BAR Brazilian Administration Review

ANPAD

Research Article

Artificial Intelligence Adoption and its Effects on Digital Transformation and Maturity: Evidence from a Mobility and Payment Ecosystem

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How to cite: Reis, C. N. A., Pinochet, L. H. C., & Caneppele, N. R. (2026). Artificial intelligence adoption and its effects on digital transformation and maturity: Evidence from a mobility and payment ecosystem. *BAR-Brazilian Administration Review, 23*(2), e250213.

DOI: https://doi.org/10.1590/1807-7692bar2026250213

ABSTRACT

Objective: This study examines the relationship between Artificial Intelligence (AI) adoption, digital transformation, and digital maturity in a Brazilian subsidiary operating in the mobility and payment ecosystem. **Methods:** An interpretivist, qualitative-dominant mixed-methods design was adopted, combining a single case study with semi-structured interviews and the CRITIC and WASPAS multi-criteria decision-making techniques. **Results:** The findings show that AI adoption is shaped by organizational structure, culture, employee training, and technological integration. When supported by governance, acculturation, and capability development, these conditions may contribute to digital transformation. In the CRITIC-based weighting structure, implementation cost presented the lowest informational contribution, while internal development emerged as the most salient alternative, followed by partial implementation and ready-made or outsourced solutions. Managers also associate AI adoption with gains in efficiency, customer experience, and competitive positioning. **Conclusions:** The study shows that AI adoption interacts with digital transformation and digital maturity in an emerging-market subsidiary, not as a universal driver of transformation, but as a contingent catalyst shaped by governance, acculturation, internal capabilities, and ecosystem coordination.

Keywords:
artificial intelligence; digital transformation; digital maturity; payment ecosystem.

JEL Code:
C44

Received:
November 02, 2025.
This paper was with the authors for four revisions.

Accepted:
May 14, 2026.

Publication date:
June 08, 2026.

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Funding:
The author stated that there is no funding for the research.

Conflict of Interests:
The authors stated that there was no conflict of interest.

Editor-in-Chief:
Ricardo Limongi
(Universidade Federal de Goiás, Brazil)

Reviewers:
Two anonymous reviewers.

Peer Review Report:
The disclosure of the Peer Review Report was not authorized by its reviewers.

Editorial assistants:
Eduarda Anastacio and Simone Rafael (ANPAD, Maringá, Brazil).

Data Availability: Due to confidentiality and ethical restrictions regarding participants' information, the original dataset cannot be made publicly available. However, the authors may provide additional methodological details upon reasonable request. BAR – Brazilian Administration Review encourages data sharing but, in compliance with ethical principles, it does not demand the disclosure of any means of identifying research subjects.

Plagiarism Check: BAR maintains the practice of submitting all documents received to the plagiarism check, using specific tools, e.g.: iThenticate.

Peer review: is responsible for acknowledging an article's potential contribution to the frontiers of scholarly knowledge on business or public administration. The authors are the ultimate responsible for the consistency of the theoretical references, the accurate report of empirical data, the personal perspectives, and the use of copyrighted material. This content was evaluated using the double-blind peer review process. The disclosure of the reviewers' information on the first page is made only after concluding the evaluation process, and with the voluntary consent of the respective reviewers.

INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, driving substantial changes in business models, organizational capabilities, and decision-making processes (Lago et al., 2026). It is estimated that by 2033, the global AI market will reach USD 4.8 trillion, representing 29% of the global technology sector, with particular emphasis on generative AI solutions (United Nations Conference on Trade and Development [UNCTAD], 2025). Organizations worldwide have increasingly integrated this technology to enhance efficiency, foster innovation, and personalize services across sectors such as healthcare, logistics, finance, and mobility (Liang et al., 2025; McKinsey & Company, 2023; Perez et al., 2024; Silva et al., 2023).

However, AI adoption in emerging economies presents specific challenges related to a shortage of digital skills, underdeveloped technological infrastructure, and cultural resistance to innovation (Academia Brasileira de Ciências [ABC], 2023; Yousaf et al., 2021). For instance, in Brazil, the digital maturity index of companies is only 3.7 on a scale of 0-10, reflecting significant weaknesses in strategic technology integration, workforce training, and data-driven decision-making (Tadeu et al., 2024). These constraints hinder the effective conversion of technological potential into value creation, especially within subsidiaries of large corporations with centralized and rigid corporate structures.

Although the literature increasingly recognizes the strategic role of AI in digital transformation and maturity, three gaps remain insufficiently addressed. First, empirical studies are predominantly concentrated in developed economies, where technological infrastructure, digital skills, and institutional stability are often implicitly assumed. This limits the understanding of how AI adoption unfolds in emerging market contexts, where organizations frequently face capability shortages, infrastructure constraints, and cultural resistance to technological change. Second, much of the existing research tends to frame AI as a broadly scalable accelerator of transformation, offering limited insights into the organizational conditions under which AI contributes to digital maturity. Third, few studies have examined subsidiary- and ecosystem-level dynamics, particularly in contexts where local units must align with global corporate strategies while also coordinating with users, partners, technology providers, and platform-based services (Chen et al., 2025; Dwivedi et al., 2023).

These gaps are particularly relevant for subsidiaries in emerging economies, where AI adoption is shaped by the simultaneous need to align with global corporate strategies and respond to local cultural, technological, and institutional constraints. By focusing on this context, the present study contributes to theory building on digital maturity and AI integration from the perspective of developing economies, offering insights into how contextual limitations reshape strategic capabilities (Akter et al., 2022; Choudrie et al., 2025; Hess et al., 2020; Teece, 2018; Vial, 2019). This study empirically examines a Brazilian subsidiary embedded in a mobility and payment ecosystem. Rather than treating AI adoption as a linear or universally effective driver of digital transformation, this study examines how AI is interpret, structure, and prioritize by managers under emerging market constraints. This study investigates how governance, acculturation, internal capability development, and ecosystem coordination shape the relationship between AI adoption, digital transformation, and digital maturity (Liang et al., 2025; Ma et al., 2025).

