use of technology simplifies accounting tasks; therefore, accounting practice becomes easier, faster, and more accurate. Plus, accountants can access their work from almost anywhere, and corporate reporting is more efficient. Undeniably, there are advantages to digitization in the accounting profession, but its implementation can also encounter some difficulties, especially in smaller accounting service companies where investments in AI involve considerable efforts [83]. Thus, to be competitive, organizations must invest in new technology that brings with it increased productivity and the creation of new types of jobs with different skills.

Conversational artificial intelligence can be successfully used for communication and prospecting [84–86]. It can connect with accounting professionals to ask specific management consulting, accounting, taxation, or international business development questions due to its acceptance in the communication process in business [87]. Therefore, the integration of artificial intelligence in accounting, accounting education, and consultancy is a necessity and a present reality [59,88–90]. Thus, the integration of AI in this field allows companies to remain present in an ever-evolving field and contribute to the application of sustainable business models. By promoting integrated thinking, the existence of a global reference framework for sustainable reporting, which ensures ethics and independence and strengthens the application of sustainable practices, is enhanced [91–93]. This can be considered a holistic approach to business that helps create value and quantify performance.

In summary, while prior research has explored AI's potential in various business functions, limited studies have focused on AI applications in sustainability reporting, particularly in the form of chatbots. Furthermore, few studies address the unique challenges faced by developing countries in adopting AI for integrated reporting. These gaps highlight the need for research on how emerging digital technologies can support sustainability reporting within developing market contexts, providing a foundation for our study's research questions and objectives.

3. Materials and Methods

For the purpose of determining how effectively accounting and consultancy firms can ensure communication with users by using artificial intelligence, this study employed a methodology that used a mixed-method approach to integrate exploratory qualitative analysis with quantitative cost amortization modeling. This design allows for a comprehensive examination of the early adoption patterns of chatbots in sustainability reporting, combining financial data insights with an interpretive analysis of their managerial and operational impacts. Specifically, this study first explored the database (compounded by 11,113 consultancy and accounting companies from Romania) based on revenues and liquidity, as these metrics were seen as indicators of companies' openness to digital technologies [94–96]. The researchers' assumption that revenues and liquidity can serve as indicators of a company's openness to digital technologies is supported by prior research. Studies on organizational innovation have demonstrated that companies with higher revenue and stronger liquidity positions are more likely to adopt new technologies due to their greater financial flexibility and risk tolerance [97,98]. Additionally, from a Resource-Based View (RBV) perspective, financial resources represent a critical asset that enables firms to invest in and experiment with innovative solutions, including digital tools such as chatbots [99,100]. Consequently, this study proposes that revenue and liquidity are relevant indicators of a company's capacity and willingness to embrace digital transformation.

The researchers used the Seaborn library in Python 3.11.0 to analyze financial data from 2018 to 2022, including revenues, profits, debt, equity, and liquidity. They found that companies with higher revenue and liquidity were more likely to make their mark on how to convey information through integrated reporting. Additionally, they analyzed the potential and cost-effectiveness of using chatbots for financial reporting because this technology can significantly improve financial reporting efficiency, accuracy, and accessibility [101]. By following a mathematical model to calculate the amortized cost of chatbot usage, this study concludes that chatbots can be a valuable tool for improving financial reporting efficiency and accuracy. The research methods used (1) exploratory data analysis to understand the openness of the companies to digital technologies [102,103] and (2) the analysis of potential and cost amortization of chatbot usage as a continuation of the potential existing in the literature [104,105]. The dataset used in this study was fully anonymized and organized using an automated system with continuous numbering to ensure confidentiality and maintain data integrity.

The methodological approach is grounded in scientific basis, with the authors selecting the exploratory data analysis (EDA) and cost amortization analysis as methods that are suitable for studying the emerging adoption patterns of chatbots. EDA allows us to understand potential barriers and analyze preliminary patterns in the data, which are crucial when dealing with early-stage adoption where established models may not yet apply. Cost amortization analysis complements this approach by examining the economic impact and long-term return associated with chatbot implementation, offering insight into the financial feasibility of digital adoption for Romanian companies. Together, these methods provide a structured yet flexible approach to understanding the relationship between chatbot adoption and economic factors in a market where the digital transformation of companies is developing. The researchers state that this methodology is well-suited to the Romanian context and helps to establish a foundational understanding that can guide further research in similar emerging markets.

The exploratory data analysis addressed Objective 1 by identifying patterns in financial readiness for chatbot adoption. Cost amortization modeling supported Objective 2 by evaluating the economic sustainability of integrating chatbots into reporting processes. Together, these methods inform Objective 3 by highlighting the potential managerial and financial benefits of chatbot deployment for stakeholder communication.

3.1. Exploratory Data Analysis (EDA)

The openness of the companies to digital technologies is determined by high values in revenues and liquidity. Based on this, the authors explored the database from the point of view of these two significant metrics. The exploratory analysis involved examining financial performance indicators (e.g., revenue, profit, equity, and liquidity) for 11,113 Romanian accounting and consultancy firms from 2018 to 2022. Using Python's Seaborn library, we computed a correlation matrix to identify patterns between financial metrics and digital adoption potential. Outliers were identified and treated using the interquartile range method, and year-over-year growth rates were calculated to evaluate financial consistency and trends.

Financial resources, risk tolerance, or strategic vision are characteristics of companies that invest in new technologies without jeopardizing their core operations and might be more forward-thinking and open to adopting technologies that could drive future growth. Assuming a possible strong influence on how to achieve integrated reporting, the authors assigned an important role of revenues and liquidity in the analysis of discovering how companies could report sustainability in an integrated manner. Thus, they explored the database and calculated the average revenue and the average liquidity for each year across all firms. The outcomes will confirm a valuable opportunity for going further and finding correlations presented in the Results Section.

By using Python 3.11.0 and the "seaborn" library, the authors intended to compute the heatmap of the correlation matrix, including total assets, revenue, number of employees, profit, debt, equity, and liquidity, between 2018 and 2022. Before this step, they checked for the lack of missing values; searched for outliers; checked data distribution; evaluated consistency across years; searched for zero or negative values; and finally, calculated correlations. By using the interquartile range (IQR) method computed by using Python 3.11.0, 733 outliers in the revenue data for 2022 were found. These outliers were identified as being significantly higher than the typical revenue values in the dataset. Data distribution was not illustrated as being normal but rather skewed to the left, indicating that most companies have relatively low revenue values, with a few companies having very high values. The consistency of revenues and profit across years was evaluated by detecting the presence of zero or negative values. Afterward, all these values were cleaned, and year-over-year growth rates were calculated.

In the continuation of the results obtained, the authors computed the correlation matrix as a heatmap to identify possible relationships between financial metrics. Each cell of it shows includes the correlation coefficient between pairs of variables, ranging from -1 to 1. Values closer to 1 indicate a strong positive correlation, values closer to -1 indicate a strong negative correlation, and values around 0 indicate no correlation. The result of the matrix was used to understand the financial context of the development of integrated reporting.

3.2. Analysis of Potential and Cost Amortization of Chatbots Usage

The cost amortization analysis was conducted to evaluate the financial feasibility of chatbot adoption. A mathematical model was developed using variables such as initial development costs, monthly operational expenses (e.g., maintenance, hosting, customer support), and estimated benefits (e.g., savings from reduced manual reporting and improved stakeholder engagement). The total costs and benefits were projected over a five-year period to calculate the net amortized cost per month. This approach ensures a realistic assessment of long-term cost efficiency.

The second part of the data analysis section is dedicated to the potential and cost amortization of chatbot usage analysis. To formalize the amortized analysis, the mathematical model is used to calculate the net amortized cost per month (ϕ_{amort}) of utilizing basic chatbots to communicate reports to stakeholders. To proceed, the authors used the following variables: (1) the initial cost of developing the chatbot (ϕ_{dev}), (2) the initial cost of integration and setup (ϕ_{int}), (3) the total initial cost (ϕ_{init}), (4) the monthly maintenance and updated cost (ϕ_{maint}), (5) the monthly hosting and data storage cost (ϕ_{host}), (6) monthly customer support fee (ϕ_{sup}), (7) the total monthly operating cost (ϕ_{op}), (8) monthly savings

from reduced manual reporting (ϕ_{rep}), (9) monthly benefits from improved stakeholder engagement (ϕ_{eng}), (10) monthly benefits from improved data analytics and feedback (ϕ_{data}), (11) total monthly benefits (ϕ_{tot}), (12) time period in months for amortized analysis (T), (13) total benefits for the period $T(\phi_{totT})$, (14) net cost for period $T(\phi_{net})$, and (15) the amortized cost per month (ϕ_{amort}). The calculation method is presented as follows:
Initial costs:

$$\phi_{init} = \phi_{dev} + \phi_{int} \tag{1}$$

Monthly operating costs:

$$\phi_{op} = \phi_{maint} + \phi_{host} + \phi_{sup} \tag{2}$$

Monthly benefits:

$$\phi_{tot} = \phi_{rep} + \phi_{eng} + \phi_{data} \tag{3}$$

Total cost for period T:

$$\phi_{tot} = \phi_{init} + \left(\phi_{op} \times T\right) \tag{4}$$

Total benefits for the period T:

$$\phi_{totT} = \phi_{tot} \times T \tag{5}$$

Net cost for period T:

$$\phi_{net} = \phi_{tot} - \phi_{totT} \tag{6}$$

Amortized cost per month

$$\phi_{amort} = \frac{\phi_{net}}{T} \tag{7}$$

Considering the hypothesized scenario with market analysis results, the size of the variables is shown in Table 1.

Table 1. Value for assumed scenario.

Variable	Notation	Value
The initial cost of developing the chatbot	ϕ_{dev}	RON 50,000
The initial cost of integration and setup	ϕ_{init}	RON 10,000
The monthly maintenance and updated cost	ϕ_{maint}	RON 1000
The monthly hosting and data storage cost	ϕ_{host}	RON 500
The monthly customer support fee	ϕ_{sup}	RON 500
Monthly savings from reduced manual reporting	ϕ_{rep}	RON 3000
Monthly benefits from improved stakeholder engagement	ϕ_{eng}	RON 1000
Monthly benefits from improved data analytics and feedback	ϕ_{data}	RON 500
Time period in months for amortized analysis	T	12 months

To analyze the long-term potential of using chatbots in the reporting process, the authors performed an analysis in which the initial state (without chatbot) is the starting point. Specifically, C_0 is the initial total cost for integrating reporting without chatbots in the communication process.

The potential function was defined as a simple equation to reflect the difference between the current situation and the desired situation (with the implemented chatbot):

$$\Phi = C_{without\ chatbot} - C_{with\ chatbot} \tag{8}$$

The authors identified long-term investment analysis (five-year potential period) as being mandatory for this study. Thus, several aspects are presented. Firstly, *the cost spread over time* allows a more accurate reflection of the utility and financial performance for sustainable reporting purposes. Also, amortizing the cost acknowledges that the chatbot will provide value over an extended period rather than the starting point of the investment. This approach helps in budget planning and management by allocating a predictable expense over multiple fiscal periods.

Secondly, approaching the long-term potential of using chatbots for integrated reporting from the point of view of *technological depreciation*. Due to advancements in technology and changes in user requirements, technology assets typically depreciate over time. Amortizing the cost of a chatbot over five years aligns with the expected lifecycle and decreases the efficacy of the technology, ensuring that cost accounting practices match the practical depreciation of the asset.

Another argument is the *matching principle* because, in accounting, it dictates that expenses should be recorded in the same accounting period as the revenues they help to generate. By amortizing the cost of the chatbot, expenses are matched with the benefits realized from its use, such as improved customer service, increased sales, or cost savings from automation, throughout its operational life.

Also, the five-year period provides a framework for evaluating the performance and return on investment of the chatbot over a realistic timeline during which its benefits can be fully assessed and quantified. By emphasizing that a five-year amortization period for a chatbot deployment is prudent financial and strategic planning for integrated reporting, it aligns accounting practices with business benefits, supports effective budgeting, and provides flexibility in managing technological advancements. Thus, based on these aspects, continuing the calculation of amortized cost ($\hat{C}$) for the five-year potential period, the authors intended to determine the $\hat{C}$ for each operation as the sum of the effective costs of the operation and potential change by using the elements in the following formula:

$$\hat{C} = C_{effective} + \Delta\Phi \tag{9}$$

To draw up the initial scenario, the values used for communication and stakeholders' engagement are presented in Table 2. Therefore, they evaluated the costs and the benefits over an extended period using data shown in Table 3 and the results obtained by applying Equations (1)–(7).

Table 2. Costs without chatbot.

Costs without Chatbot (C_0)	Value
Manual reporting	
Monthly cost for manual reporting	RON 5000
Annual cost for manual reporting: (12 months)	RON 60,000
Five-year cost for manual reporting	RON 300,000
Costs for communication and stakeholders' engagement	
Monthly costs for communication and engagement	RON 2000
Annual costs for communication and engagement	RON 24,000
Five-year cost for communication and engagement	RON 120,000

Table 3. Costs with chatbot.

Costs with Chatbot ($C_{with\ chatbot}$)	Value
Initial costs	
Chatbot development	RON 50,000
Integration and setup	RON 10,000
Total initial costs	RON 60,000
Monthly operating costs	
Maintenance and updates	RON 1000
Hosting and data storage	RON 500
Customer support	RON 500
Total monthly operational costs	RON 2000
Five-year costs with chatbot	
Annual operating costs	RON 24,000
Five-year operating costs	RON 120,000
Annual economies and benefits	RON 54,000
Five-year economies and benefits	RON 270,000

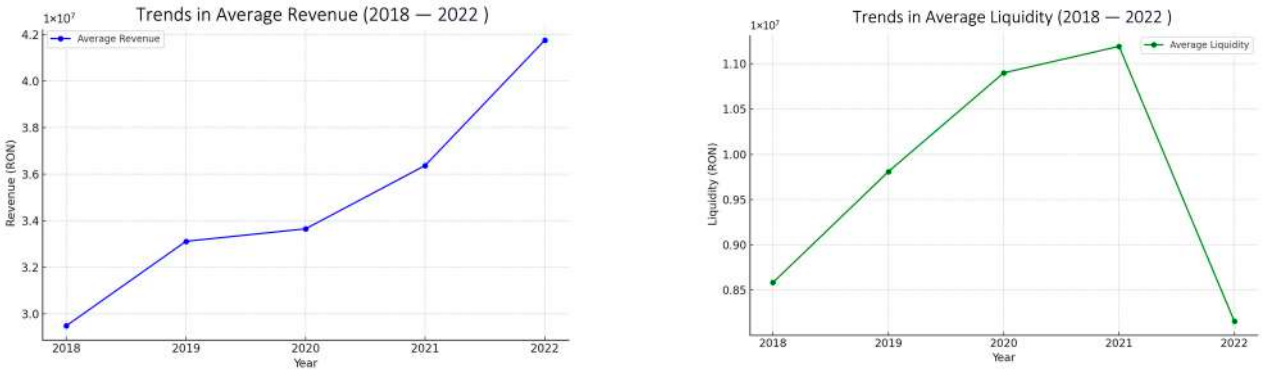
After calculating the five-year total costs for the current (C_0) and desired situation ($C_{with\ chatbot}$), the authors calculated the function of potential (Equation (9)).

4. Results

This section provides a comprehensive overview of the study's findings, focusing on three key areas. Firstly, it presents the results of an exploratory analysis, which presents the current state of chatbot usage and identifies potential areas for improvement. Secondly, it explores the potential cost savings and revenue generation opportunities that chatbots can offer. Lastly, it examines the factors influencing the return on investment for chatbot implementations, including cost amortization and long-term benefits.

4.1. Exploratory Analysis Outcomes

The EDA outcomes illustrate the trends for the average of two of the most significant financial performance indicators, namely, revenue and liquidity. Figure 1 shows a noticeable increase in average revenue in 2022, indicating a high financial performance over the years; however, regarding the average liquidity, the trend suggests fluctuations, with a general upward trend towards 2022, indicating improvements in terms of financial stability.



(**a**) (**b**)

Figure 1. The evolution in average revenue (**a**) and liquidity (**b**) between 2018 and 2022. Source: authors' conceptualization based on the dataset.

To determine what generates a consistency of revenue and profit across years, the authors first detected the presence of zero or negative values (Table 4). After this step, they cleaned the t database, and year-over-year growth rates were calculated (Table 5).

Table 4. The number of occurrences of zero and negative values.

Year	Occurrences of Zero or Negative Values
2018	1109
2019	968
2020	937
2021	943
2022	950

Source: calculated by the authors using Python 3.11.0.

There was significant revenue growth in 2019, followed by moderate growth rates in the subsequent years. Profit growth was the highest in 2019 and showed a decreasing trend in the following years but still maintained relatively high growth rates. Visualized as a heatmap, Figure 2 illustrates all the relationships between firms' indicators. After the heatmap presentation, the centralization of the outcomes can be found in Table 6.

Table 5. Year-over-year growth rates for revenue and profit.

Year	Average Revenue Growth (%)	Average Profit Growth (%)
2019	50.5	172.01
2020	12.3	110.81
2021	17.11	90.17
2022	16.64	88.44

Source: calculated by the authors using Python 3.11.0.

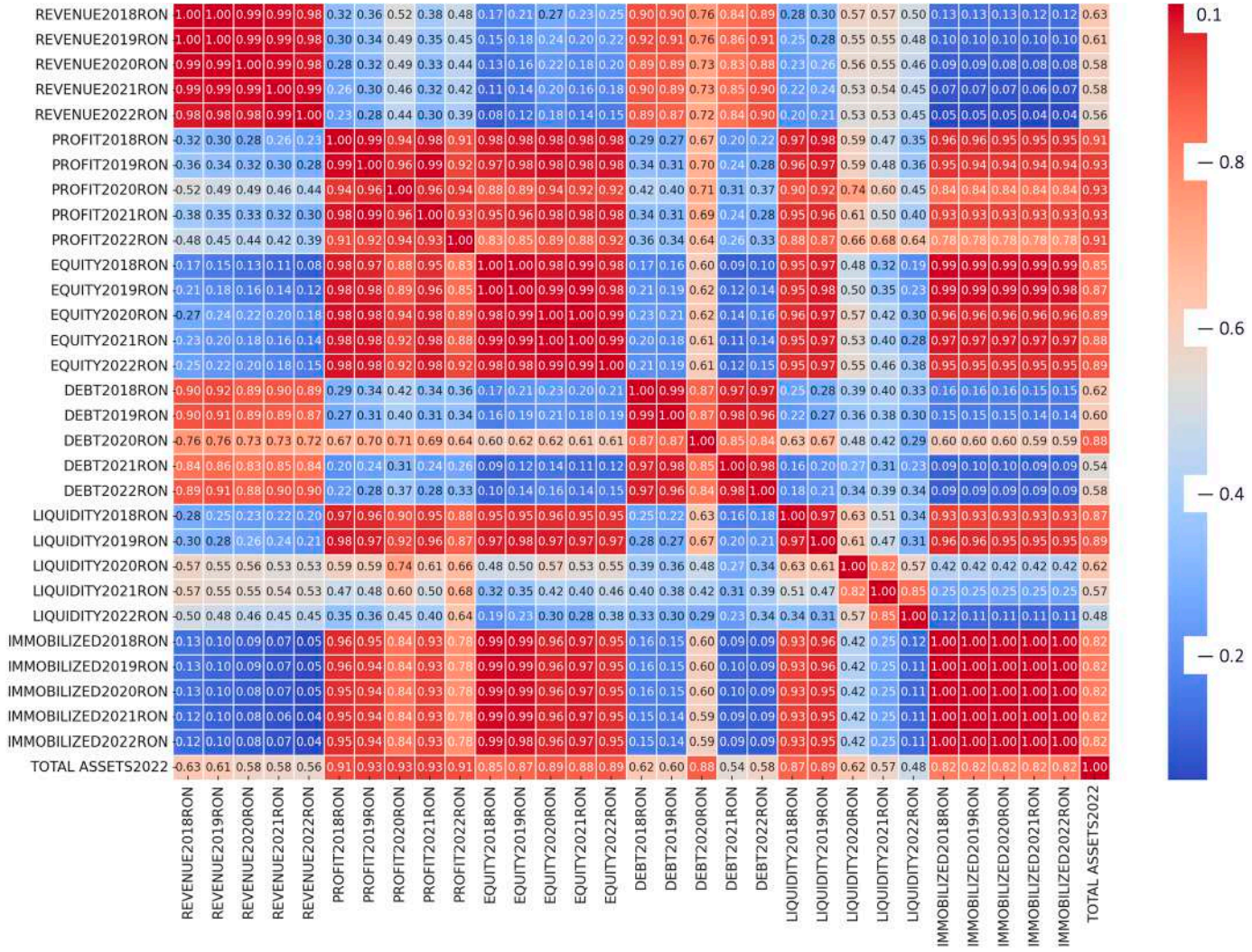


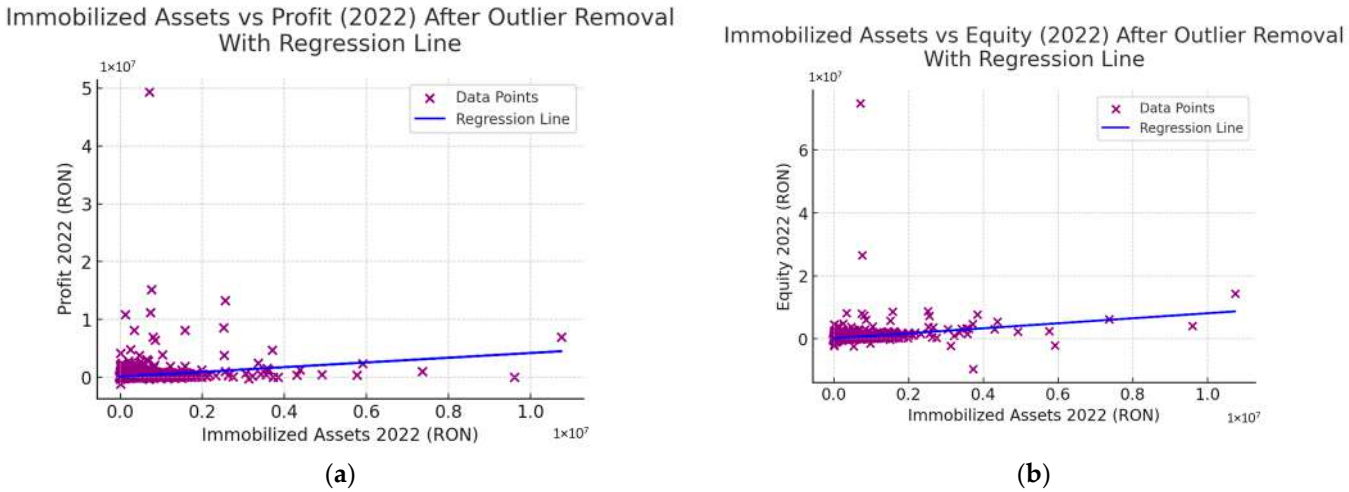
Figure 2. The heatmap of correlation matrix for financial metrics. Source: authors' computation using Seaborn library in Python 3.11.0. The currency used: RON (Romania's currency). Not relevant to convert it to euros or dollars. The relationships are not affected [106].

Table 6 highlights the strong positive correlation between profit and equity, underscoring how efficient management of digital tools like chatbots can enhance financial stability. This correlation supports the study's conclusion that investments in AI technologies contribute to both operational efficiency and profitability in sustainability reporting.

After outlier removal, correlations between immobilized assets and profit, and immobilized assets and equity, were illustrated (Figure 3).

Table 6. The centralization of the correlation matrix outcomes.

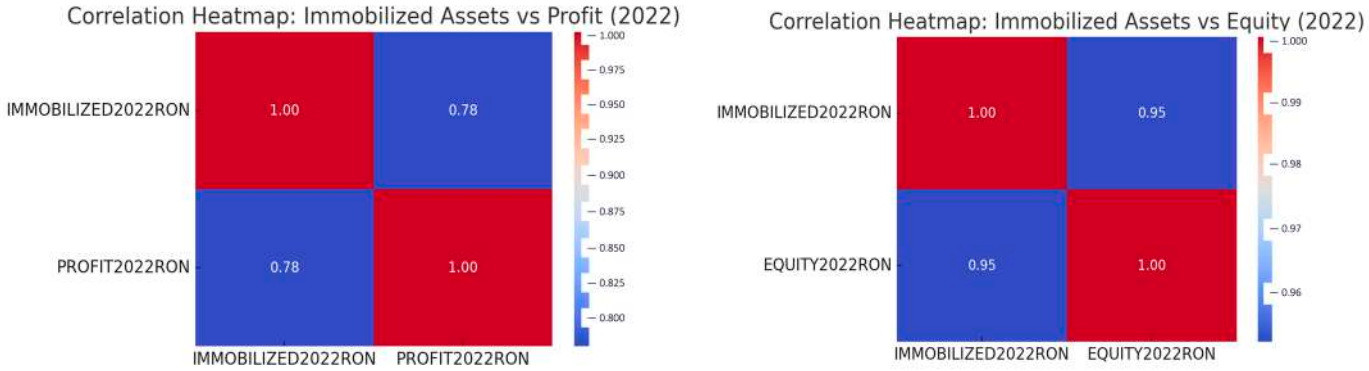
Relationship	Observation
Revenue and profit across years	Revenue and profit present which relation indicates a consistent performance year over year, suggesting effective business strategies, consistent demand for their services, or consistent profitability, which could reflect effective cost management and stable operational efficiency. This indicates that the company's ability to generate revenue has a direct and significant impact on profitability. While revenues in one year do influence profits in future years, the strength of that influence tends to weaken as the time gap increases.
Debt and revenue	A strong positive correlation between debt and revenue suggests that as revenue increases, debt levels also increase, and vice versa. This relationship can be indicative of several underlying dynamics within a business. It demonstrates significant implications for sustainable accounting. Debt should not just be seen as a financial burden but as a catalyst for growth. Especially, within the context of using digital technologies used in integrated reporting to ensure and enhance transparency, accuracy, and strategic insights into financial management, this correlation can be addressed effectively through digital technologies in integrated reporting for sustainable purposes. However, if revenue growth does not keep up with increases in debt (as is shown for 2020), it could signal potential financial distress or inefficiency in using borrowed capital.
Profit and equity	The strong positive correlation between profit and equity highlights effective financial management and successful operations, primarily because profits contribute directly to retained earnings, thereby enhancing equity. This correlation signifies sustainable growth as higher profits enable further investment into the business, enhancing the equity base and financial stability. This outcome is valuable to assess a company's long-term viability and operational efficiency.
Profit and liquidity	A strong and positive relationship between profit and liquidity was discovered. This kind of relationship is symbiotic. Strong profitability supports and often enhances liquidity, providing a company with a protection period against financial instability and the means to capitalize on growth opportunities without needing external financing. This dynamic is integral to maintaining the day-to-day operations and strategic flexibility.
Total assets and profit	A strong, positive correlation between total assets and profit implies that as the assets of a company increase, its profits generally also increase. This relationship suggests effective asset management and the ability to use assets to generate higher income.
Total assets and equity	The companies demonstrated a similarly strong, positive relationship between total assets and equity. This fact highlights that as a company's asset base grows, its equity does as well. This relationship can be attributed to the reinvestment of profits back into the company (increasing both equity and assets) or/and effective overall growth management. This outcome became very interesting for the researchers during the process of data analysis. Total assets include immobilized assets, the ones that can highlight the investments made for the adoption of technologies in the company. Based on this premise, the authors tried to identify a possible correlation between immobilized assets and other indicators (Figure 2) to find out if the company could be oriented to the adoption of digital technology to become more sustainable.



(**a**) (**b**)

Figure 3. The correlation between immobilized assets and profit (**a**) and the correlation between immobilized assets and equity (**b**). Source: authors' computation.

The trend between immobilized assets and profit (a) appears flatter. The same trend is related to the relationship between immobilized assets and equity. The positive correlation is still present but is less pronounced compared to the version with extreme values. However, visually emphasizes the strong positive correlations, namely, 0.78 and 0.95, respectively (Figure 4).



(**a**) (**b**)

Figure 4. The heatmap for visualizing the correlation between immobilized assets and profit (**a**) and the correlation between immobilized assets and equity (**b**). Source: authors' computation.

The strong correlation between immobilized assets and profit indicates that as the value of immobilized assets increases, profit also tends to increase. This finding can suggest that investments in assets that are not readily convertible in cash, potentially including long-term investments such as digital technologies, especially in the case of consultancy and accounting companies. Also, a strong and positive relationship between immobilized assets and equity was identified. This very strong positive correlation indicates a robust link between the value of immobilized assets and the equity of the company.

Investments in immobilized assets, potentially including substantial expenditures on digital technologies, are directly correlating with an increase in the company's total equity. The strong correlations of immobilized assets and profit and equity suggest that the value of long-term assets held by these companies changes proportionately, reflecting consistent investment or depreciation policies over time. This indicates that such investments are not only enhancing operational capabilities but are also significantly increasing the company's net worth, far beyond just impacting profitability. The correlation underscores that digital technology investments, (immobilized assets), are a critical driver of both profitability and overall company value (equity). Investments in technology can be seen as capital investments that substantially increase the worth of a company, reflecting confidence and growth potential. The almost direct proportionality (with a correlation close to 1) suggests that equity growth is heavily dependent on how much is invested in these fixed assets.

These aspects highlight the strategic importance of investing in digital technologies such as chatbots. These investments are crucial not only for maintaining competitive advantage but also for significantly enhancing shareholder value through increased equity. In conclusion, this might involve long-term commitments to digital development through sustainable and integrated reporting.

4.2. The Analysis of Potential and Cost Amortization of Chatbot Usage Results

In the first stage, the authors obtained results for amortized costs:
Initial costs:

$$\phi_{init} = \phi_{dev} + \phi_{int} = \text{RON } 50{,}000 + \text{RON } 10{,}000 = \text{RON } 60{,}000 \quad (10)$$

Monthly operating costs:

$$\phi_{op} = \phi_{maint} + \phi_{host} + \phi_{sup} = \text{RON } 1000 + \text{RON } 500 + \text{RON } 500 = \text{RON } 2000 \quad (11)$$

Monthly benefits:

$$\phi_{tot} = \phi_{rep} + \phi_{eng} + \phi_{data} = \text{RON } 3000 + \text{RON } 1000 + \text{RON } 500 = \text{RON } 4500 \quad (12)$$

Total cost for 12 months:

$$\phi_{tot} = \phi_{init} + \left(\phi_{op} \times T\right) = \text{RON } 60{,}000 + (\text{RON } \ 2000 \times 12) = \text{RON } 84{,}000 \quad (13)$$

Total benefits for the period T:

$$\phi_{totT} = \phi_{tot} \times T = \text{RON } 4500 \times 12 = \text{RON } 54{,}000 \quad (14)$$

Net cost for the period T:

$$\phi_{net} = \phi_{tot} - \phi_{totT} = \text{RON } 84{,}000 - \text{RON } 54{,}000 = \text{RON } 30{,}000 \quad (15)$$

Amortized cost per month:

$$\phi_{amort} = \frac{\phi_{net}}{T} = \frac{RON\ 30{,}000}{12} = \text{RON } 2500 \quad (16)$$

Thus, the method of amortized analysis of chatbot usage for reporting shows that the net amortized cost per month of using chatbots to communicate sustainability reports is RON 2500 over the first year.

Secondly, the five-year total cost without a chatbot shows the amount of C_0 = 300,000 + 120,000 = RON 420,000.

Therefore, the five-year total cost with a chatbot is $C_{with\ chatbot} = \text{RON } 60{,}000 + \text{RON } 120{,}000 - \text{RON } 270{,}000 = -\text{RON } 90{,}000$.

The equation of the potential calculated, $(\Phi = C_{with\ outchatbot} - C_{with\ chatbot})$ resulted in $\Phi = \text{RON } 420{,}000 - (-\text{RON } 90{,}000) = \text{RON } 510{,}000$. Thus, the five-year amortized cost is

$$\hat{C} = \frac{\text{RON } 510{,}000}{5 \times 12} = \text{RON } 8500 \quad (17)$$

These results demonstrate that using artificial intelligence through chatbots for integrated reporting and sustainable communication can lead to significant long-term savings. Over a five-year period, the net savings represent RON 510,000, and the monthly amortized cost is RON 8500. This result suggests that implementing chatbots not only covers the initial costs but also offers considerable savings over time.

5. Discussion

Examining chatbot applications is a novel development in sustainable reporting, a domain that has predominantly focused on analytics and predictive AI tools. By addressing this gap, this study contributes to the literature on AI by demonstrating how chatbots can improve real-time communication with stakeholders and enhance the accessibility and transparency of sustainability reporting practices in emerging markets. These contributions provide a unique perspective, particularly in the context of Romania's emerging digital landscape, offering insights applicable to similar markets globally. By examining chatbot adoption among Romanian accounting firms, this study not only fills the empirical gap in AI research but also provides actionable insights for similar emerging markets with comparable challenges in digital adoption.

Regarding the objectives formulated, the authors highlight the importance of understanding the potential of accounting and consulting companies to deploy mechanisms that use artificial intelligence to gain more sustainable assets. Figure 5 visualizes the study's

key findings, demonstrating how chatbot adoption facilitates a more integrated approach to sustainability reporting, balancing financial and non-financial objectives. It serves as a practical framework for organizations seeking to align technological investments with sustainability goals.