This study makes two related contributions to the literature. First, it shows that AI should be understood as a contingent catalyst of digital maturity rather than a universally effective driver of digital transformation (Kane et al., 2017; Teece, 2018; Vial, 2019), since its organizational effects depend on acculturation, governance, and capability recombination within the subsidiary context. Second, it demonstrates the value of an interpretive mixed-methods design in which multi-criteria decision-making (MCDM) techniques (CRITIC and WASPAS) serve an analytical rather than a confirmatory role, helping to organize managerial perceptions of trade-offs, priorities, and strategic alternatives (Miyashita & Pinochet, 2025, 2026) without implying causal validation or generalizable inference. Based on this perspective, this study addresses the following research question: How does the adoption of artificial intelligence influence digital transformation and digital maturity pathways in a subsidiary located in an emerging economy, given its cultural, organizational, and institutional specificities?

By answering this question, this study contributes to a more nuanced and contextually grounded understanding of AI-enabled transformation, offering theoretical refinement and analytically bounded insights relevant to scholars and practitioners concerned with digital transformation in complex organizational environments.

THEORETICAL BACKGROUND

Digital transformation and digital maturity: Concepts and implications

Digital transformation is a profound organizational shift that involves the strategic integration of digital technologies into business models, products, services, and processes (Choudrie et al., 2025; Lago et al., 2026;

Täuscher & Laudien, 2018). It goes beyond digitizing tasks and emphasizes innovation, agility, and value creation (Bonnet & Westerman, 2020; Keding, 2021; Vial, 2019). This shift helps organizations adapt to changing competitive, regulatory, and social contexts (Haefner et al., 2021), but success depends on aligning technological, organizational, human, and cultural factors (Akter et al., 2022; Carvalho et al., 2021). It also requires new leadership approaches, stakeholder engagement, and dynamic capabilities (Teece, 2018).

In Brazil, organizational culture and a lack of digital competence are key barriers. Approximately 97.5% of companies struggle with team analytical skills despite recognizing the role of digital transformation in competitiveness and innovation (Tadeu et al., 2024). Digital maturity, an organization's readiness to adopt digital technologies, requires integration with strategies and culture (Kane et al., 2017). Digitally mature firms adopt tools and foster learning and experimentation (Westerman et al., 2014). This maturity supports innovation through data-driven decisions and interdepartmental integration (Jie et al., 2025), leading to efficiency, customer personalization, and agility. Achieving this requires investment in people, structural changes, and updated governance.

Mobility ecosystems and the CalmMobility paradigm

Mobility ecosystems are increasingly shaped by the convergence of digital platforms, payment infrastructure, data-driven services, and user-centered mobility solutions. In this context, mobility is not limited to physical displacement but also involves access to services, social and economic inclusion, environmental responsibility, and the orchestration of multiple actors, such as platform providers, customers, technology partners, service operators, public institutions, and complementary organizations. This view is consistent with the understanding of mobility as a socio-technical system in which infrastructure, behavior, governance, and lived experience intersect (Turoń, 2025). Thus, digital transformation in mobility ecosystems depends not only on internal organizational capabilities but also on the coordination of data, services, infrastructure, and interactions across organizational boundaries (Akter et al., 2022; Teece, 2018; Vial, 2019).

Recent debates on sustainable urban mobility have introduced the CalmMobility paradigm as a response to fragmented, accelerated, and poorly sequenced mobility transition. According to Turoń (2025), although sustainable mobility approaches are often normatively justified, their implementation may become fragmented when they lack sequencing, citizen participation, social embedding, and long-term coordination. CalmMobility therefore proposes a more comprehensive, paced, inclusive, and future-ready approach, emphasizing resilient, citizen-centered, socially grounded, and innovation-oriented mobility transition. This perspective aligns with debates on Mobility Justice, the Avoid–shift–improve framework, Sustainable Urban Mobility Plans, Mobility as a Service, shared mobility, and smart city initiatives (Pagoni et al., 2026; Turoń, 2025).

The CalmMobility paradigm is relevant to platform-based mobility and payment ecosystems because these contexts depend on integrating services, actors, and technological layers. Service architectures such as Mobility as a Service, shared mobility, electromobility, and charging infrastructure operate as mechanisms for connecting modes, users, data, payment systems, operators, and service providers (Pagoni et al., 2026; Turoń, 2025). Similarly, in the organizational context analyzed in this study, AI adoption is not restricted to internal process automation; it is also associated with customer service, personalization, operational efficiency, strategic alignment, and the expansion of mobility and payment ecosystems. This interpretation is consistent with digital transformation research that understands technological adoption as a process of business model adaptation, capability recombination and value creation (Chen et al., 2025; Dwivedi et al., 2023; Kane et al., 2017; Teece, 2018; Vial, 2019).

In this study, CalmMobility was not used as a direct measure of urban mobility outcomes but as an interpretive lens to discuss how AI-enabled services may reduce informational, operational, and relational frictions in a mobility and payment ecosystem. By improving customer service, personalization, operational responsiveness, data-based decision-making, and platform integration, AI adoption may support more predictable, coordinated, and user-centered mobility experiences for users. However, these insights remain bound to the studied organization and should not be interpreted as evidence of broader urban mobility transformation. Instead, CalmMobility helps position the findings within debates on mobility transitions, demand management, human-centered mobility systems, and the alignment between technological innovation, governance, social acceptance, and ecosystem coordination (Hess et al., 2020; Ma et al., 2025; Turoń, 2025).

Formulation of research propositions

In the qualitative phase, the research propositions were designed to deepen the understanding of AI adoption and its effects on digital transformation and digital maturity within companies in the mobility and payment sector. In the quantitative phase, these propositions were framed as expected outcome indicators based on the literature on the relationships among the studied variables, with analytical structuring using multi-criteria decision-making techniques. The overarching proposition is that local challenges in subsidiaries from emerging countries drive AI adoption, helping to position such units as benchmarks for both headquarters and affiliates. To address the research question, all propositions stemmed from the literature review and reflected the subsidiary's specific context.

AI Adoption and changes resulting from digital transformation and digital maturity

Digital Transformation represents an ongoing process of organizational adaptation to market changes, requiring the restructuring of business models, resources, and internal capabilities (Carvalho et al., 2021; Lago et al., 2026; Täuscher & Laudien, 2018). In a dynamic and competitive global landscape, companies seek greater operational efficiency and enhanced customer experience as key pathways to value creation (Haefner et al., 2021; Liang et al., 2025; Vial, 2019). However, low levels of digital maturity still limit the ability to leverage the full potential of emerging technologies, such as Artificial Intelligence (Tadeu et al., 2024).