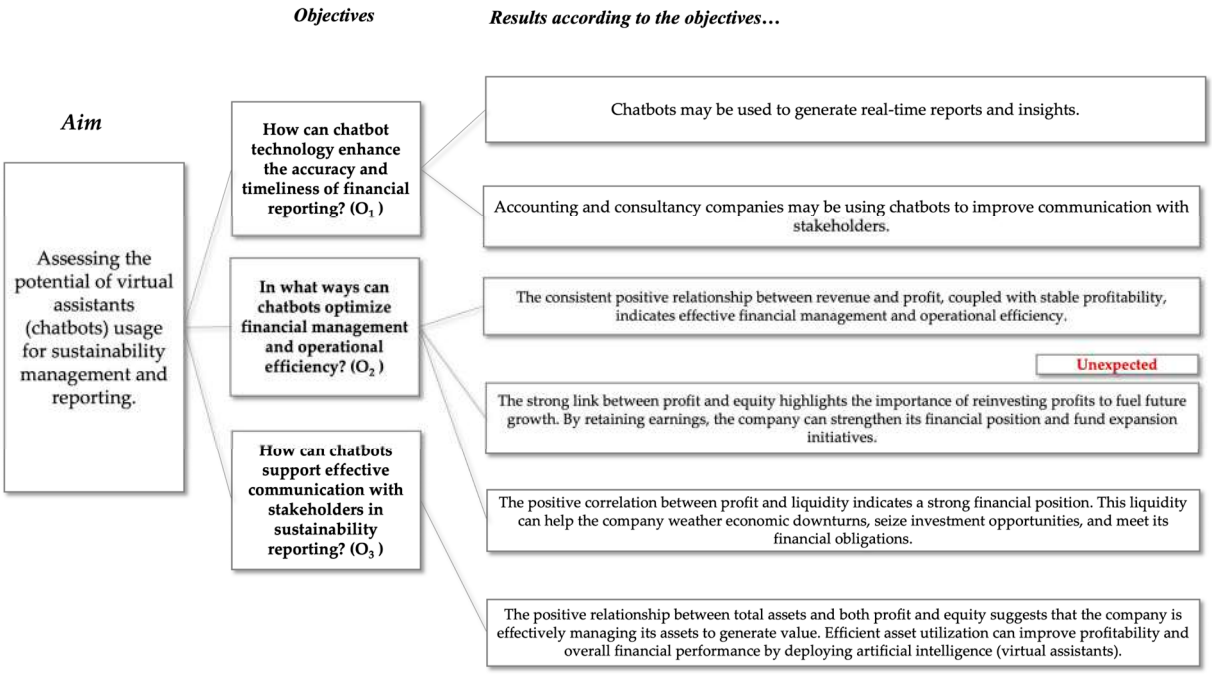


Figure 5. The overall picture of the study performed. Source: authors' conceptualization.

The findings suggest that chatbots can contribute to economically sustainable practices by enhancing financial reporting efficiency and management transparency. While these improvements may indirectly support broader sustainability goals, further research would be needed to assess their impacts on social and environmental dimensions directly. Hence, all three objectives were achieved. In addressing Objective O1, the authors investigated the potential of chatbot technology to enhance financial reporting in sustainability management. The observed correlation between asset investment and profitability underscores the strategic value of adopting digital tools like chatbots. For instance, investments in AI technologies specifically tailored for sustainability reporting contribute not only to operational efficiency but also to enhanced stakeholder trust, which indirectly drives long-term profitability. However, this relationship is contingent upon the effective implementation of these technologies and their alignment with organizational objectives. Implementing chatbots to automate data collection and analysis for real-time reporting can significantly improve financial reporting by providing timely, accurate insights. This approach is valuable not only for accounting and consulting companies, but for a broad range of businesses as evidenced in fields such as corporate finance [107], consumer behavior analysis [108], construction [109], or even government frontline services [110]. For accounting and consultancy firms specifically, chatbots offer opportunities to streamline stakeholder communication, with recent studies indicating the benefits of chatbots integrating for engaging collaborators [111] and supporting data-driven business decision-making [112]. By utilizing chatbots to generate interactive reports and answer stakeholders' queries, companies can deliver personalized financial information, enhancing transparency and facilitating more informed business decisions. This alignment with a chatbot-enabled reporting process allows organizations to provide stakeholders with real-time insights into financial performance and trends, ultimately supporting a sustainability-oriented business environment.

In exploring strategies to optimize financial management and operational efficiency (Objective O2), the researchers examined how integrated chatbots can streamline a range

of financial and administrative tasks. Chatbots can automate routine processes such as expense tracking, invoice processing, and transaction monitoring, thereby reducing manual workload and minimizing errors. Revenue and profit trends are addressed to identify areas for improvement and optimization, reinvest profits strategically to fuel future growth and strengthen the company's financial position, or maintain a healthy liquidity position to weather economic downturns and seize investment opportunities, which are three of the principal directions to develop sustainable reporting [113,114]. The outcomes generated by the correlation matrix presented in Table 6 could be aligned with the list of methods for financial management optimization (predictive analytics by using profitability and opportunity identification [115] or relationship analysis between information systems, demand, revenue, and profit management [116]). For example, the strong positive correlation between debt and revenue can be very useful for real-time reporting and dashboards communicated through a chatbot. Integrated reporting can be enhanced with real-time insights that provide a comprehensive view of financial metrics. A dashboard can be customized to alert partners about key financial ratios or other relevant metrics that exceed predefined thresholds. Real-time reporting enables quicker decision-making processes and ensures that stakeholders are consistently informed about the company's financial status.

To evaluate whether chatbot deployment can improve overall management efficiency by supporting sustainability-related functions, (Objective O3), the authors explored the relationship between technology deployment and financial performance indicators, such as profit and revenue. The findings suggest that effectively managing assets with AI-driven solutions, including chatbots, can enhance profitability and overall financial performance. The positive relationship between total assets and both profit and equity suggests that the company is effectively managing its assets to generate value. The literature supports the view, highlighting that AI technology can play a crucial role in improving profitability by maximizing resource efficiency and asset utilization [117–119].

In the context of sustainable development, the use of AI, including chatbots, offers both opportunities and challenges for accounting professionals. AI-driven automation in areas such as data entry, compliance verification, and complex financial analysis is transforming traditional practices. This shift provides new insights into financial management while also raising ethical considerations around data use. Additionally, advances in AI have led to developments in repetitive task automation, fraud detection, financial forecasting, and compliance checks, which can improve cost efficiency and support informed decision-making. The integration of ERP systems, blockchain, and virtual assistants like chatbots, not only enhances operational efficiency but also aligns with sustainability objectives by supporting ethical and accurate financial reporting.

Therefore, the findings contribute to the Technology Acceptance Model (TAM) [25,120] by demonstrating that chatbot integration in financial management might be perceived by users as both useful and easy to use, which aligns with TAM's primary constructs. Additionally, this study extends the Resource-Based View (RBV) [121,122] by showing that chatbots enhance organizational resources through the automation of repetitive tasks and the optimization of asset utilization, thereby supporting economic sustainability. Also, this study acknowledges that the dynamics of the business environment require a conceptual framework that extends strategic management and defines stakeholders as groups or individuals that can influence the achievement of a company's objectives [123]; also, it acknowledges that organizational efficiency is based on contingent factors such as technology development, the size of the organization, etc. (Contingency Theory) [124,125]. This finding suggests that chatbots can be viewed as strategic assets that improve operational efficiency, a perspective that is particularly relevant for sustainability-oriented business models. Investments in chatbots, as demonstrated in this study, enhance profitability by reducing manual reporting costs, improving operational efficiency, and fostering stronger stakeholder relationships, particularly in the context of sustainability reporting.

In a more specific way, using AI in accounting involves setting guidelines and standards to ensure fairness, transparency, and accountability. Also, a series of risks must be considered, including data security, professionalism in the use of AI, reliability of results, and, finally, compliance with copyright, etc., which we mention in this study. Accounting professionals and consultants in the financial field must participate through professional judgment in synthesizing data, completing analysis, and presenting and disseminating results. The accounting profession actively participates in the application of the latest technologies in the context of placing a special emphasis on sustainability and social responsibility. Its evolution leads to the improvement of technical skills for data analysis, presentation, and the disclosure of information. In the context of the integration of AI and other innovative technologies, the role of the accounting professional and accounting firms is changing, and they must focus on the strategic impact they can have on their clients' businesses. Finally, accounting teams can include people with expertise in various areas such as digital marketing, data analysis, or the use of AI.

6. Conclusions

This study aimed to explore the potential of chatbot technology to enhance sustainability reporting and financial management in Romania. Guided by the research questions, the authors used a mixed-method approach to collect and analyze data from Romanian accounting and consultancy firms. The outcomes of this study contribute to the existing field of knowledge. The authors emphasize analyzing the relationship between total assets, profit, and equity to identify areas for improvement in asset allocation and management and to develop strategies to increase the efficiency of asset utilization and reduce costs. This study contributes to the literature by showing a strong positive relationship between immobilized assets, equity, and profit, indicating that companies investing in long-term assets, such as infrastructure and sustainable resources, tend to experience higher profitability and equity.

The outcomes of this study highlight several theoretical implications. One of them is the importance of balancing financial and sustainability goals, considering ESG factors, and optimizing asset utilization for sustainable growth. This study underscores the importance of long-term asset investment for enhancing firm performance and also emphasizes the need to balance financial and sustainability goals. By considering environmental, social, and governance factors, firms can optimize asset utilization and achieve sustainable growth. The findings align with theoretical frameworks such as the Resource-Based View, Stakeholder Theory, and Contingency Theory, suggesting that long-term asset investment should be performed in specific firm and industry contexts. This has implications for academic research in areas like sustainable finance, accounting, and strategic management, as well as for practitioners seeking to make informed investment decisions.

For managers, this highlights the importance of balancing asset investments not only with operational efficiency and financial strategy but also with sustainability goals. This includes considering the environmental, social, and governance impacts of these investments. The key takeaway is that while investing in immobilized assets can enhance profitability and financial health, the long-term effectiveness and sustainability of these investments depend on firm-specific and industry-specific factors. Companies should ensure that their asset utilization is optimized for sustainable growth and aligned with ESG objectives, incorporating responsible resource use, minimizing environmental impact, and fostering social responsibility. Through this, firms can achieve both financial success and sustainable development, addressing the expectations of stakeholders and contributing to a more sustainable economy. Moreover, artificial intelligence has penetrated all fields of activity in the field of accounting services. This process also includes the accounting education of professionals.

A primary limitation of this study is its focus on the Romanian market, where the adoption of chatbots and other digital technologies is still emerging. From this, a key limitation of this study is its focus on a selected country, where specific market and cultural

conditions may influence the adoption and perception of chatbot technology. Factors such as digital infrastructure, regulatory frameworks, and cultural attitudes toward automation in Romania may differ significantly from those in other regions, which could limit the generalizability of the findings. This study is intended as an exploratory analysis within a regional context, and, while the results offer valuable insights, further research is needed to determine how these findings might apply in other markets with different economic and cultural dynamics. Also, as a result, the potential long-term savings and the benefits of AI chatbots, particularly in terms of scalability and 24/7 availability, may be underestimated. A more extensive analysis would require a specialized sample, including companies that have extensively implemented AI chatbots, to fully capture their impact on communicating sustainable aspects, customer service, and operational efficiency. In this ideal context, further study om the existence of chatbots and a quality assessment could provide additional insights.

Further research could focus on quantifying the impact of chatbots on specific stakeholder engagement metrics, such as response time and satisfaction rates. Additionally, employing longitudinal studies to track the scalability and cost-effectiveness of chatbot implementations over extended periods would provide deeper insights. Comparative analyses across different emerging markets would also help generalize the findings and identify regional variations in adoption patterns.

The study contributes to the literature by being one of the first to explore chatbot applications in sustainability reporting within an emerging market context. It provides actionable insights for organizations aiming to improve reporting accuracy, timeliness, and stakeholder engagement through AI technologies. Future work should focus on developing industry-specific frameworks for chatbot integration, accounting for unique regulatory, infrastructural, and cultural factors in emerging markets.

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Article

The Use of Technology Assisted by Artificial Intelligence Depending on the Companies' Digital Maturity Level

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Abstract: Major companies in the global market have made significant investments in artificial intelligence-assisted technology to increase the value of their products and services, which gives the implementation of artificial intelligence an extremely important role. Starting from these premises, the authors set out to evaluate the transformation level of companies in terms of adopting technology based on artificial intelligence according to their level of digital maturity. For this purpose, qualitative research was used by deploying the inductive method, which allowed five distinct categories of companies with unique characteristics to be identified, generating an interval scale that illustrates the level of digital maturity and the ability to adopt and implement viable solutions based on artificial intelligence technology. This paper, in addition to identifying the digital transformation level of companies, offers solutions and recommendations for addressing the challenges encountered by the business environment, thus contributing to the understanding and development of strategies adapted to each situation that may appear on the market.

Keywords: artificial intelligence; digital maturity; companies; digital marketing agencies; business strategies

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1. Introduction

Major players in the global market have invested in artificial intelligence (AI)-assisted technology to improve their products and services. Notable examples include companies such as Google, IBM, Amazon, Tesla, Meta or Microsoft, Netflix, and Airbnb, which have implemented AI-based solutions within the actions related to the optimization of internal processes and up to the commercial strategies applied to offer innovative products and services on the market. Considering the tone set by large companies operating globally, the authors raised the issue of implementing solutions aligned to the 5.0 society to other companies of different sizes, medium or small, to which the trends and exigent requirements of consumers dominated by the typology of digital informers bring, for the most part, only challenges that are difficult to manage.

In this context, the authors intended to find out how ready companies are to adopt technology assisted by artificial intelligence. This aspect led to the formulation of the research question around which the entire paper was built. Starting from the premise that the importance of small- or medium-sized companies (SMEs) is crucial [1] for the digital development of society [2], this research aimed at identifying which companies are ready to use AI, as well as which companies are being pressured to adopt AI. The authors intended to build a theoretical framework aimed at evaluating companies readiness to integrate AI-assisted technology, with a particular focus on marketing agencies, based on their digital maturity level. Their objective was to address existing concepts and models to develop a tool for measuring readiness in this context. To achieve this goal, the

authors employed a qualitative research approach, specifically utilizing inductive research methods, to capitalize on existing models and relevant observations to their research topic. Consequently, an explanatory model was formulated, delineating five distinct categories of companies characterized by varying levels of digital maturity.

This research makes a significant scientific contribution to the specialized literature by not only advancing the theoretical understanding of the topic but also by providing practical solutions to the challenges that companies encounter in implementing artificial intelligence solutions based on digital maturity level. The objectives stated to this end were to (O1) classify companies in terms of digital maturity level, (O2) identify activities that can become more profitable through artificial intelligence, and (O3) highlight the challenges, limits, and opportunities for companies regarding the implementation of solutions based on artificial intelligence.

Carrying out the research allowed five typologies of companies to be determined, each of them being described in detail according to the explanation of the challenges and limits they present in relation to the adoption of technology based on artificial intelligence. In essence, the authors' work fills a crucial gap by providing a holistic perspective on the interplay between digital maturity and AI adoption readiness, thereby empowering organizations to make informed decisions and devise strategic plans to deploy technology for competitive advantage.

Considering the premises presented, the authors organized this paper into four main sections: a review of the existing literature, an explanation of the research methodology, an analysis of the obtained results along with supplementary discussions, and a final section comprising conclusions and suggestions for future research directions.

Literature Review

Artificial intelligence (AI) has attracted increasing interest recently, being considered by specialists and representatives of the business environment as a technology that will have an unprecedented impact on human development [3]. AI should not be seen as a single technology, as it represents a combination of technologies used in several industries which can improve the performance of companies in these fields [4]. The use of AI can lead to optimization of the structure of management processes [5] and to improvement of "the operational and business processes of organizations" [6].

AI can be a tool for building sustainable business models and innovative processes, leading to important economic, social, ethical, and legislative changes [7]. The implementation of AI imposes the need to analyze the specifics of each organization and the stage at which this implementation process is situated [8], creating favorable conditions for cultivating implementation, information, and understanding by managers and staff and studying both positive and negative aspects [9].

While concerns about bringing AI into business are not new, there is still a gap regarding the understanding of how AI can drive business value [10], of the concrete way success factors can have an impact on the adoption of AI [11], and the implications for environmental sustainability [12]. There are also negative aspects of artificial intelligence, such as the lack of control, the poor quality of data, and the insufficient training of personnel, that can generate inefficiency in the activity of companies and are studied too little by specialists [13]. Studies show the importance of employees' knowledge and understanding of AI processes, the need to create "sociotechnical capital", and the implementation of "AI socialization" to successfully integrate AI systems with employees [14,15]. Previous research has highlighted a number of issues that need to be resolved regarding the integration of AI, namely the modification and rethinking of the organizational structure, the skills required of employees and the education of the future workforce, ethical and legislative issues regarding data protection and defining the role of robots in society, and how these innovative tools can lead to predictions for future development [16]. The effective integration of these technologies indicates the digital maturity status of both a company and, at a broader scale, a country [17]. Specialists consider digital maturity as a pivotal factor

bridging the digital orientation of companies and their financial prosperity [18]. Also, the main goal of the digital transformation of companies is to rethink the business model to improve productivity and reduce costs [19].