The literature suggests that incorporating AI into organizational processes can expand capabilities, promote innovation, and increase customer satisfaction, provided it is integrated into a broader digital transformation strategy (Chen et al., 2025; Jie et al., 2025).

> Proposition P1: The adoption of artificial intelligence solutions is positively associated with increased customer satisfaction, which is one of the core objectives of digital transformation and maturity.

AI adoption and challenges in digital transformation and digital maturity

Digital transformation often encounters cultural barriers within organizations as its main obstacle, especially when there is resistance to change and difficulty in accepting new technologies (Tadeu et al., 2024). Users' perceptions of AI benefits and complexity can hinder its adoption, directly impacting employees' intention to use it and their behavior. Overcoming such resistance requires a shift in organizational patterns and an adaptive response from leadership and staff to advance digital maturity (Kane et al., 2017).

> Proposition P2: The existence of cultural barriers slows the implementation of AI and requires specific adaptive strategies to ensure effectiveness.

AI Adoption and competencies for digital transformation and digital maturity

The shortage of professionals with digital skills is one of the main obstacles to digital transformation in Brazilian organizations (Tadeu et al., 2024). The development of specific competencies, especially in data analysis and the use of AI, is essential for companies to successfully integrate these technologies into their processes and foster innovation (Akter et al., 2022). The absence of such capabilities limits organizational performance and constrains the advancement of digital maturity (Jie et al., 2025), making investment in training and change management increasingly urgent and necessary.

> Proposition P3: Effective AI adoption requires the continuous development of digital competencies, training, and change management to ensure innovation and operational efficiency.

AI adoption and perceptions of digital transformation and digital maturity

Digital transformation involves simultaneous responses to social, market, and macroeconomic demands, requiring the integration of technology, governance, leadership, culture, and business models (Carvalho et al., 2021; Haefner et al., 2021; Lago et al., 2026; Täuscher & Laudien, 2018; Vial, 2019). Digital maturity reflects the degree of organizational readiness to use technologies strategically, encompassing people, processes, and technologies aligned with the needs of customers and stakeholders (Chen et al., 2025; Jie et al., 2025). In this context, structural and operational changes are essential for capturing value and sustaining competitive advantage (Vial, 2019). The following propositions should be interpreted as analytical lenses grounded in managerial sensemaking within the studied context rather than as causal or generalizable claims.

> Proposition P4: In the analyzed organizational context, managers interpret changes in the operational model associated with digital transformation and AI adoption as relevant conditions that shape perceived competitiveness and organizational sustainability.

AI adoption and strategies for digital transformation and digital maturity

The effective implementation of Artificial Intelligence requires organizational strategies aligned with business objectives, focusing on the continuous development of teams and the technological integration of existing processes. In emerging countries such as Brazil, subsidiaries face specific challenges related to deficient infrastructure, a shortage of qualified professionals, and cultural resistance to innovation (Ma et al., 2025; Tadeu et al., 2024; Yousaf et al., 2021).

In this scenario, the literature suggests that hybrid approaches that combine internal development with specialized outsourcing may be more effective. Additionally, strategies that prioritize the development of internal capabilities and the mitigation of organizational risks are essential for enabling sustainable AI adoption (Hess et al., 2020; Yousaf et al., 2021).

> Proposition P5: Within the studied subsidiary, managers perceive hybrid AI adoption strategies combined with internal capability development as viable pathways for addressing organizational risks and supporting digital transformation under emerging market constraints.

METHODOLOGY

This study adopts a qualitative-dominant mixed-methods approach, centered on a single case study of a company in the mobility and digital payments sector. It combines semi-structured interviews with multi-criteria decision support methods, CRITIC and WASPAS (Pinochet et al., 2025), to explore both subjective perceptions and technical factors that influence AI adoption in complex organizational settings.

The qualitative focus is justified by the need to understand managerial interpretations of AI adoption and digital transformation, particularly in subsidiaries in emerging markets (Dwivedi et al., 2023; Langley, 1999). The quantitative phase complements the qualitative findings by structuring the prioritization of strategies through multi-criteria analysis, which aligns with the pragmatic research paradigm (Creswell & Plano Clark, 2018). This approach helps reveal how managers in a Brazilian subsidiary perceive and navigate AI-related challenges, which are shaped by cultural, structural, and institutional contexts.

The exploratory and descriptive research design selected the company because of its strategic role and innovative trajectory in a market with limited digital skills and infrastructure (ABC, 2023; Tadeu et al., 2024). By integrating interviews, content analysis, and multi-criteria tools, this study identifies and ranks key strategies for AI adoption. Triangulation with the literature and model outputs strengthens the validity of the findings and reveals the barriers, competencies, and strategic alternatives relevant to digital transformation (Akter et al., 2022; Yousaf et al., 2021).

Epistemological positioning of the mixed-methods design

This study is grounded in an interpretivist epistemological stance, seeking to understand how organizational actors construct meanings, priorities, and strategic interpretations regarding the adoption of artificial intelligence within a specific institutional and organizational context. From this perspective, digital transformation and digital maturity are not treated as objective states or linear outcomes but as socially constructed and context-dependent processes shaped by managerial sensemaking, organizational culture, and governance arrangements.

Consistent with this interpretivist orientation, this study follows an abductive logic of inquiry in which empirical observations and theoretical constructs iteratively inform one another. Rather than testing predefined causal hypotheses, this study aims to refine and extend existing theoretical frameworks by identifying the plausible mechanisms through which AI interacts with digital transformation trajectories in subsidiaries located in emerging economies. This abductive approach allows for theoretical sensitivity to unexpected patterns and contextual specificities that would be obscured under a strictly deductive or positivist design.

Within this epistemological framework, the quantitative component of the research does not serve a confirmatory or validation function. The quantitative component does not aim to produce objectified or causal evidence but to structure and contrast managerial interpretations. Specifically, multi-criteria decision-making (MCDM) methods, CRITIC for weight generation and WASPAS for ordering strategic alternatives, were used as analytical devices to organize perceived trade-offs, relative salience, and internal coherence among decision criteria (Triantaphyllou, 2000).