The massive role artificial intelligence is playing in reshaping society cannot be denied. Beyond the undeniable opportunities it brings to development and progress, from economic and social points of view, AI is to a significant extent fraught with risks, at least in terms of privacy, transparency, and discrimination. Ethics in AI refers to a framework of moral values and methodologies designed to steer the ethical deployment of artificial intelligence, with the aim of safeguarding human welfare [20].

The first ethics guide in the field of AI was the Principles of Artificial Intelligence signed by governments in 2019—OECD [21]. In parallel, a code of ethical instructions in the field of AI was developed by the European Parliament [22], which underscores concerns regarding the ethical, legal, and economic dimensions linked with AI, impacting essential human rights and liberties. These concerns encompass the effects of AI and robotics technologies on employment, such as job displacement due to automation. There are also demands for evaluating the influence of algorithms and automated decision-making systems on safety and trust levels. Furthermore, considerations extend to digital currencies and transaction systems facilitated by networked computers, such as blockchain technology and the propagation of disinformation (fake news), as well as the potential military applications of algorithms (autonomous weapon systems and cyber security). Continuing these trends, UNESCO generated the first global standard in AI ethics "Recommendation on the Ethics of AI", recognizing that AI systems have the potential to bring privileges, to constitute a threat to human rights, to contribute to the degradation of the environment, etc. [23].

The most pressing ethical issues when considering AI in organizations' interaction with the human factor can be extracted from the literature. AI systems can perpetuate, by taking in a massive amount of data, the biased approach that is embedded in previously practiced social norms. If the algorithms are not unbiased or unrepresentative for all categories, the results generated by them may exclude minority categories [24]. Discrimination brought by algorithms can also be the result of wrong or biased input data or caused by the mathematical architecture of the algorithm [25]. Moreover, AI can limit autonomy to the extent that it provides predefined choices, and there is a risk of replacing interpersonal relationships when communication tends to take place exclusively through AI-generated assistants [26]. In some studies, transparency and responsibility are issues that appear as a priority in AI-related ethics, being assimilated to the concept of trustworthiness [27]. Relevant information provided to participants can help them make an assumed and agreed decision [28].

If, in the case of an artist making a work, they can assign copyright, when a digital work is generated with the help of AI, by an individual or an organization, given that the AI systems were generated by others, it is questioned which of the two parties is more entitled to being attributed the result [29]. Moreover, AI algorithms have the capability to produce misinformation, manipulate public sentiment, and exacerbate social divisions. AI systems multiply the ability to use personal data that can harm individual interests, through the ability to process data at an impressive level of power and speed [30]. AI systems may collect data that are not necessarily required, or even prohibited by the privacy policy, without users being notified. The extensive collection of data and their transfer can impact the confidentiality and privacy of individuals [31]. Simply obtaining consent does not solve the problem of ethics in AI [32]. As AI systems evolve, automation has the potential to replace human labor, creating unemployment and exacerbating social inequalities. Even with the development of new branches based on AI, the emergence of new jobs requires professional conversion measures and economic support for the transition of the workforce involved.

Organizations willing to implement AI systems face several difficulties, conceptual as well as practical. The challenges of using AI are divided, according to the study by

Mökander [33], into ethical, legal, and technical challenges. Another recent study [34] was able to categorize the barriers to AI adoption into three major areas: technological, organizational, and cultural. The same study demonstrated that the majority of the decision makers interviewed (91%) faced challenges in all three areas, citing the following major barriers: laws and regulations (which hinder innovation and learning because compliance is costly and restrictive); lack of employee experience in AI implementation; lack of understanding of AI, both in the organizational environment and among customers; resistance to change.

A challenge with their significant major impact on organizations is the very high costs of deploying and sustaining AI solutions [35]. Additional barriers identified in this paper include a lack of comprehension and confidence in AI, as also referenced in the literature [34]. Challenges highlighted encompass data quality and connectivity, involving the integration of data from diverse sources like suppliers, customers, and internal systems. Furthermore, there is the task of integrating AI into existing processes and workflows. Issues related to data quality and management, including concerns over data privacy and security, pose additional challenges. Moreover, inadequacies in IT infrastructure, reliance on external AI providers, and cultural and organizational barriers compound the issues faced. In order to be aware of the challenges in implementing AI and to propose strategies for managing and mitigating the risks associated with adopting AI in business, organizations need to develop deep business-wide analyses. These analyses start from evaluating the vision of the organization, the staff, the transformation of the processes and technologies used, and the availability of data [36]. At the same time, the major implications of managerial decisions [37] and different risk management assessment methodologies, as well as cyber security concerns, must be mentioned.

The data privacy barrier starts from the fundamental notion that having more data allows AI systems to become better. The strategic solution provided by [38] is the implementation of a data-sharing policy in the company, a method by which the need for data duplication is reduced. Related to the establishment of the AI team, a possible strategic managerial option (other than hiring dedicated staff) is to improve the skills of existing employees (by participating in dedicated development programs, training, experts who can make practical presentations within companies, etc.).

The study of Hopf [39] proposes a model that identifies challenges, tensions, and tactics in implementing AI in organizations. Among the tactics developed in the model, the following are mentioned: establishing verification tools on what AI can and cannot do, calling on external experts to start AI projects, training managers and establishing appropriate indicators, and creating bridges between AI and IT. From the specialized literature point of view, the optimal option regarding the personnel involved in the adoption of AI by companies has not yet been identified, each company having to carry out its own analysis and apply the personnel strategy considered appropriate.

2. Materials and Methods

In the initial phase of the methodology, the authors aimed to build a theoretical framework focused on evaluating companies' readiness to integrate AI-assisted technology, particularly within marketing agencies, based on their digital maturity level potential. This concept can be described as highlighting a particular level of social and economic consciousness that empowers businesses to adeptly deploy digital technologies in pursuit of their objectives [40]. In recent times, experts have concentrated on devising models to evaluate the digital maturity of small- and medium-sized enterprises (SMEs), outlining the stages they need to trace to realize their digital transformation aspirations [41] At the same time, there is the issue of proactively developing employees' skills and their mentality so that they can control digitization and see it as an opportunity [42]. A company is fully digitally mature when it uses technology in all activities and operations that take place within it, being, however, different from the level of digitization (since the latter refers to digital technology usage within systems, processes, and activities related to the company's services and products). This aim drove the authors to address existing concepts and

models, employing a qualitative research approach, specifically utilizing inductive research methods [43] based on existing models and observations identified as highly useful for the research topic, capitalizing on existing models and observations relevant to the research topic. Through this approach, the authors aimed to classify companies according to their digital maturity level, identify key activities for enhancement through artificial intelligence, and elucidate the challenges, limits, and opportunities surrounding the implementation of AI solutions. Subsequently, this research led to the determination of five typologies of companies, each meticulously described in terms of the challenges and limits they face in adopting AI-based technology. Each category was placed into a scale to be easier for practitioners and theorists to evaluate. Thus, the study contributes significantly to bridging the gap between digital maturity and AI adoption readiness, equipping organizations with the insights needed to make informed decisions and strategic plans for leveraging technology to gain a competitive edge.

The motivation behind this choice was the possibility to formulate some specific observations that turned into general ideas, making it possible for the authors to use a "bottom-up" method [44] and to develop a theoretical, explanatory model on the topic of the utilization of AI-assisted technology according to the digital maturity level of companies.

According to the evaluation tool originally developed for assessing non-profit organizations, and later developed for other organizations, the authors were able to develop an explanatory model that draws the boundaries of the levels and promotes, in the foreground, the status of five typologies created in accordance with the potential of using AI-assisted technology.

To reach the intended objective, the authors have structured this section into three parts. The first of them presents the methodology of digital maturity assessment and the creation of typologies that this model claims. The second part refers to the understanding of the classification of tasks performed by AI, mentioning and explaining three types of tasks, and the last one presents the motivation for choosing the case study of marketing agencies.

2.1. Digital Maturity Assessment Methodology and the Outlining of Typologies

To be able to build a measuring scale to analyze the level of digital maturity and AI-assisted technology integration for digital marketing agencies, the researchers utilized a standard questionnaire, developed by [45], which comprises 17 cross-referenced skills categorized into five stages of digital maturity. This questionnaire allowed researchers to assess digital marketing agencies' potential across various dimensions, providing insights into their digital maturity levels.

The questionnaire was structured around four key areas: attitudes and foundations, people, skills, and processes, systems and information, and outcomes and experiences. Through the respondents' answers, authors considered a percentage representing the level of digital maturity for each evaluated company, ranging from 0% to 100%. Based on the responses from the 2077 participants to the digital maturity study, the distribution of digital maturity assessment results across different areas was determined, as illustrated in Figure 1.

This analysis provided a comprehensive understanding of the digital maturity landscape, which was used for the marketing agencies case study because of its validity. Furthermore, research was elaborated into the classification of tasks performed by AI, categorizing them into banal tasks, formal tasks, and expert tasks. By elucidating the characteristics and examples of each task category, the authors aimed to facilitate a deeper comprehension of how AI can be applied across various processes and activities within this type of organization. Finally, they conducted a case study focused on digital marketing agencies to exemplify the practical implications of research findings. Through a rigorous analysis of specialized literature and identification of activities that can be made more efficient through AI implementation, the potential impact of AI on digital marketing processes is highlighted and presented in the next section.

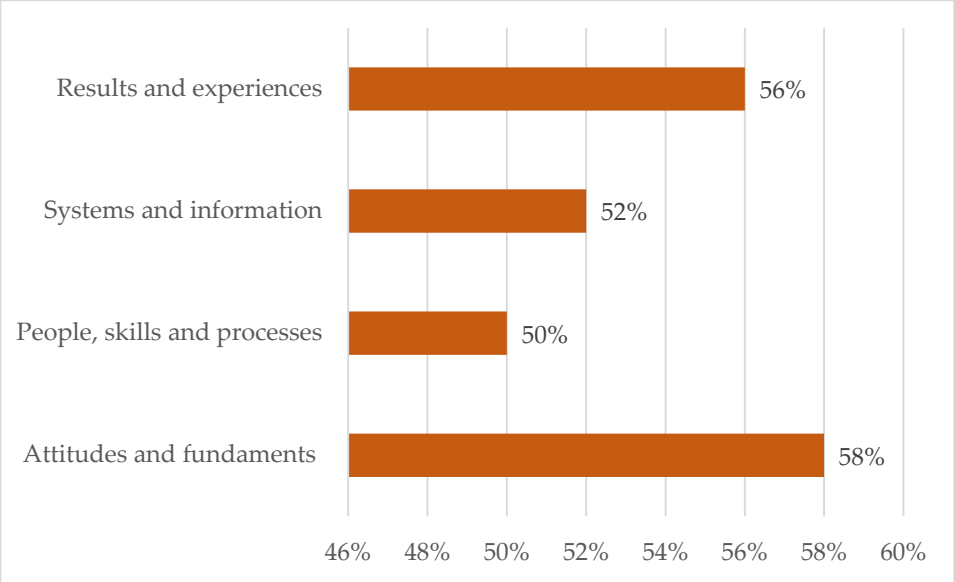

Figure 1. Distribution of digital maturity assessment results by area for 2077 companies: 0–29% (level 1); 30–49% (level 2); 50–69% (level 3); 70–89% (level 4); 90–100% (level 5). Source: (Digital Maturity, 2023).

2.2. Understanding the Classification of Tasks Performed by AI

Tasks performed through AI are divided into the following categories: banal tasks, formal tasks, and expert tasks [46–48]. For each type of classification there are examples of ways in which AI can be applied to facilitate various processes or activities. For example, in the category of banal tasks, AI can be implemented for operations related to computer vision or speech (related to perception), natural language processing (language generation or translation and understanding), or robotics (through interventions on locomotion). On the other hand, formal tasks are related to disciplines such as logic, mathematics or geometry, verification, and often proving a theory. Finally, expert tasks belong to scientific analysis, financial analysis, creativity, or even medical diagnosis. For humans, thanks to perception, speech, the use of language, and locomotion, banal tasks are the easiest to learn, followed by formal ones, the most difficult being those of expertise. In the case of technology, the advancement and implementation of certain very complex algorithms have meant that expert tasks can be handled easily. A relevant example is the use of AI in performing scientific analysis through the Cognos online application, created by IBM. Nowadays, it has become easy to generate graphs, tables, or conclusions about the questions that a researcher raises based on a file containing the raw data required for a complicated analysis, where it is even necessary to highlight some unexpected results.

Aspects were highlighted for an easy understanding of the category of tasks that AI performs to review that category needed in the development of the explanatory model, through which it was possible to answer how ready companies are to use AI-assisted technology.

2.3. Case Study of Digital Marketing Agencies

In focusing on marketing agencies, the authors recognize a crucial aspect of contemporary business operations [49]. Marketing agencies play a pivotal role when it comes to shaping brand perception, driving consumer engagement, and influencing purchasing decisions in the current digital landscape. [50,51]. As such, understanding the readiness of marketing agencies to embrace AI-assisted technology is paramount for several reasons.

Firstly, marketing agencies operate at the forefront of technological innovation [52], constantly seeking ways to optimize their strategies and deliver good results for their clients. The integration of AI into their operations has the potential to revolutionize marketing practices, enabling agencies to analyze vast amounts of data, personalize customer experiences, and streamline campaign management processes [53].

Secondly, marketing agencies serve a diverse range of clients across various industries, each with unique needs and challenges. Assessing the readiness of marketing agencies to adopt AI technology provides valuable insights into the broader trends and opportunities within the marketing industry. It offers a glimpse into the evolving landscape of marketing practices and the emerging technologies shaping the future of the industry. By uncovering the challenges, limitations, and opportunities associated with AI adoption in marketing agencies, this study offers good practices and actionable insights for marketers, business leaders, and industry stakeholders alike. It prompts discussions on the strategic implications of AI integration, the ethical considerations surrounding data-driven marketing approaches, and the skills and capabilities required to thrive in an AI-powered marketing ecosystem. By focusing on marketing agencies, the authors addressed a critical sector at the intersection of technology and business, offering valuable insights into the readiness of organizations to embrace AI and paving the way for future advancements in marketing practices.

Furthermore, as AI continues to reshape marketing practices, it becomes increasingly crucial for organizations and their decision makers to cultivate a culture of innovation and adaptability, equipping both employees and leadership with the skills and knowledge needed to harness the full potential of AI technologies in their day-to-day work. The specialized literature presents the theory of replacing manual tasks with AI tasks, emphasizing its impact on digital marketing. Experts from various industries say that the impact of using AI in marketing processes will be strongly felt in the coming years, with company administrators and decision makers having to prepare both organizations and employees to implement AI-based solutions in their day-to-day work [54]. Following a rigorous analysis of the specialized literature, eight activities were identified that digital marketing agencies can make more efficient by implementing AI.

3. Results and Discussions

The findings of this research emerged after assessing digital maturity and delineating typologies. Through the utilization of an analytical tool to gauge the digital maturity level of companies, five typologies were discerned (refer to Figure 2), each delineating distinct attributes across 17 dimensions: culture, leadership, collaboration, budget, innovation, capacity, recruitment, learning, project management, technology, data, reporting, insights, communication, optimizations, service delivery, and internal systems.

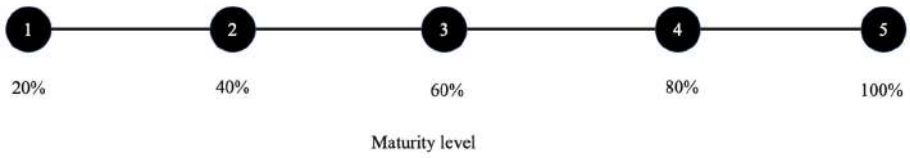

Figure 2. Interval scale of the digital maturity level of companies. Source: figure made by the authors.

The interval scale depicted in Figure 2 was established through a rigorous process of analyzing the convergence of response patterns determined from the survey's variants of responses. Rather than relying on explicit questions, the scale was derived from the intersection of various response variants provided by respondents, reflecting their inherent maturity levels within the assessed dimensions. By synthesizing these response patterns, the scale offers a detailed description for each individual level, providing insights into the nuanced progression of digital maturity within the studied context.