Accordingly, the numerical output generated by MCDM procedures should be interpreted as context-specific representations of comparative salience and preference rather than as statistically robust estimators or generalizable measures of effect. Given the exploratory nature of this study and the limited number of respondents, the analysis explicitly refrains from statistical inference. Instead, the value of quantitative analysis lies in its capacity to enhance analytical transparency, reduce arbitrary weighting, and support systematic comparison of strategic alternatives within the interpretive framework established by the qualitative findings.

By integrating qualitative interpretation with quantitative structuring, the mixed-methods design employed in this study supports a complementary analytical logic in which qualitative insights provide depth and meaning, whereas quantitative tools offer structure and comparability. This integration strengthens the internal coherence of the analysis without collapsing interpretive richness into numerical abstraction, ensuring epistemological alignment between the research question, methodological choices, and nature of the empirical evidence.

Data collection

Data were collected through semi-structured interviews organized into four thematic blocks and a multi-criteria questionnaire. Nine executives from the company operating in the mobility and digital payments ecosystem participated in the interviews, including specialists, coordinators, managers, directors, vice presidents, and the president of the B2C division.

Data collection took place between March and April 2025, primarily in person, with the exception of one interview conducted virtually via Microsoft Teams because of the geographical location of one participant. The interviews lasted an average of 20 minutes and were recorded with prior consent from the respondents in accordance with established ethical guidelines. All interviews were fully transcribed to ensure the accuracy of the information collected.

Participants were selected through purposive sampling based on their direct involvement in the company's digital transformation and AI adoption processes. The sample included nine senior-level professionals, ranging from specialists to the president of the B2C unit. These diverse roles made it possible to capture multiple perspectives on the studied phenomenon, strengthening the reliability of the findings and enabling data triangulation.

To complement the qualitative stage, an electronic questionnaire was administered based on multi-criteria decision-making methods (CRITIC and WASPAS). After the interviews were conducted, participants received a Google Forms link to rate, on a scale from 1 (least important) to 7 (most salient within this context), five strategic alternatives for AI adoption, which were evaluated according to seven predefined criteria. The instrument could be completed either synchronously with the researcher's support or asynchronously, depending on each manager's availability.

This quantitative approach aimed to systematize managers' perceptions of strategic priorities, allowing for cross-analysis with qualitative data and deepening the practical understanding of the findings. The triangulation of interviews, multi-criteria questionnaire, and literature contributed to strengthening the analytical consistency of the findings, as suggested by Langley and Abdallah (2011).

Methodological triangulation was inspired by Langley and Abdallah's (2011) proposal and integrated three distinct data sources: semi-structured interviews, specialized literature, and the application of CRITIC and WASPAS. This triangulation enabled a more robust and multifaceted analysis of the investigated phenomena, particularly when comparing participants' perceptions with the results obtained through mathematical modeling and preexisting theoretical propositions. Thus, this study enhances the consistency of data interpretation by examining strategic decisions related to artificial intelligence adoption through different analytical lenses.

The inclusion of the CRITIC and WASPAS methods in the methodological design is justified by the need to enhance analytical transparency in structuring decision criteria related to organizational decision-making on artificial intelligence adoption.

The data collection plan also included a set of specific research strategies, organized into five stages:

(1a) identification of the main AI solutions used in the company.

(1b) interviews regarding the contributions of AI to decision-making and customer satisfaction.

(2) Investigation of practices to overcome cultural and technological barriers.

(3) Analysis of initiatives aimed at developing digital competencies.

(4) Collection of perceptions regarding the results of digital transformation and AI adoption.

(5) Application of a multi-criteria questionnaire to prioritize organizational strategies.

Before conducting the interviews, rigorous ethical procedures were followed: the participants were informed about the research objectives, the expected duration of the interview, and the need for recording. Formal authorization was obtained through informed consent, ensuring transparency and respect for participants' integrity.

Conducting qualitative data analysis

Qualitative data were analyzed using inductive content analysis to uncover patterns, meanings, and emerging categories from the managers' narratives on digital transformation and AI adoption. This immersive approach deepens the understanding of the challenges, strategies, and impacts of implementing AI in an organizational context.

The analysis involved iterative steps: reading the transcripts, identifying significant excerpts, and coding the content. Codes, descriptions, and categories were developed to extract meaning from the participants' responses (Miles et al., 2014). Although the interview guide followed thematic blocks, the analysis remained flexible to new themes, thereby expanding the study's depth of interpretation. Table 1 summarizes the operationalization of the criteria in this study.

Table 1. Analysis criteria.

Criteria	Procedures	Research phase
Credibility	Semi-structured interviews, giving voice to participants Transcription Triangulation of interview data and multi-criteria questionnaire	Data collection Data analysis
Transferability	Detailed description of the organizational context allows analysis of potential application in other organizational environments	Case presentation
Dependability	Systematic recording of all stages of the study Case study protocol during data collection Semi-structured interview guide	Data collection
Confirmability	Triangulation multi-criteria method to complement qualitative analysis	Data analysis

Note. Developed by the authors.

The construction of analytical categories in the qualitative stage adopted a hybrid coding approach. Some codes were established a priori based on theoretical assumptions extracted from the literature and operationalized as criteria in the multi-criteria matrix (such as criteria C5 and C6). However, the process also revealed the post-priori emergence of categories directly derived from the interviewees' statements, such as codes related to operational efficiency, AI acculturation and strategic perception. This mixed strategy increases the sensitivity of the analysis, allowing us to capture both the structuring concepts of the field and the empirical contextual particularities.

Quantitative data analysis

Complementing the qualitative analysis, the study employed quantitative decision-support techniques through the Multi-Criteria Decision-Making (MCDM) approach using the CRITIC and WASPAS methods. This approach enabled the evaluation and ranking of AI adoption strategies based on the criteria derived from the categorization of the interview data. The objective was to systematically structure managers' perceptions of the most relevant strategic alternatives. The criteria represent the factors guiding the decision-making process, whereas the alternatives are independent strategies evaluated using quantitative attributes on a scale from 1 to 7. The choice of multi-criteria methods is justified by the complexity of the decision context, where multiple criteria may conflict and no clearly optimal solution exists. This technique, commonly used in Operations Research, supports the systematic structuring of strategic alternatives in complex decision contexts (Pinochet et al., 2023; Pinochet et al., 2025). The analysis resulted in a comparative ordering of alternatives based on the evaluative structure derived from the participants' responses rather than a simple classification. This ranking facilitated the comparison of strategies and supported a practical understanding of managerial preferences regarding AI adoption and its impact on a company's digital transformation and maturity.

The use of Likert-type scales in multi-criteria instruments is acknowledged as an analytical approximation rather than a representation of interval or ratio-level measurement. While the numerical transformation of ordinal responses enables the operationalization of the CRITIC and WASPAS procedures, the resulting calculations should be understood as heuristic and exploratory devices. In this sense, correlation estimates and weight derivations are not treated as stable statistical parameters, but as analytical aids that support the structured comparison of perceived priorities under bounded empirical conditions (Triantaphyllou, 2000).

Decision alternatives and criteria

The alternatives (Table 2) represent different strategies that an organization can adopt to implement Artificial Intelligence (AI) in its processes, varying in terms of scope, effort, investment, and organizational impact (Thakkar, 2021). Each alternative proposes a specific way to integrate technology, considering the available resources and the company's level of digital maturity. The criteria (Table 3) are the parameters used to evaluate and compare these alternatives, enabling the analysis of their relevance in relation to the study's objectives. They provide the analytical foundation necessary for a structured comparison, allowing the evaluation of strategic alternatives in light of how AI adoption relates to digital transformation and digital maturity in the studied context.

Table 2. Definitions of the alternatives used in the multi-criteria method.

Alternatives	Description of the alternatives	Authors
Full implementation (A1)	The comprehensive adoption of AI applies technology across all business processes. It is recommended for organizations with high digital maturity and solid infrastructure to use it. It has a significant impact but requires high investment, complex integration, and strong internal training.	Reim et al. (2020); Ellefsen et al. (2019); Nortje and Grobbelaar (2020)
Partial implementation (A2)	Phased adoption applies AI in specific areas, such as customer service and administrative automation. It is suitable for companies that are beginning their digital transformation. It reduces risks, but limits outcomes and hinders technology scaling.	Reim et al. (2020); Ellefsen et al. (2019); Nortje and Grobbelaar (2020)
Acquisition of ready-made solutions and/or outsourcing (A3)	Outsourcing involves hiring external providers to develop and manage the AI. This is useful for companies with limited internal resources. It facilitates implementation, reduces costs in the short term, and increases dependency risks and communication failures.	Aitzaz et al. (2016); Van Mieghem (1999)
Internal development of solutions (A4)	In-house development gives companies full control over AI. It requires qualified staff, investments, and ongoing dedication. It offers greater data protection but may involve slower delivery and lower scalability than public clouds.	Aitzaz et al. (2016)
Hybrid development of solutions (A5)	The hybrid approach combines external providers and internal teams. This allows for flexibility and customization of solutions. This is ideal for companies that value adaptive customization but requires complex coordination and incurs additional costs.	Sarvari et al. (2018)

Note. Developed by the authors.

Table 3. Definitions of the criteria used in the research.

Criteria	Description of the criteria	Authors
Implementation cost (C1)	Refers to the total cost of adopting AI, including licenses, equipment, and losses during adaptation. It is useful for comparing internal, outsourced, or hybrid solutions.	Gurjar et al. (2024); McKinsey & Company (2023); Westerman et al. (2014)
Implementation time (C2)	Time required to implement AI in company processes. It involves data updates, training, and systemic adjustments. The more data involved, the longer the implementation process.	Westerman et al. (2014)
Operational efficiency (C3)	Represents the potential for reducing operational costs. AI automates tasks, reduces errors, and increases productivity by making processes more efficient.	Tadeu et al. (2024); Vial (2019); Westerman et al. (2014)
Technological complexity (C4)	It measures the difficulty of integrating AI into existing systems. It requires technical compatibility and a robust infrastructure to ensure functionality.	Barton et al. (2022); Gurjar et al. (2024)
Internal Capabilities and Capacity Building (C5)	This criterion refers to an organization's ability to develop, integrate, and reconfigure the internal skills, knowledge, and technological competencies required for the effective adoption and scaling of artificial intelligence. It encompasses employee training, learning processes, cross-functional collaboration, and the accumulation of AI-related expertise that supports sustainable digital transformation.	Vial (2019); Kane et al. (2017)
Organizational risks (C6)	This reflects cultural barriers, privacy risks, management failures, and resistance to change. It involves challenges related to security, communication, and planning.	Gurjar et al. (2024); Mehr et al. (2017)
Strategic alignment (C7)	This indicates how well the AI solution aligns with the company's strategic objectives. It considers improved customer experience and enhanced competitiveness.	Albino et al. (2023); Chen et al. (2025); Westerman et al. (2014)

Note. Developed by the authors.

CRITIC method analysis

The Criteria Importance Through Inter-criteria Correlation (CRITIC) method is an objective approach for assigning weights to criteria in a decision matrix while minimizing direct subjective biases (Diakoulaki et al., 1995). However, in the CRITIC procedure, criterion weights should not be interpreted as representing intrinsic managerial importance. Rather, they express the relative informational contribution of each criterion within the decision matrix based on its variability and degree of non-redundancy in relation to the remaining criteria. In this sense, criteria that receive higher CRITIC weights are those that simultaneously display greater contrast across alternatives and lower overlap with other criteria, thereby contributing more information to the decision structure. Accordingly, the CRITIC method was used here as a data-structured weighting procedure that enhances analytical transparency, rather than as a direct measure of substantive priority.

The method provides a structured basis for weighting through four steps: (1) normalization of the decision matrix; (2) calculation of correlation coefficients; (3) computation of the CRITIC index (C), which combines each criterion's standard deviation and inter-criterion correlation; and (4) determination of weights reflecting the comparative informational contribution of each criterion in the matrix.

Step 1 involves constructing a matrix in which the rows represent the alternatives and the columns represent the criteria, with each cell indicating the performance value of an alternative on a criterion.