For ***Level 1***, the culture dimension describes this level as marked by staff who keep away from the digital domain and try to avoid it. At the management level, there is no orientation towards the digital approach, the company's budget covering only those basic aspects necessary for the activity, such as, for example, financing the hosting of the domain for the company's website. In companies at this level, innovation is not considered important or does not happen at all. In terms of work capacity, one person handles the

website and email. Also interesting is the fact that this person may not have a digital background or have a special skill set aligned to the field. Staff recruitment is carried out with an emphasis on technical skills only for the position aimed at website maintenance. In terms of the learning dimension, digital experts teach other employees on an ad hoc basis, and the budget allocated to training is very small. Another important aspect is that project management is performed differently for different projects. The existing systems within the company are limited and not integrated, not being secure. Data within the organization are scattered and mostly represent the company's offline activity. Performance indicators exist, but progress is measured ad hoc. Insights are collected but used inconsistently. The digital medium is used as a channel for communicating non-digital activity. Information is shared online, and traditional offline services are displayed on the website, with no will or budget to digitize systems or processes.

Level 2 of digital maturity is characterized by an organizational culture where employees are satisfied that specialists handle digital aspects. However, management sees the role of digital technology primarily as a tactical one, and the allocated budget supports the current setup without allowing for significant improvements. In terms of innovation, it occurs occasionally within existing projects, and basic digital skills are covered by experienced specialists. Recruitment includes specialized digital skills in specific roles that support engagement. There is a small budget for developing core digital skills in digital expert roles, and common principles are used in project management. Technological systems are not keeping pace with the needs of the organization, and data are considered important, improving their quality and use in various fields. Relevant KPIs are set and reported, but the lessons from these reports are not always put into practice. Insights from multiple sources are combined to build understanding, and digital advice is sought when deemed necessary. There is also some experimentation with service delivery using digital channels, but the availability and use of internal digital tools are irregular.

Level 3 of digital maturity is characterized by a deep understanding of digital value within the organization and its desire to learn more in this area. Management encourages the digital leader to take a strategic approach when time permits. The allocated budget allows for the testing of new ideas in priority areas, and there is an innovative reimagining of some aspects of the products or services. There is a core team of digital specialists, and extensive digital skills are required across all areas of the organization. Organizational training normalizes digital skills and projects heavily due to the structure and it being a very long process. The systems are stable and allow basic operations. There is a clear policy for data management, this being integrated and analyzed. Performance data are collected and linked, but access to them is difficult. Knowledge about people's identity is combined with behavioral insights. Digital technology is involved from the beginning in communication planning, and digital services are considered as important as traditional offline services. Good digital tools are available, and their support and integration are provided upon request.

Level 4 of digital maturity represents the stage at which digital technology is perceived to be key to success and are integrated into all aspects of the organization. There is a senior digital leader, and management is actively investing in digital technology. The budget is increasingly supporting digital ways of thinking and acting. There exists one or more teams, and digital opportunities are growing. Strategic digital skills are standard and included in job descriptions. Increasing digital skills represent a top priority for employees, with teams understanding their impact on digital changes. Project management principles and practices are used, with a launching, testing, and continuous improvement approach in place. Tools and systems bring improvements in efficiency. Quality and integrated data are used throughout the organization. Insights play a pivotal role in shaping both planning and delivery strategies. Communication strategies are predominantly designed with a digital-first approach. Providing online services is based on research and rigorous testing. Organizations prioritize investments in digital tools aimed at enhancing the overall work experience of their staff.

Level 5 of digital maturity highlights that digital technology is the primary way to reach the organization's mission. It is fundamentally integrated into the overall strategy, and digital leadership is present at all levels. A healthy budget for the continuous evolution of digital operations increases the impact of the organization. A structured innovation program creates transformative change. A very experimental digital leadership type exists across the organization, with effective teams. New hires present digital skills, and all job descriptions express a need for them. The learning function drives the development of digital skills and behaviors at all levels of the organization. Principles of digital project management are used consistently across all projects to improve efficiency and impact. Interconnected tools and systems provide a smooth and efficient experience for internal and external users. Real-time data are used across the organization to shape decisions and performance. Holistic performance data are always available and used strategically. All work is based on rich and constantly updated insights, being iteratively improved. The digital environment is used to create adaptive and integrated communications. Online services are iterative and integrated, generating impact and coverage never seen before. A large range of connected digital tools is used, with proactive staff support.

The characteristics of each level of digital maturity of the companies led not only to the description of the 17 dimensions according to each level but also to the outlining of related typologies (Figure 3).

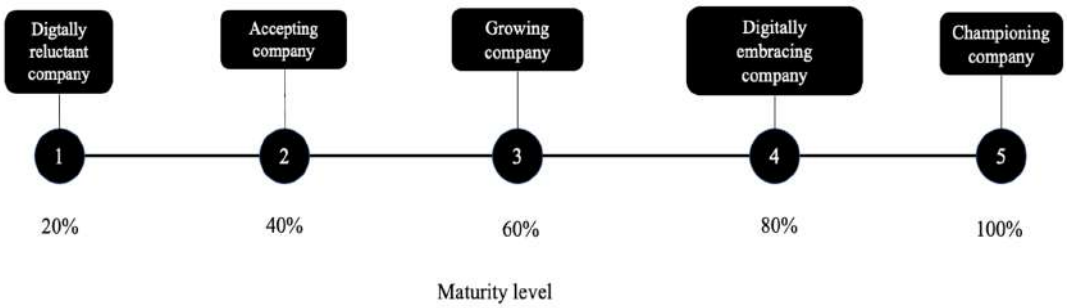

Figure 3. Interval scale of company typologies according to the level of digital maturity. Source: figure made by the authors.

The ***reluctant company*** typology shows that the organization is not convinced that digital technology can contribute to achieving its mission and goals. As a result, the digital environment is underrepresented and underfunded. Not only is the organization missing out on opportunities, but there is a risk that it will not keep up with trend alignment. Reluctant company workers prefer to do things the way they have always been done rather than experiment with new technologies, systems, and processes. A reluctance to evolve in line with the external environment makes the organization increasingly self-focused. In the case of this typology, it is necessary to change attitudes to establish bases in the digital field.

The ***accepting company*** typology shows that the organization's attitude towards the digital environment can be characterized as "accepting". In other words, the company has a good understanding of digital potential and allocates some resources to the basics. However, technology, systems, processes, and digital skills are disparate, and obtaining a budget for new digital projects is a difficult battle. The organization is open to considering innovative uses but has difficulty with adopting new and different ways of working.

The ***growing company*** typology and the ***technology-embracing company*** typology are actively using the digital environment to be more efficient and effective. It is not yet integrated in all aspects, but there is an organizational understanding that the digital environment is crucial to operations, culture, and the experience that customers have when interacting with the organization. Digital staff are supported and encouraged. Resources do not always match ambitions, meaning that people, systems, and digital processes are occasionally under pressure. In the case of this typology, simplification and improvement will increase efficiency, effectiveness, and well-being.

In the case of the ***champion company*** typology, digital maturity can be characterized as "promoting" or "championing". Individuals employed within the company perceive the digital environment as the primary means to actively engage with current and potential supporters. Digitalization serves as a central component for operational and engagement activities, encompassing a diverse array of functions including strategic leadership and communications planning, brand experience, user engagement, supporter services, program or service delivery, and technology development and maintenance, as well as innovation endeavors.

All these characteristics related to the activities that digital marketing agencies can make more efficient by implementing AI led to the highlighting of the challenges, limits, and opportunities presented in Table 1.

Table 1. Activities of advertising agencies made more efficient through AI according to the typology of the company regarding the level of digital maturity.

Activity	Description	Opportunities Depending on the Level of Digital Maturity *
1. Target audience segmentation and identification	By applying AI algorithms for advanced data analysis and identifying behavioral patterns, they allow marketing specialists to refocus their efforts on more relevant audience segments and deliver personalized content. Precise segmentation of the target audience using AI-based solutions can be achieved with the help of specific clustering and/or classification techniques. Also, through this technology, applied machine learning models can be used to identify consumer patterns and behaviors but also to use the information obtained in personalized marketing campaigns [55–57].	**For level 1.** Using basic tools for simple audience identification and segmentation.
2. Personalized recommendations	In the scope of this aspect, the operation of AI recommendation systems, in the form of collaborative filtering algorithms or neural networks, and how they are used to anticipate user preferences, but also to evaluate and optimize the performance of recommendation systems, were identified [58,59].	**For level 1.** Providing simple, generic recommendations based on basic data.
3. Automation of advertising campaigns	Analysis of different techniques and optimization of the process of making pay-per-click campaigns by allocating the budget in real time to maximize the effectiveness of digital marketing campaigns. Machine learning algorithms adapt to changes in user behavior and the data-driven online environment [60].	**For level 1.** Implementing simple automations in advertising campaigns.
4. Content creation	On this topic, the use of AI refers to the application of language generation models, such as recurrent neural networks (RNNs) or generative adversarial networks (GANs) and how they are used to produce relevant and engaging content. Also, for content creation, AI can be applied in operations related to the analysis of the quality and originality of the content generated in the context of the needs and preferences of the target audience [61].	**For level 2.** Using AI to generate simple and personalized content.

Table 1. *Cont.*

Activity	Description	Opportunities Depending on the Level of Digital Maturity *
5. Sentiment analysis and receiving feedback	Interpreting and analyzing user feedback and feelings about brands or products through AI technologies such as natural language processing (NLP) and sentiment classification algorithms. Around this topic, there are also discussions regarding ethics and the correct interpretation of collected sentiments and how this information can influence marketing strategies [62,63].	**For level 2.** Using AI to analyze feedback and sentiment from customer interactions
6. Search engine optimization	AI algorithms are used for search engine optimization purposes by identifying search trends and optimizing content for increased search engine visibility. Through specific techniques such as semantic analysis or machine learning, specialists can more efficiently create more relevant content [64].	**For level 3.** Implementing advanced search engine optimization strategies with the help of AI.
7. Customer support and assistance	With the help of the technologies that are the basis of the functionality of chatbots, namely natural language processing and dialog models, it is possible to provide automated assistance and personalized interaction with customers [65–67].	**For level 3.** Using AI to provide customer support and assistance through a more complex system.
8. Advanced forecasting and analyses	Through machine learning algorithms and predictive models used for marketing purposes, user behavior can be anticipated, and through advanced data analysis techniques it is possible to provide essential information for making strategic marketing decisions [68].	**For level 4.** Use of AI for predictive analyses and advanced analyses in various areas of business interest.

* **For level 5:** The mentioned activities are integrated into almost all operational and strategic aspects of the organization, including all the mentioned activities at lower levels, but using a varied and complex range of AI techniques to achieve advanced and integrated results. In other words, each level encompasses not only the specific tasks outlined for that level but also includes the activities listed at lower levels. This integration ensures a progressive and comprehensive approach to digital maturity, wherein the capabilities and techniques introduced at lower levels serve as foundational elements for the advanced and integrated results achieved at higher levels.

4. Discussions and Conclusions

The authors' study addresses a critical gap in the existing literature by offering a comprehensive understanding of the relationship between companies' digital maturity levels and their readiness to integrate technology assisted by artificial intelligence. While previous research has recognized the importance of digital maturity and AI adoption separately, there remains a lack of cohesive insight into how these factors intersect and mutually influence each other within organizational contexts. To bridge this gap, the authors developed a theoretical model that illuminates the preparedness level of companies in adopting AI-assisted technology based on their digital maturity. Drawing on insights from established models, empirical observations, and specialized literature, the authors synthesized a framework that harmonizes digital maturity assessments with AI adoption strategies. Notably, they established a nuanced interval scale, shaped by the convergence of answer variants within their questionnaire, to offer a detailed depiction of each digital maturity level.

Through this approach, the authors presented a comprehensive framework that not only evaluates companies' digital maturity but also guides strategic decision making concerning AI implementation. By effectively addressing this gap, their study contributes to both theoretical advancement and practical implications for organizations navigating the complexities of digital transformation in the AI era, whereas the scientific novelty of the work results from the evaluation tool of companies from the point of view of the level of digital maturity in relation to the use of technology assisted by artificial intelligence, outlining five typologies that describe the stages of digital adaptation of organizations, es-

pecially digital marketing agencies. This study's focus on marketing agencies is significant not only due to their pivotal role in the digital landscape but also because they serve as early adopters and trendsetters in the application of innovative technologies, such as AI. As pioneers in digital marketing, these types of agencies are at the forefront of deploying AI to enhance their operations and deliver superior results for clients. By examining the readiness of marketing agencies to embrace AI, the authors provided valuable insights that extend beyond individual firms to the broader marketing industry. Their research contributes to a deeper understanding of the challenges and opportunities associated with AI adoption in marketing, paving the way for the development of strategies and best practices that can drive transformative change across the sector.

The authors' research significantly advances the discussion on digital maturity levels and their implications for organizational readiness to adopt AI-assisted technology, especially for marketing agencies. While existing studies provide valuable insights into digital maturity assessment and its applications across diverse sectors [69–71], this study stands out for its focused investigation into creating an interval scale methodology and scrutinizing 17 dimensions across five distinct levels of digital maturity, offering a nuanced understanding of organizations' readiness to embrace AI technology. Whereas previously mentioned research may have offered broad assessments of digital maturity or concentrated solely on technological aspects, this paper focuses on organizational dynamics influencing digital readiness. By identifying typologies, the authors provided actionable insights into the unique characteristics and challenges associated with each level of digital maturity, thereby enabling targeted strategies for AI adoption and digital transformation initiatives. Furthermore, our research not only advances theoretical understanding but also provides practical guidance for organizations seeking to enhance their digital capabilities. By furnishing a comprehensive framework for assessing digital maturity and informing strategic decision making, our study addresses a crucial gap in the literature, empowering organizations to leverage AI-assisted technology effectively for competitive advantage and sustainable growth.

This study's managerial implications underscore the imperative for organizational leaders, particularly those in digital marketing agencies, to proactively instigate strategic shifts toward valuing the benefits of technology assisted by artificial intelligence. Leaders must adapt their approaches and refine their leadership models to cultivate a favorable environment for innovation and adaptation to new technological demands. Crucially, developing and implementing a robust HR strategy assumes paramount importance in this digital transformation journey. Cultivating an organizational culture that encourages continuous learning and adaptability is crucial in this digital transformation process. Moreover, integrating AI into management practices requires solid and transparent ethical approaches, as well as effective risk management to ensure appropriate and sustainable adoption of the technology within organizations. This study highlights the pivotal role of organizational leadership in driving the successful adoption of AI-assisted technology. By embracing proactive strategic changes and encouraging a culture of innovation and adaptability, leaders can position their organizations for successful digital transformation.

In terms of theoretical implications, this study presents the evolving landscape of artificial intelligence-assisted technology, offering valuable insights for researchers and theorists. By deepening existing models, a new theoretical paradigm was discussed to understand the foundation and deep implications of the application of AI in digital marketing areas. Additionally, the interval scale generated from this research holds relevance across diverse disciplines such as philosophy, psychology, cognitive science, computer science, and mathematics, all of which contribute to the development of fundamental theories underpinning AI. From mathematical models and learning algorithms to theories of consciousness and ethics, theoretical research seeks to explore and answer the fundamental and conceptual challenges involved in the development and use of AI, providing solid foundations for future progress and its implications in various fields of activity.

Qualitative research and inductive analysis are methods that have produced valuable results, but they also present certain limitations and challenges. One of the main limitations of qualitative research is the subjectivity involved in the process of data collection and interpretation. Being based on observation and interpretation, qualitative research can be influenced by the subjectivity of researchers. This may lead to different conclusions or varying interpretations of the same data, which may affect the validity and reliability of the results. Another limitation of qualitative research is the impossibility of generalizing the results. Because qualitative research focuses on in-depth study, it is difficult to extend results to the entire study population. These limitations do not invalidate the value of qualitative research or inductive analysis but emphasize the importance of awareness and management of these aspects to ensure the validity and relevance of the results obtained.

Following the results and findings obtained from the assessment of digital maturity and the outlining of typologies within companies, it is possible to identify some directions for future research, namely understanding how organizational culture influences the adoption and use of digital technology. Future research can explore how organizational cultures can be shaped to encourage greater responsiveness and adaptability to change regarding technological innovations. Further research could aim to clearly evaluate the effectiveness and impact of digital technology adoption in different business areas. This could include identifying and measuring specific performance indicators that are relevant to different levels of digital maturity, as well as assessing long-term benefits. Another direction could be to develop and test different strategies and approaches to increase the level of digital maturity in companies. Research could explore specific tools, methods, or programs to support organizations in their transition to higher levels of digital maturity, adapting to the specifics of each company.