Step 2 normalizes the matrix using linear min-max scaling to ensure that the values are comparable and dimensionless. This procedure considers both the benefit criteria (higher values are preferable) and cost criteria (lower values are preferable).

For the benefit criteria (Equation 1):

$$x_{ij}^* = \frac{x_{ij} - min\,(x_{ij})}{max(x_{ij}) - min\,(x_{ij})}, i = 1, 2, \dots, m\ e\ j = 1, 2, \dots, n \quad (1)$$

For the cost criteria (Equation 2):

$$x_{ij}^* = \frac{max(x_{ij}) - x_{ij}}{max(x_{ij}) - min\,(x_{ij})}, i = 1, 2, \dots, m\ e\ j = 1, 2, \dots, n \quad (2)$$

After normalization, all values lie within the interval [0,1]. The higher the normalized value, the better the alternative's performance with respect to that criterion.

Step 3. To determine the criteria weights, the standard deviation of each criterion and its correlation with the other criteria were considered. In this sense, the weight of the *k*-th criterion (w_j) is obtained as (Equation 3):

$$w_j = \frac{c_j}{\sum_{k=1}^{n} c_k} \quad (3)$$

where c_j is the amount of information contained in the kth criteria, determined as (Equation 4):

$$c_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \quad (4)$$

where σ_j is the standard deviation of the kth criteria and ρ_{jk} is the correlation coefficient between the two criteria. Accordingly, the method assigns greater weight to criteria that display high dispersion and low correlation with the remaining criteria (Diakoulaki et al., 1995; Pinochet et al., 2024). Thus, a higher value of c_j indicates that the criterion contributes comparatively more discriminative and less redundant information to the decision matrix. Therefore, the resulting weights should be interpreted as indicating the comparative informational contribution of each criterion in the matrix, rather than its intrinsic or universal importance. Criteria with higher CRITIC weights simultaneously provide greater discriminative power across alternatives and less redundant information than the remaining criteria. In this sense, the CRITIC procedure supports a more transparent weighting structure derived from internal data properties.

Therefore, higher values of the index (*c*) indicate greater comparative informational contribution of criterion *j* within the decision matrix, meaning that the criterion contributes more discriminative and less redundant information to the evaluation structure (Diakoulaki et al., 1995; Pinochet et al., 2024).

WASPAS method analysis

The weighted aggregated sum product assessment (WASPAS) method merges the Weighted Sum Model (WSM) and Weighted Product Model (WPM) to evaluate and rank alternatives based on quantitative attributes (Thakkar, 2021). Its strength lies in the combination of additive (WSM) and multiplicative (WPM) models, which enhances the accuracy (Pinochet et al., 2024). The WSM is simple and widely applied, whereas the WPM is more suitable for criteria modeled using ratios.

Step 1 involves constructing a decision matrix and defining the criteria weights.

Step 2 normalizes the matrix using linear Min–Max scaling, applying specific formulas for benefit and cost criteria, as done in CRITIC. The benefit and cost criteria require different normalization procedures (Equation 5), as follows:

$$\bar{x}_{ij} = \frac{x_{ij}}{max_i(x_{ij})}, \quad (5)$$

where $\bar{x}_{ij}$: is the normalized value for a specific tuple (alternative, criterion); x_{ij} is the original value to be normalized; $max_i(x_{ij})$ is the maximum value in the set of values for a specific benefit monotonic criterion for all alternatives. For the cost monotonic criteria, we normalized the vector of performance values obtained for the specific criterion by dividing the minimum value within this set by each of the values obtained for the criterion. In this case, to normalize the performance values of alternatives with respect to the criterion, a function applied to the vector of values x_{ij} of the j-th criterion, which divides the minimum value of the criterion's value vector by the value of the i-th alternative. If $max_i(x_{ij})$ values are preferable (Equation 5) or if $min_i(x_{ij})$ value is preferable (Equation 6).

$$\bar{x}_{ij} = \frac{min_i(x_{ij})}{x_{ij}}, \quad (6)$$

Step 3. The performance of the alternative is calculated based on the WSM by summing the weighted normalized values of the alternative for all criteria (Equation 7).

$$Q_i^{(1)} = \sum_{j=1}^{n} w_j \cdot \bar{x}_{ij} \quad (7)$$

Step 4. The performance of the alternative based on the WPM is calculated using the product of the alternative's normalized values raised to their respective weights across all criteria (Equation 8).

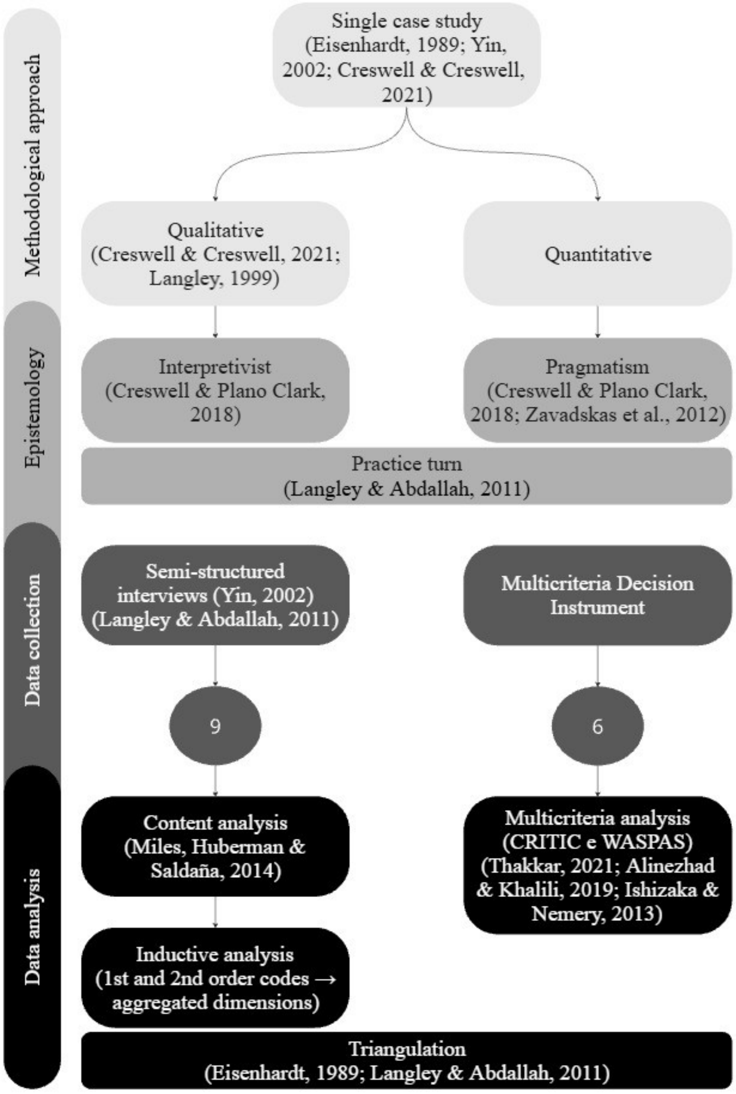
$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \quad (8)$$