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The Future of ESG in Multinationals: How Digital Twin Technologies Enable Strategic Value Creation

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Abstract

This study examines the role of Digital Twin technologies in advancing Environmental, Social, and Governance performance within multinational corporations. Grounded in socio-technical systems theory and stakeholder theory, the research investigates how digital twins facilitate the integration of organizational capabilities with external accountability mechanisms. A multi-method research design is employed, comprising in-depth case studies, capital market event analysis, and machine learning-assisted regression to capture both qualitative and empirical insights. Case evidence from Siemens, Unilever, Tesla, and BP reveals that DT adoption is associated with measurable ESG gains, including reduced emissions, improved safety, enhanced supplier compliance, and accelerated reporting cycles. Event study findings show statistically significant abnormal returns following ESG-oriented DT announcements, while regression analysis confirms a positive association between DT adoption and ESG performance. Governance structures are explored as potential moderators of this relationship. The findings underscore DTs as strategic enablers of ESG value creation, beyond their technical utility. By enhancing transparency, auditability, and stakeholder trust, DTs contribute to both internal transformation and external legitimacy. This research advances the discourse on ESG digitalization and offers actionable implications for corporate leaders and policymakers seeking to foster sustainable, technology-driven governance in complex global value chains. However, because the quantitative component relies on cross-sectional data, the relationships identified should be interpreted as associations rather than definitive causal effects.

Keywords: digital twins; ESG; sustainability; governance; stakeholders; value creation; innovation

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1. Introduction

Environmental, Social, and Governance (hereinafter ESG) frameworks have evolved from voluntary compliance mechanisms to strategic imperatives for multinational corporations (MNCs), driven by accelerating climate change, geopolitical instability, and rising stakeholder expectations [1,2]. In this context, regulatory advances, particularly the Corporate Sustainability Reporting Directive (CSRD), have redefined the contours of corporate responsibility [3,4] mandating comprehensive, auditable disclosures of ESG metrics across more than 50,000 firms in the European Union alone [5,6]. This shift presents both an opportunity and a challenge. While ESG strategies are increasingly embedded in corporate agendas, many organizations continue to face fundamental obstacles in operationalizing ESG goals, including fragmented data infrastructures, reactive compliance

cultures, and a lack of dynamic tools for monitoring and decision support [7,8], the gap between ESG ambition and ESG execution remains a persistent issue in both research and practice. At the same time, the rapid diffusion of technologies such as artificial intelligence, IoT, and blockchain has prompted calls for digital innovation to improve ESG performance [9–12]. However, academic research has largely siloed ESG and digitalization into parallel conversations. ESG studies have primarily focused on frameworks, regulatory compliance, and financial materiality, while digital twins (DTs, hereinafter) research has been concentrated in engineering domains, targeting manufacturing efficiency, smart infrastructure, or supply chain automation [13–16]. What remains underexplored is the strategic intersection between DT technologies and ESG management, particularly in how DTs can act as real-time, data-driven enablers of sustainability reporting, decision-making, and governance transformation.

This study explores how DT technologies enhance ESG performance in multinational corporations by integrating socio-technical systems and stakeholder theories. It investigates (1) the impact of DTs across ESG dimensions, (2) how organizational factors such as ESG maturity and governance influence this impact, and (3) how capital markets react to DT-ESG announcements. Using a multi-method approach, namely, case studies, event study analysis, and machine learning regression, the study tests three hypotheses relating DT adoption to ESG outcomes and investor perception. The research offers both conceptual insights and practical implications for ESG-aligned digital transformation.

The application of DT technology is rapidly evolving across various sectors, yet its integration as an enabler for ESG frameworks remains comparatively underexplored. DTs function as digital replicas of physical entities, processes, or systems, utilizing real-time data to improve operational efficiency. In the context of environmental sustainability, DTs can significantly contribute to minimizing resource consumption and optimizing energy use. For instance, DT technology integrated with predictive maintenance can enhance the performance of renewable energy systems, such as photovoltaic panels, by facilitating early fault detection, thus improving reliability and lifespan. The effective monitoring of volatile organic compound (VOC) emissions in additive manufacturing further demonstrates the utility of DTs in real-time environmental management, showcasing the technology's potential in minimizing environmental impact while adhering to sustainability standards. Moreover, the synergistic effect of DTs and Building Information Modeling (BIM) is noteworthy in the construction sector, where it significantly supports lifecycle management of buildings aimed at achieving net-zero carbon emissions [16]. By fostering better decision-making and facilitating stakeholder communication, DTs enhance building sustainability, providing a framework that aligns with broader ESG principles. The integration of DT in urban infrastructure, particularly in managing the Water-Energy-Food-Environment (WEFE) nexus, illustrates a holistic approach to resource governance that supports social sustainability [17].

In industrial contexts, the application of DTs in conjunction with advanced data analytics is emerging as a strategy to enhance operational efficiencies within the production lifecycle. DTs can use real-time data to optimize manufacturing processes and support sustainability initiatives by reducing waste and improving energy efficiency, aligning directly with ESG goals [18,19]. Failure to harness these technologies represents a missed opportunity for industries striving to comply with increasing sustainability regulations and investor demands for responsible governance practices [20].

Despite these advancements, the widespread adoption of DT technologies specifically applied for ESG integration remains limited. Industries must adopt these innovative tools systematically to overcome existing barriers to implementation, including technological maturity and stakeholder engagement complexities [21,22]. Additionally,

fostering knowledge-sharing initiatives and developing best practices for DT applications related to ESG frameworks will be crucial for driving broader acceptance and integration [23–25]. In conclusion, while the potential of DTs as enablers of ESG objectives is recognized, their implementation is still in its early stages across various sectors. A concerted effort towards understanding and deploying these technologies could profoundly influence sustainable practices, ultimately benefiting environmental quality, social equity, and corporate governance.

To understand the role of DT technologies in enhancing ESG performance to create value, this study draws on two interrelated theoretical lenses: socio-technical systems theory and stakeholder theory. These frameworks provide a conceptual foundation for explaining how digital innovations create global value, reshape organizational structures, decision-making processes, and accountability mechanisms in response to both technological capabilities and external stakeholder demand. To synthesize socio-technical systems theory and stakeholder theory, this study conceptualizes Digital Twins as *mediating infrastructures* that connect internal organizational capabilities (data integration, operational control, ESG governance) with external accountability requirements (regulators, investors, consumers, NGOs). DTs improve ESG outcomes by enabling real-time monitoring, automated disclosure, and enhanced auditability. A visual representation of this conceptual positioning is later presented in Section 4; however, its logic is introduced here to anchor the theoretical argument.

1.1. Socio-Technical Systems Theory

As described by Lyytinen and Newman [26] and reviews in recent literature [27–30], socio-technical systems (STS) theory posits that organizations are composed of two interdependent subsystems: the technical system, encompassing tools, technologies, and workflows, and the social system, comprising people, culture, roles, and governance. The central argument is that optimal organizational performance can only be achieved through the joint optimization of both subsystems. Technological change, therefore, cannot be treated as a purely operational issue, but must be considered in relation to the social structures and professional competencies that it disrupts and reconfigures [31–33].

In the context of ESG reporting, STS theory is especially pertinent. The implementation of technologies such as DTs involves more than system automation; it introduces new decision paradigms, accountability structures, and organizational routines. For instance, DTs allow for real-time ESG data flows, predictive scenario modeling, and automated compliance checks. However, their effective deployment also necessitates the retraining of personnel, creation of new professional roles (such as ESG data analysts, digital compliance officers), and restructuring of interdepartmental collaboration across sustainability, finance, and IT functions.

This dual transformation, technological and organizational, lies at the core of this study's argument: that DTs are not merely tools for efficiency but architects of ESG-driven transformation, reshaping how firms perceive, measure, and act upon sustainability metrics.

1.2. Stakeholder Theory and ESG Legitimacy

While STS explains the internal dynamics of change, stakeholder theory [34–37] situates ESG transformation within the external environment. ESG strategies are fundamentally driven by the need to align organizational behavior with the expectations of diverse stakeholders, including regulators, investors, customers, employees, and communities [38–41]. In this view, ESG reporting serves not only a compliance function but also a legitimization function, enabling firms to justify their social and environmental impact and secure long-term stakeholder trust. Recent studies [42,43] emphasize that stakeholder expectations have

evolved from passive information demands to active scrutiny of corporate sustainability performance. Technologies that enhance transparency, verifiability, and accountability are increasingly valued—not only as operational tools but as mechanisms of stakeholder reassurance and reputational capital [44–46].

DTs, with their ability to produce traceable, audit-ready ESG data and simulate future sustainability outcomes, align directly with these stakeholder imperatives. They enable firms to move from retrospective disclosure to predictive, scenario-based sustainability planning, which enhances both regulatory compliance and strategic legitimacy [20,25,47].

The study presents a theoretical model positioning DT technologies as mediators between organizational capabilities and stakeholder accountability in ESG performance. From a socio-technical angle, DTs enhance real-time data integration and process transformation; from a stakeholder view, they boost transparency and trust. As boundary-spanning technologies, DTs drive both internal change and external legitimacy. The model also identifies key mediators (like data quality and organizational readiness) and moderators (such as industry context and ESG maturity) that influence DT effectiveness.

2. Materials and Methods

This study adopts a multi-method research design to examine the strategic contribution of DT technologies to ESG performance in MNCs. The methodological framework integrates three complementary components, namely (1) qualitative case study analysis, (2) event-based capital market evaluation, and (3) quantitative panel regression modeling, thereby ensuring both conceptual richness and empirical robustness. The research design is grounded in the triangulation of secondary data sources, including ESG disclosures, technology implementation reports, financial market data, and third-party sustainability ratings.

2.1. Research Design

2.1.1. Case Study Analysis

To investigate the role of DT technologies in enhancing ESG performance by creating global value, this study employed a comparative multiple-case study design. The approach is rooted in the principles of qualitative inquiry and theory building through case research [10,11,48–50] with an emphasis on extracting nuanced, context-specific insights. This study used in-depth case studies of four MNCs, namely, Siemens, Unilever, Tesla, and BP, to explore how digital twins support ESG objectives. Data were triangulated from ESG reports (2019–2023), whitepapers, technical roadmaps, press releases, and ESG ratings (MSCI, Sustainalytics). In addition to the MSCI World Index, sector-specific benchmark indices were used to better capture systematic variations in returns within individual industries. Expected returns were therefore estimated against the following indices: MSCI World Industrials (manufacturing), MSCI World Energy (oil and gas), MSCI World Consumer Staples (fast-moving consumer goods), and MSCI World Automobiles (electric vehicle and automotive manufacturing). Daily prices for all indices were retrieved from Yahoo Finance. Using sector-aligned benchmarks improves model precision by controlling for heterogeneous risk–return dynamics across industries. Using cross-case synthesis, the analysis identified both common and sector-specific patterns across environmental, social, and governance dimensions. Each firm was analyzed individually, followed by comparative analysis. This design ensured both depth and analytical rigor, revealing digital twins as strategic tools for real-time ESG monitoring, simulation, and compliance.

2.1.2. Event Study Analysis

To empirically assess investor perceptions of DT technology as a strategic enabler of ESG performance, author employed an event study methodology [51–54]. This method evaluates the abnormal return (AR) in the stock price of a firm surrounding a specific event, in this case, announcements related to DT adoption aimed at enhancing ESG reporting, risk management, or sustainability performance.

Event identification and selection criteria

Event study methodology was employed by utilizing the market model to calculate expected returns. The estimation window included the 120 trading days preceding each event. Cumulative abnormal returns (CARs) were computed over a symmetric ±5-day window to capture immediate and slightly delayed market reactions, while reducing noise from broader macroeconomic movements. Thus, a systematic search of press releases, ESG reports, and financial news databases (Factiva, Bloomberg Terminal) using keywords such as "DT," "ESG reporting," "real-time sustainability monitoring," and "sustainability simulation." To ensure relevance and significance, selected events met three criteria:

(1) Public announcement of DT adoption was explicitly to ESG objectives such as emissions monitoring, compliance with CSRD, or ethical supply chain management.
(2) The firm is publicly listed and has sufficient stock market data available.
(3) No confounding events, such as earnings releases or mergers, occurred within a 10-day window of the announcement. A relevant example for this includes Siemens' announcement of its "Sustainability DT" module in 2022 and General Electric's 2021 launch of a DT framework for decarbonization in heavy industry.

2.1.3. Estimation and Event Windows

The market model was used to estimate normal return, applying the following formula:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$$

where R_{it} is the return on stock i on day t, R_{mt} is the market return and ϵ_{it} is the error term.

Abnormal returns were calculated as:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt})$$

where AR_{it} is the abnormal return for firm i on day t, R_{it} is the actual return, and R_{mt} is the market return proxied by the MSCI World Index. The coefficients α_i and β_i were estimated using OLS over the estimation window.

2.1.4. Sample and Data Source

The study included a set of 30 ESG-active MNCs from sectors such as manufacturing, energy, consumer goods, and transportation. Daily stock return data were sourced Yahoo Finance. Market indices used for benchmarking were sector-specific to control for systemic fluctuations.

2.1.5. Quantitative Modeling Variables

To empirically investigate the impact of DT adoption on corporate ESG performance, the author developed a panel dataset purpose-built for quantitative analysis. This dataset comprises publicly listed MNCs that are among the top ESG performers in their respective sectors, allowing for structured comparison across industries and technological maturity levels. The construction of the dataset relied on sources and methodological rigor for using CSRHub (Est.) and Sustainalytics Risk Ratings which provided comprehensive estimates of ESG-related exposure and performance at the firm level. To harmonize ESG measurement

across sectors and providers, a proxy ESG score was constructed by triangulating data from Yahoo Finance, CSRHub (est.), and Sustainalytics risk scores, facilitating the calculation of firm size and economic scope. Annual and sustainability reports, as well as patent filings and technology roadmaps, were examined to verify DT adoption. Only firms with clear, disclosed use of DTs in sustainability-related domains (such as emissions tracking, supply chain simulation, carbon scenario modeling) were marked as adopters. Only companies with documented, operational deployment of DTs in ESG-linked domains were coded as adopters. Corporate governance documentation was reviewed to determine the presence of a dedicated ESG committee at board level, a proxy for internal ESG institutionalization. ISIC Rev. 4 codes were used to classify industry sectors, enabling the implementation of industry-level fixed effects in the econometric model. Thus, each observation in the dataset includes the variables depicted in Table 1.

Table 1. The presentation of the variables.

Variable	Description
Company	Name of the publicly listed firm.
ESG Score	Normalized score on a 0–100 scale (later rescaled to [0, 1] for analysis).
DT adopter	Dummy variable: 1 = firm has adopted DT technology; 0 = otherwise.
Log(Total Assets)	Natural logarithm of total assets (in billions USD) to capture firm size.
ESG Committee	Binary variable indicating presence of a board-level ESG oversight body.
ISIC Code	Four-digit industry classification used for fixed effects modeling.
Company	Name of the publicly listed firm.

To ensure sectoral representativeness and analytical clarity, the dataset includes the top 10 ESG-ranked firms within each of the 11 GICS-aligned sectors, as defined by MSCI ESG benchmarks. This cross-sectoral design enables the identification of patterns that transcend industry idiosyncrasies, particularly in relation to ESG innovation and digital capability.

To generalize the findings, a machine learning-supported panel regression analysis was employed. A dataset was constructed from ESG scores and firm-level indicators for a sample of publicly listed firms (n = 110), segmented into two groups as follows: (1) DT adopters: organizations that have publicly disclosed the use of DT technologies for ESG-related activities such as predictive carbon modeling, real-time environmental monitoring, or digital sustainability reporting; (2) non-adopters, the firms that do not exhibit documented implementation of DTs in sustainability contexts, serving as a counterfactual benchmark. This segmentation allows for hypothesis testing regarding the differential ESG outcomes of DT integration.

Two regression models were sequentially estimated. Model 1 examined the direct effects of DT adoption, firm size, and ESG committee presence on normalized ESG performance scores, with industry fixed effects applied via ISIC codes. To deepen this analysis, Model 2 introduced an interaction term between DT adoption and ESG committee presence (DT Adopter × ESG Committee), allowing assessment of whether governance structures condition the impact of digital technologies. Together, these models enable both a baseline and a conditional interpretation of how DT capabilities influence sustainability outcomes in multinational firms.

Variable operationalization

The regression models employed are structured to evaluate the influence of DT adoption on ESG performance, while accounting for firm-level controls and structural differences across industries.

Dependent variable:

$$ESG\ performance_i = \frac{ESG\ Score_i}{100}$$

The ESG score is normalized to a 0–1 scale to standardize the dependent variable for regression.

Independent variable:

$$ESG\ DT\ Adopter_i = \begin{cases} 1\ if\ firm\ i\ has\ adopted\ digital\ twin\ technology\ for\ ESG\ use \\ 0\ of\ firm\ i\ has\ not\ adopted\ digital\ twin\ technology\ for\ ESG\ us \end{cases}$$

This binary variable captures whether a firm has publicly documented and operationalized DT technologies in domains such as carbon modeling, supply chain simulation, or sustainability monitoring.

Control variables:

Company size, as log-transformed to correct for scale distortion and allow elasticity-based interpretation:

$$Company\ size_i = log(Total\ Assets_i)$$

ESG committee, a binary indicator reflecting the presence (1) or absence (0) of a board-level ESG oversight structure.

Industry fixed effects were included to control for sectoral heterogeneity using categorical dummy variables derived from ISIC Rev. 4 codes. Each firm was matched to a four-digit ISIC code representing its primary economic activity. This allows the model to account for time-invariant industry-specific characteristics that may systematically influence ESG practices or digital adoption.

To capture the conditional effect of internal ESG governance on the relationship between DT adoption and ESG performance, a second model introduced an interaction term between DT adoption and ESG committee presence:

$$\begin{aligned} ESG\ Performance_i = \beta_0 + \beta_1 DT\ Adopter_i + \beta_2 CompanySize_i + \beta_3 ESG\ Committee \\ +\beta_4 (DT\ Adopter_i\ \times\ ESGComittee_i) +\ \gamma_{Industry} + \varepsilon_i \end{aligned}$$

This formulation allows for testing whether the presence of a board-level ESG oversight body amplifies the sustainability impact of DT implementation. The interaction term takes the value 1 only when both conditions are met, capturing potential synergistic effects between digital infrastructure and governance capacity. Model 3 was originally designed to test ESG maturity as a moderator of the DT–ESG relationship. However, the ESG Maturity Index contains the ESG score, which is also the dependent variable. Including ESGMI in the regression would therefore induce structural multicollinearity and artificially inflate model fit (pre-tests yielded $R^2 \approx 1.00$ and unstable coefficients). For this reason, Model 3 was excluded from inferential testing to protect validity. ESGMI is used only for exploratory comparison between firms with high versus low ESG maturity because, in its current form, it cannot serve as an econometric moderator without overlapping with the dependent construct.

ESG maturity index as moderator

To capture organizational ESG readiness, the researcher constructed an ESG Maturity Index (ESGMI) that combines ESG performance, governance structure, and resource capacity:

$$ESGMI_i = (0.5 \times ESGScore_i) + 0.2 \times ESGC_i + 0.3\ \times\ Normalized\ Log(Assets)_i)$$

which is,

$$ESGMI_i = \left(0.5 \times \frac{ESG\ Score_i}{100}\right) + (0.2 \times ESGC_i) + \left(0.3 \times \frac{log(Assets)_i - min[log(Assets)]}{max[log(Assets)] - min[log(Assets)]}\right)$$

Each component serves a distinct conceptual role: ESG score reflects sustainability performance; ESG committee represents internal governance and strategic alignment; firm size reflects implementation capacity and resource mobilization potential. Because ESGMI includes the ESG score—which is also the dependent variable—using it in the regression models would create structural multicollinearity and overfitting. Therefore, ESGMI was not included in the regression models. Instead, ESGMI is used only for exploratory comparison between firms with high versus low ESG maturity. This approach ensures methodological robustness while preserving the theoretical relevance of ESG maturity. Accordingly, the inferential analysis focuses on two regression models: (i) a baseline model testing the direct association between DT adoption and ESG performance, and (ii) an interaction model assessing whether the presence of a board-level ESG committee conditions this association. The descriptive comparison based on ESGMI is revisited in the Section 3 to contextualize differences in technological and governance readiness across firms.

2.2. Methodological Rigor

The study ensured methodological rigor through multiple validation strategies. Construct validity was secured via standardized measures and data triangulation, while internal validity was strengthened through robust case analysis and controlled regressions. External validity was supported by a diverse, global sample of ESG-leading firms. Reliability was maintained with transparent coding and consistent data processing. These measures collectively enhance the study's credibility and support its findings on DTs' role in ESG value creation.

2.3. Validity and Reliability

This study ensured rigor through a multi-method design supported by multiple layers of validity and reliability. Two regression models tested both direct and moderated effects of DT adoption on ESG performance. Construct validity was achieved via standardized indicators (ESG scores, ISIC codes) and triangulated sources. Internal validity was ensured through cross-case synthesis, temporal scoping (2019–2023), robustness checks ($\pm 3/5/7$ days), and control variables (firm size, ESG committee, industry effects). An interaction term (DT $\times$ ESG Committee) captured the conditional effect of internal governance. ESGMI was used only descriptively due to multicollinearity with the dependent variable. External validity was enhanced by including ESG-leading MNCs across 11 sectors. Reliability was upheld through transparent coding, Python-based analysis, and consistent data transformations.

To conclude the methodological section, the following hypotheses were tested in the empirical stage of the research:

H1: *Digital Twin (DT) adoption is positively associated with corporate ESG performance in multinational corporations.*

H2: *The presence of a board-level ESG committee amplifies the association between DT adoption and ESG performance.*

H3: *Firms with higher ESG maturity exhibit stronger ESG performance effects from DT adoption compared with firms at lower levels of maturity.*

Although H1 and H2 were tested through the panel regression models, H3 could not be estimated because the ESG Maturity Index contains the ESG score (the dependent variable). For this reason, H3 was assessed descriptively rather than inferentially.

3. Results

The results are organized around the research questions, following the multi-method design outlined in the methodology. The triangulated evidence from qualitative case studies, event-based capital market analysis, and quantitative regression modeling provides a cohesive understanding of how DT technologies contribute to ESG performance in multinational corporations.

3.1. Case Study Analysis Results

In order to systematically assess the contributions of DT adoption to corporate ESG outcomes, the analysis proceeds by examining improvements along each dimension, starting with environmental performance.

3.1.1. Environmental Performance

The case study analysis reveals that all four MNCs demonstrated quantifiable environmental improvements directly linked to the adoption of DT technologies. Siemens achieved a 25% reduction in energy consumption and a 20% decrease in CO_2 emissions at its Amberg Smart Factory. These gains were realized through the integration of AI-enhanced DT simulations enabling real-time process optimization, and are documented in the company's 2023 Corporate Sustainability Reporting Directive compliant disclosure. Unilever reported comparable progress, with a 25% decrease in food waste and a 30% reduction in plastic usage. These outcomes were driven by circular economy initiatives underpinned by DT-enabled simulations of supply flows and packaging optimization. Tesla deployed DT models to enhance sustainability in its Gigafactories, improving battery recycling efficiency by 10% and increasing energy efficiency in electric vehicle (EV) production by 12%. Finally, BP adopted AI-driven DT platforms for methane leak detection on offshore rigs, achieving a 15% reduction in methane emissions through predictive analytics and early-warning systems. Collectively, these examples highlight the capacity of DT technologies to generate substantial environmental performance improvements across diverse industrial contexts, supporting their strategic relevance in operationalizing ESG goals.

3.1.2. Social and Human Capital Impact

DT technologies have also contributed significantly to improvements in labor conditions and ethical practices within supply chains. Siemens deployed hazard detection DT systems within its manufacturing units, resulting in a 30% reduction in workplace injuries and a 50% increase in emergency response speed, demonstrating the value of real-time monitoring in enhancing occupational health and safety. Unilever adopted blockchain-integrated DT solutions to automate labor audits, leading to an 18% decrease in unethical supplier practices, as verified through Sedex assessments and internal ESG compliance reviews. Tesla focused on ergonomic simulations using DTs to mitigate repetitive strain injuries in its assembly lines, achieving a 16% reduction over a two-year period. Similarly, BP used DT-enabled simulation platforms to enhance emergency preparedness and crew scheduling on offshore installations, resulting in a 22% improvement in response efficiency based on internal audit metrics. These cases illustrate how DTs not only support operational optimization but also act as catalysts for strengthening human capital resilience and ethical supply chain governance.

3.1.3. Governance and ESG Reporting Improvements

DT technologies have also played a pivotal role in enhancing ESG governance and automating sustainability disclosures. Siemens succeeded in shortening its ESG reporting cycle from eight weeks to just three by deploying a CSRD-aligned dashboard built on its proprietary MindSphere DT infrastructure, illustrating the efficiency gains possible through real-time data integration. Unilever utilized DT-powered scenario simulations to validate compliance with both the EU taxonomy and U.S. SEC guidelines, thereby strengthening the traceability of its disclosures across multiple regulatory regimes in 2023. Tesla institutionalized ESG oversight through the implementation of a digital "ESG control tower" at board level, contributing to a 12.5-point increase in its Sustainalytics disclosure quality score over the period 2021–2023. BP also leveraged DT-based greenhouse gas simulation models within its compliance systems, which facilitated three successive external ESG audits without major findings—highlighting the transparency and auditability benefits of DT deployment. Together, these cases emphasize the capacity of DTs to reinforce governance structures, support multi-framework alignment, and institutionalize ESG accountability in large multinational corporations. For a better visualization of comparisons between MNCs, Table 2 shows synthesized data.

Table 2. Cross-Company comparison of environmental, social, and governance improvements attributed to digital twin adoption.

Company	Environmental Gains	Social Impact	Governance and Reporting
Siemens	−20% CO_2, −25% energy use	−15% methane, +10% carbon capture	−63% reporting time, full CSRD alignment
Unilever	−30% plastic, −25% waste	+18% supplier compliance	Multi-regime simulation, ESG audit support
Tesla	+12% energy efficiency	−16% strain injuries	+12.5 pts disclosure score (Sustainalytics)
BP	−15% methane, +10% carbon capture	+22% emergency efficiency	3 clean audits, TCFD-aligned simulation

The author finds that DTs enable substantial improvements across all ESG dimensions. Specifically, they function as integrative infrastructures that automate compliance, enable simulation-driven foresight, and enhance traceability and safety. The evidence validates the conceptual proposition that DTs are not merely technical enablers, but strategic instruments for ESG transformation, adaptable across sectors when institutional maturity and data capabilities are present.

3.1.4. Event Study

The author examined how financial markets respond when companies publicly link DT technologies to ESG commitments. The results reveal that investors consistently reacted positively, although with different magnitudes, to announcements explicitly connecting digital innovation with sustainability goals. Across the cases, market reactions were most favorable when DT announcements were clearly and explicitly linked to ESG objectives (Table 3).

Table 3. Cumulative abnormal returns (CARs) following public announcements of digital twin adoption for ESG objectives.

Company	Announcement Date	Context	CAR %	Significance	Interpretation	Significance
Siemens	6 January 2025	Launch of "Sustainability DT" for Scope 3 monitoring.	+1.87%	$p < 0.01$	Strong investor endorsement of ESG-aligned industrial digitalization	
Unilever	18 March 2025	Use of Omniverse DTs for ESG lifecycle simulation.	+1.34%	$p < 0.05$	Market rewards ESG transparency in global supply chains.	
Tesla	August 2021	AI-driven DTs for energy modeling in Gigafactories.	+0.42%	Not significant	Weak reaction; ESG framing was ambiguous, embedded in broader tech announcements	
BP	September 2020 and January 2025	Integration of DTs for methane emissions detection offshore	+0.96%	$p < 0.1$	Moderate optimism, tempered by fossil sector ESG skepticism.	

Source: author's elaboration based on case data.

In the case of Siemens, the substantial abnormal return reflects investor confidence in the company's ESG technology strategy, particularly its alignment with the European Union's CSRD. The announcement emphasized real-time emissions modeling and digital audit readiness, the capabilities increasingly valued by institutional investors.

Unilever's announcement also generated a statistically significant gain, reinforcing its position as an ESG leader. The deployment of NVIDIA-powered DTs to simulate product emissions demonstrated a credible commitment to scope-based accountability and net-zero planning across its global value chains.

BP experienced a more cautious yet positive response. While the integration of methane-monitoring DTs was welcomed, investor sentiment was tempered by the sector's reputational legacy. The result suggests that even in traditionally high-emission industries, digital ESG tools can signal credible intent, provided transparency is strong.

By contrast, Tesla's announcement drew a relatively muted market response. The lack of statistical significance suggests that investors did not interpret the DT implementation as a strong ESG signal, likely due to insufficient framing of the sustainability impact. For Tesla, the cumulative abnormal return of +0.42% was not statistically significant. Examination of the announcement text indicated that the deployment of digital twin technology was communicated primarily as part of a wider update on production automation and AI-driven manufacturing efficiency, with only a brief reference to energy modeling and sustainability implications. Because ESG benefits were not clearly emphasized, investors may not have interpreted the announcement as an ESG-oriented digital transformation initiative. This lack of explicit ESG framing provides a plausible explanation for the muted market reaction.

These findings support the idea that DTs are not only technical infrastructures, but also strategic signaling mechanisms. Investors appear to reward companies that use DTs to enhance transparency, simulate compliance, and align operations with emerging sustainability expectations. The author concludes that DT technologies, when embedded

in a coherent ESG narrative, can contribute directly to capital market legitimacy, potentially lowering risk premiums and enhancing long-term firm valuation.

3.2. Quantitative Regression Analysis

The quantitative analysis aimed to evaluate the relationship between DT adoption and ESG performance, using a machine learning-supported panel regression model built from a structured dataset of 110 MNCs. These firms, selected from the top ESG performers across 11 GICS-aligned sectors, were categorized into DT adopters and non-adopters based on validated disclosures related to DT deployment in ESG-relevant contexts.

3.2.1. Descriptive Statistics and Variable Distribution

The descriptive analysis revealed balanced representation across sectors, with DT adoption observed in approximately 38% of the sample. Mean ESG scores (normalized to 0–1) were generally higher among adopters than non-adopters, suggesting a potential link between technological sophistication and sustainability outcomes. The average ESG score among DT adopters was 0.79, compared to 0.72 for non-adopters. Firms with board-level ESG committees consistently outperformed those without, reinforcing governance structures as key facilitators of ESG effectiveness. As expected, firm size (log of assets) was positively correlated with ESG performance, indicating the enabling role of organizational capacity.

3.2.2. Model 1—Baseline Regression

The first regression model assessed the direct relationship between DT adoption and ESG performance, controlling for firm size, ESG governance, and industry effects. The findings confirm that DT adoption is associated with stronger ESG performance, even after accounting for firm size and governance structures (DT Adopter: $\beta_1 = 0.0228$, $p = 0.029$ —statistically significant positive effect; Company size (log assets): $\beta_2 = -0.0119$, $p = 0.013$; ESG Committee: $\beta_3 = -0.00198$, $p = 0.070$ (marginally significant; although the p-value does not meet the conventional 0.05 threshold, it is close enough to suggest a meaningful trend, especially in fields like management, strategy, or sustainability research, where complex constructs (like governance) are often noisy but theoretically important). Firm size (Log Assets) exhibits a statistically significant negative association with ESG performance ($\beta = -0.0119$, $p = 0.013$). Because this finding diverges from mainstream ESG literature expectations, detailed theoretical interpretation is deferred to the Section 4. These results encapsulate three important aspects: (i) DT adopters exhibit a higher median ESG score and a tighter interquartile range, (ii) DT adoption is positively associated with ESG performance, and (iii) Figure 1 highlights a few outliers, especially among non-adopters, reinforcing the variability and potential lack of structural ESG alignment in that group. Although larger firms typically possess greater resource capacity for ESG initiatives, the negative coefficient for firm size suggests that scale alone does not translate into higher ESG performance. Large multinationals may face higher structural complexity, dispersed supply chains, and fragmented governance arrangements, which can reduce consistency across sustainability metrics. This result indicates that organizational complexity may outweigh resource advantages when ESG integration is not strongly coordinated.

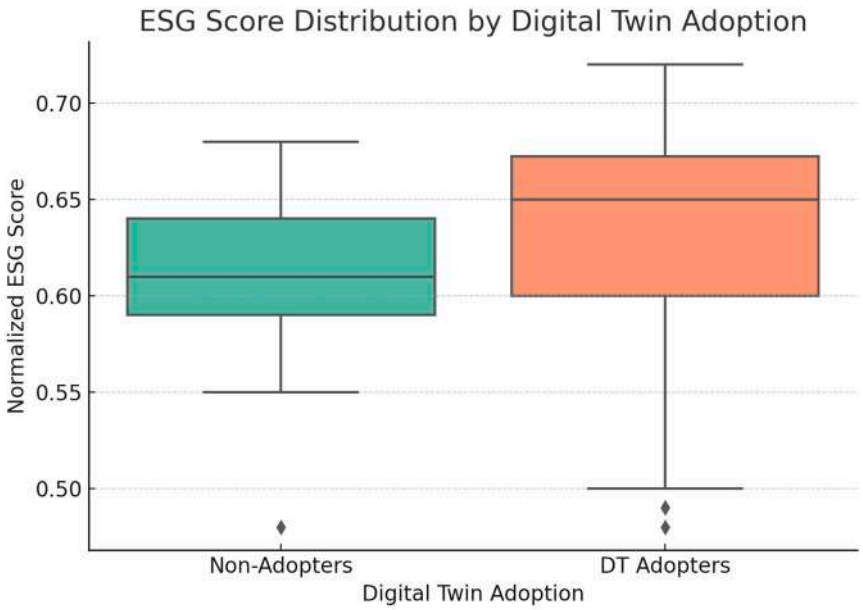

Figure 1. Boxplot of distribution on normalized ESG scores between firms that adopted DT technology and those that did not.