Step 5. The combined WASPAS index Q_i was calculated using a lambda coefficient (Equation 9), which varies within the interval [0,1]. $\lambda \in [0,1]$ is the balancing coefficient (typically, λ=0.5 is used to assign equal weights to the WSM and WPM).

$$Q_i = \lambda \cdot Q_i^{(1)} + (1 - \lambda) \cdot Q_i^{(2)} \quad (9)$$

The lambda coefficient balances the contributions of the WSM and WPM in the result: if λ=1, WASPAS reduces to WSM; if λ=0, WASPAS reduces to WPM.

Step 6. Ranking of Alternatives, in which the alternative with the highest perceived salience Q_i value is considered the best, the second highest is the second best, and so on. The final ranking obtained by WASPAS represents the order of preference among the alternatives based on a balanced combination (defined by λ) of the WSM and WPM. In summary, the use of the λ factor enables a sensitivity analysis of the ranking of alternatives—not only by testing the extent to which the different models (WSM or WPM) influence the outcome, thereby ensuring greater robustness in decision-making, but also by assessing the accuracy in the face of potential errors or uncertainties in the initial data. The general framework representing the methodology applied in this study is shown in Figure 1.

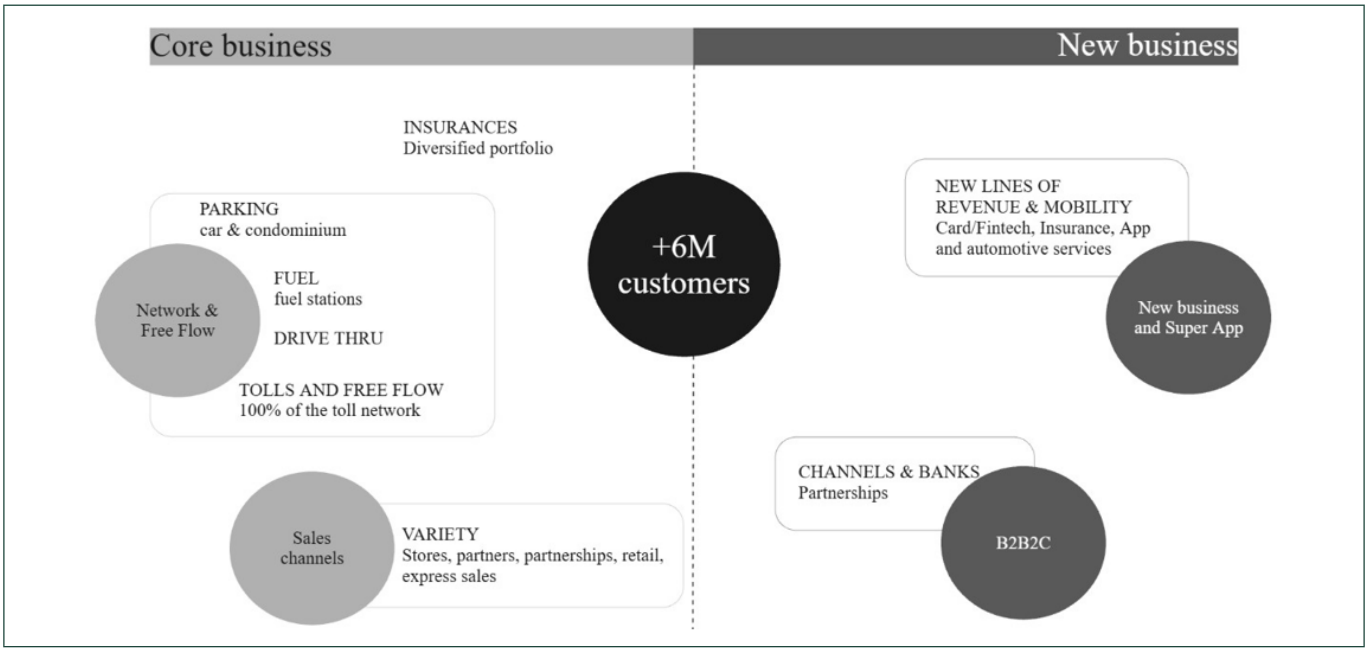


Source: Developed by the authors.

Figure 1. Graphical Representation of the Applied Methodology.

Case presentation

A pioneering company in tag-based automatic payments in Brazil, it has served over 6 million customers and operates more than 7 million active tags in Brazil. Since 2000, it has expanded from toll booth automation to services at parking lots, gas stations, drive-thrus, and car washes, among others. It also offers vehicle-related services, including tax payments and other assistance. In 2023, it adopted the Free Flow toll system, and by 2024, it positioned itself as a mobility ecosystem through a SuperApp with over 30 features. Operating in approximately 6,400 accredited locations, the company was acquired in 2024 by a U.S. payment firm and expanded by acquiring Zapay, which manages vehicle debts. It also created a corporate division that offers integrated vehicle and employee benefit solutions. With over 3,000 employees, it is recognized for its customer service and is guided by pillars such as trust, reach, innovation, and efficiency. Figure 2 presents the mobility ecosystem of the company.



Source: Developed by the authors.

Figure 2. Mobility ecosystem.