3.2.3. Model 2—Governance Interaction

To test whether internal governance mechanisms amplify the effect of DT adoption, Model 2 included an interaction term and findings show (i) interaction (DT × ESG Committee): $\beta_4 = 0.028$, $p = 0.202$ (not statistically significant), (ii) the main effect of DT adoption becomes nonsignificant when the interaction is added ($p = 0.33$) and (iii) firm size remains negatively significant ($p = 0.027$). Although firms that combine DT adoption with a board-level ESG Committee show higher mean ESG scores, the interaction effect is not statistically significant. Therefore, the governance-based synergy should be interpreted as a descriptive pattern rather than a statistically validated moderation. This potential synergy is illustrated in Figure 2, which shows that firms combining DT adoption with the presence of a board-level ESG committee achieve higher mean ESG performance than those lacking one or both components.

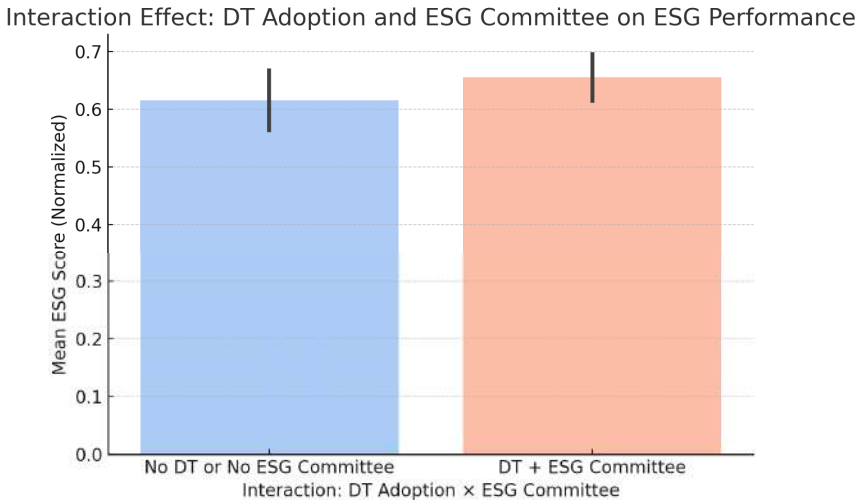

Figure 2. Bar chart–Interaction effect between DT adoption and the presence of an ESG Committee on ESG performance.

Firms that simultaneously adopted DT technologies and maintained a board-level ESG committee achieved the highest average ESG performance, as shown in the comparative

bar chart. This group outperformed those lacking one or both attributes, reinforcing the theoretical proposition that governance structures may enhance the effectiveness of digital transformation efforts in ESG domains. Although the statistical interaction term in Model 2 was not significant at conventional thresholds, the observed difference in mean ESG scores suggests a potential synergistic relationship. The presence of formal ESG oversight may provide the strategic alignment and accountability mechanisms necessary to fully employ the capabilities of DT technologies in pursuit of sustainability outcomes.

3.2.4. Model 3—ESG Maturity Index

ESGMI was not used in the final regression models due to multicollinearity caused by the inclusion of the dependent variable (ESG score) within the index. In preliminary exploratory tests, adding ESGMI and its interaction with DT adoption produced overfitting ($R^2 \approx 1.00$) and unstable coefficients, confirming the structural dependency. The researcher, therefore, discarded this model and does not interpret its coefficients. Instead, the author used ESGMI descriptively, comparing firms with high and low ESG maturity based on a median split (Table 4).

Table 4. High ESGMI vs. low ESGMI.

Indicator	Low ESGMI	High ESGMI
ESG Score (mean)	0.622	0.619
DT Adopters (proportion)	40%	56%
Firm Size (log assets)	4.00	5.39
ESG Committee (%)	14%	58%

A significantly higher proportion of DT adoption was found among firms with high ESGMI (56% vs. 40%). DT adoption was 16 percentage points higher among firms with high ESG Maturity Index values, supporting the idea that organizations with greater ESG maturity are more inclined to adopt advanced technologies such as DTs. This difference appears to be driven by the higher prevalence of ESG committees and larger firm size among the high-ESGMI group (Figure 3).

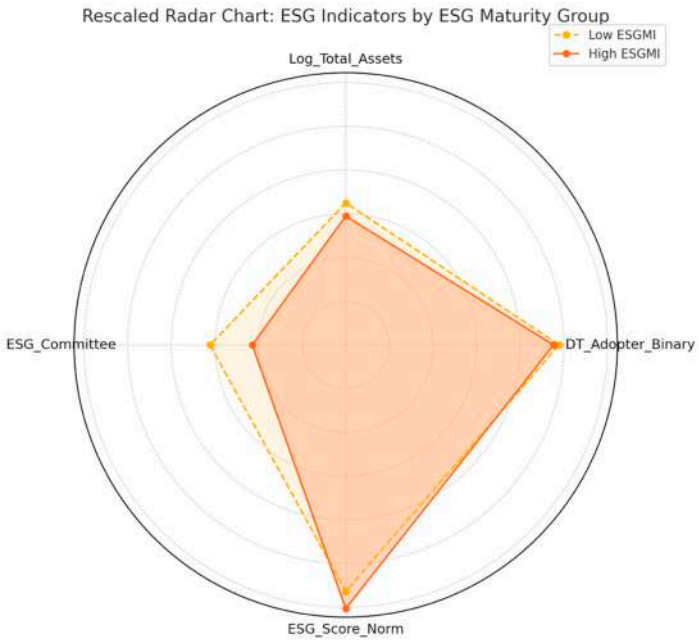

Figure 3. Radar chart–high vs. low ESGMI. Re-scaled for better visualization. Source: author's elaboration based on case data.

The radar chart compares firms by ESG Maturity Index across four indicators (DT adoption, firm size, ESG committee presence, ESG performance), normalized to a 0–1 scale. High-ESGMI firms outperform in governance and DT adoption—key enablers of readiness—while firm size adds further capacity for scaling ESG technologies. Similar ESG scores across groups are expected, as ESG performance feeds into the index. The chart's shape highlights that ESG maturity is not about isolated scores but integrated organizational alignment. These findings support the index's value in distinguishing firms prepared to leverage DTs for ESG outcomes.

4. Discussion and Conclusions

This study set out to examine how DT technologies contribute to ESG value creation in MNCs. For a better understanding of the logical structure of the study, the author has created Figure 4 to present the flow of the process deployed to confirm or reject H_1, H_2, and H_3.

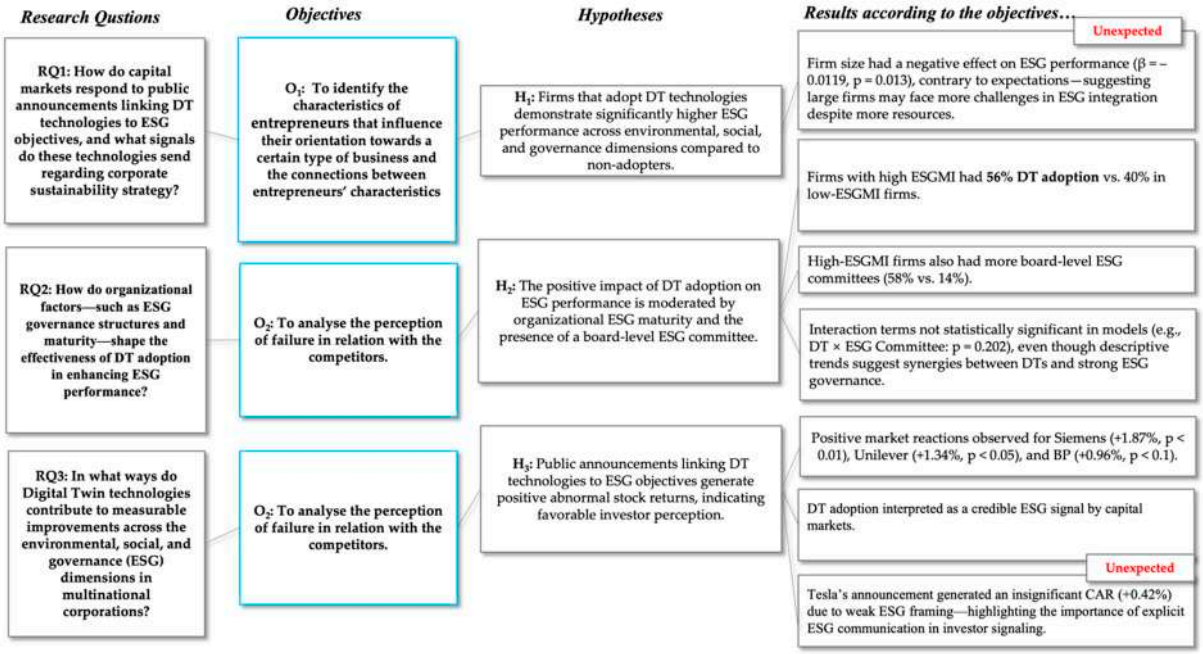

Figure 4. Alignment between research questions, objectives, hypotheses, and empirical findings.

The study successfully met its objectives using a multi-method approach. Case studies showed that DT adoption is associated with ESG improvements, and this association is consistent with the quantitative results, which support the link between DT adoption and higher ESG scores. While the governance interaction was not statistically significant, descriptive patterns suggest that both ESG governance and ESG maturity may enhance DT impact. Although the results show a positive association between DT adoption and ESG performance, the cross-sectional research design does not allow for determination of whether DTs improve ESG performance or whether firms with strong ESG practices are better positioned to adopt DTs earlier. Event study analysis found positive investor reactions to DT-ESG announcements, especially for Siemens and Unilever, though not for Tesla, likely due to weak ESG framing. A surprising negative link between firm size and ESG score suggests larger firms may face integration challenges. A key empirical insight of this study is the negative relationship between firm size and ESG performance. While large firms possess superior resource capacity for ESG initiatives, they also face greater integration challenges, operational dispersion, and regulatory heterogeneity across geographies. This suggests that scale introduces institutional complexity that may offset resource

advantages unless strong coordinating ESG governance is in place. In other words, firm size improves ESG outcomes only when governance structures are sufficiently integrated to manage cross-unit consistency and accountability. Overall, the study highlights that DTs can enhance ESG performance, but their effectiveness depends on governance, maturity, and strategic communication. The interaction term in Model 2 was not statistically significant, indicating that the moderating role of ESG governance is not supported by inferential evidence and should be interpreted only as a descriptive tendency rather than a tested causal mechanism.

Also, the negative association between firm size and ESG performance suggests that resources alone do not guarantee sustainability excellence. Large multinationals typically operate across multiple jurisdictions, supply chains, and regulatory environments, introducing complexity that may outweigh the advantages of resource abundance. ESG progress in such firms requires coordination across diverse business units, extensive compliance infrastructures, and cultural alignment—a process that often advances more slowly than in smaller, more agile organizations. This finding indicates that firm size enhances ESG performance only when governance and organizational integration mechanisms are sufficiently strong to manage institutional complexity.

4.1. Theoretical Implications

While ESG maturity remains theoretically relevant as a potential enhancer of DT effectiveness, the current dataset did not allow a statistically valid moderation test because ESGMI included the dependent variable. For this reason, the moderation hypothesis remains theoretically plausible but empirically untested. This study advances ESG and digital innovation literature by framing DT as boundary-spanning technologies that drive both internal transformation and external legitimacy. From a socio-technical systems view, DT adoption reshapes decision-making and governance through real-time data integration and cross-functional collaboration. From a stakeholder perspective, DTs can enhance transparency and trust, as confirmed by positive investor reactions to ESG-linked announcements. Overall, the findings position DTs as strategic enablers of ESG, not just technical tools, challenging traditional compliance-driven views and broadening the scope of digital innovation research.

4.2. Practical and Managerial Implications

For managers and sustainability leaders, the study provides practical guidance on using DT beyond compliance. DTs enable real-time ESG management through simulation, automation, and predictive monitoring. Effective implementation requires cross-functional integration of ESG into IT and operations, as well as digitally skilled teams. Success also depends on organizational readiness-firms with mature ESG governance benefit more. Additionally, positive investor reactions to DT-ESG initiatives highlight their value as tools for enhancing both reputation and financial performance. For large multinationals, successful deployment of DT technologies for ESG requires strong internal coordination; without robust governance integration, the scale and complexity of operations may limit the sustainability benefits that DTs can generate.

4.3. Policy and Regulatory Implications

From a policy standpoint, the study underscores the importance of DTs as digital infrastructure for effective ESG regulation. As standards like the CSRD raise disclosure requirements, many firms struggle with outdated systems. DTs can streamline compliance by automating data integration and producing audit-ready outputs. Policymakers should consider mandating or incentivizing DT adoption, especially in high-impact sectors. Additionally, public–private efforts to develop open, interoperable ESG data systems are

essential to ensure reporting drives real change rather than becoming a mere formality. More actionable policy pathways can be identified based on the sector-specific challenges observed in this study. First, governments can incentivize DT adoption through mechanisms such as tax credits for DT-enabled ESG reporting, subsidies for digital infrastructure upgrades, and preferential access to green financing for organizations deploying DTs in emissions-intensive domains. Second, development of open ESG data systems requires clear technical standards to ensure interoperability and auditability. Relevant examples include standardized application programming interfaces for emissions reporting, alignment with CSRD and ISSB disclosure taxonomies, and mandatory timestamping and traceability protocols for real-time ESG data exchange. Third, early policy support would be most impactful in high-emission and safety-critical sectors, including energy, heavy manufacturing, logistics, and construction, where DTs can rapidly reduce environmental and social risks. These recommendations aim to provide practical guidance for policymakers seeking to scale digital sustainability infrastructures while maintaining market competitiveness and regulatory integrity. These measures illustrate that policy support for DTs should go beyond general encouragement and extend to targeted economic incentives, infrastructure standards, and sector-specific deployment priorities. The policy suggestions presented here derive directly from observable successful corporate practice. For instance, Siemens' CSRD-aligned Digital Twin dashboard shows how real-time ESG reporting infrastructures can reduce reporting cycles by over 60% while increasing audit reliability, demonstrating the value of regulatory-ready digital systems. Similarly, BP's methane-detection Digital Twin deployment illustrates how targeted DT incentives in high-emission sectors can translate into measurable environmental impact. These examples underscore the need for policy frameworks that reward not only disclosure but also technology-enabled traceability and verification.

4.4. Limitations

While the study has methodological limits, such as reliance on proxy data and potential confounders in event analysis; it remains a rigorous early exploration of how DTs intersect with ESG strategies in MNCs. Case firms were chosen for depth, not breadth, capturing leaders shaping future norms. Despite attribution challenges, consistent positive market reactions strengthen the findings' credibility. The regression model, though constrained by current disclosure practices, was built with methodological care. Overall, the study captures a pivotal transition (2018–2023) in ESG digitalization, offering a solid theoretical base and setting the stage for future research. Also, the moderating role of ESG maturity could not be statistically validated because available maturity proxies contain ESG performance indicators, creating multicollinearity. Future research should employ non-overlapping maturity indicators such as years of ESG reporting, clarity of sustainability strategy, third-party ESG assurance, or dedicated sustainability budgeting. Finally, while the results show a positive association between DT adoption and ESG performance, the cross-sectional dataset does not permit strong causal inference. It remains plausible that firms with higher ESG performance, stronger governance structures, and greater resource capacity are more likely to invest in advanced technologies such as digital twins. Therefore, reverse causality cannot be ruled out. Establishing the direction of causation requires longitudinal or quasi-experimental designs, such as difference-in-differences analysis around the timing of DT deployment or instrumental variable strategies based on regulatory technology shocks. Future research applying these methods can clarify whether DTs improve ESG outcomes or whether leading ESG performers adopt DTs earlier.

4.5. Future Research

Future research should explore the long-term impact of DTs on ESG performance through longitudinal studies. Comparative analyses across industries and regulatory contexts can reveal sector-specific dynamics. Micro-level studies are needed to understand how DTs reshape roles, training, and organizational culture. A systems-level view could unpack how different tech stacks influence ESG outcomes. Ethical and political questions—like data control and algorithmic governance—warrant critical inquiry. Finally, policy-focused research should assess how regulation and public support can foster DT adoption, especially for SMEs and firms in the Global South, ensuring inclusive and responsible digital ESG transitions. As ESG disclosure standards evolve, future datasets may allow a clean test of whether ESG maturity amplifies the impact of digital twin adoption on sustainability performance. Future work using longitudinal datasets may allow a clearer test of whether ESG governance strengthens the impact of DT adoption.

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