RESULTS AND DISCUSSION

Qualitative analysis

The objective of the qualitative analysis was to understand the impact of Artificial Intelligence (AI) adoption on a company's digital transformation process and the advancement of its digital maturity. The interviews, which were recorded and transcribed, were analyzed using content analysis techniques, as proposed by Miles et al. (2014), with successive coding cycles. Initially, 181 first-order codes were identified through reading nine transcripts and were organized in a spreadsheet based on Eisenhardt's (2021) structure. Then, axial coding was applied, resulting in 16 second-order codes grouped into five aggregate dimensions: (1) the impact of AI on customer experience; (2) organizational and technological challenges; (3) development of digital competencies; (4) perceptions of AI's potential and limitations; and (5) AI as a driver of digital maturity.

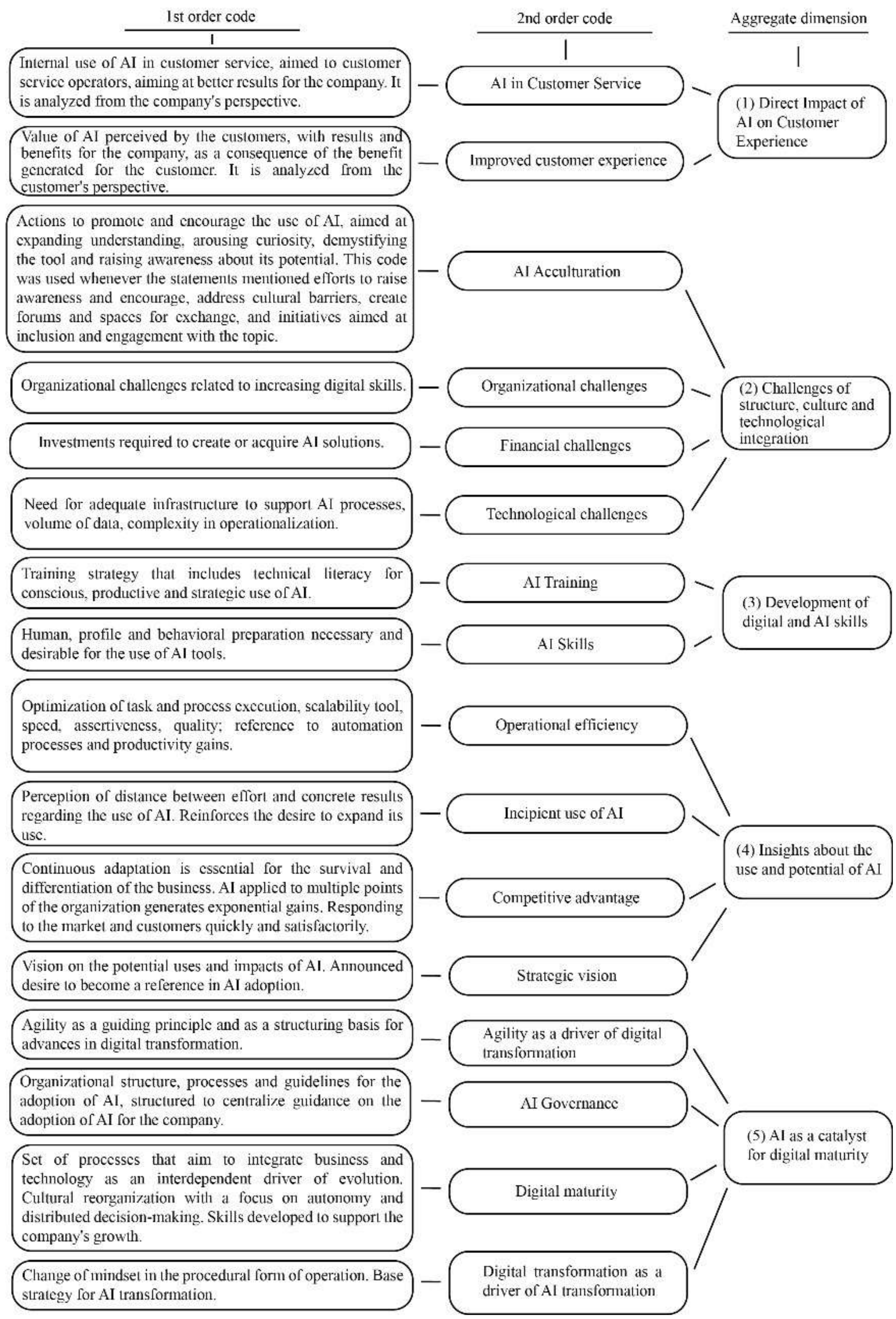
The results suggest that AI is strategically use by the company to promote operational, structural, and cultural changes. The distribution of the codes revealed a higher concentration in the dimensions related to perceptions of AI and the development of competencies (Table 4 and Figure 3).

Table 4. Count of second-order codes by aggregated dimension.

Row labels	(1) Direct impact of AI on customer experience	(2) Challenges of structure, culture, and technological integration	(3) Development of digital and AI-related competencies	(4) Perceptions about AI use and potential	(5) AI as a catalyst for digital maturity	Overall Total
AI acculturation		21				21
Agility as a driver of digital transformation					7	7
AI training			14			14
Financial challenges		4				4
Organizational challenges		1				1
Technological challenges		8				8
Operational efficiency				19		19
AI governance					14	14
AI skills			8			8
AI in customer service	14					14
Digital maturity					12	12
Improvement in customer experience	23					23
Digital transformation as a driver for AI transformation					2	2
Incipient use of AI				12		12
Competitive advantage				12		12
Strategic vision				10		10
Total	37	34	22	53	35	181

Note. Developed by the authors.

Table 4 presents the distribution of the codes across the main analytical dimensions. The analysis revealed a higher frequency of references associated with digital governance and organizational capabilities, followed by innovation and cultural alignment. Code frequency is reported as an indicator of thematic salience within the empirical material rather than as a direct proxy for importance or causal relevance.



Source: Developed by the authors.

Figure 3. Coding Tree.

The following section presents the main findings organized by aggregated dimensions, providing a structured overview of the emerging themes identified through interview analysis. This approach facilitates an understanding of the relationships between the impact of AI and the digital transformation processes observed within the company.

Direct impact of AI on customer experience

AI's impact of AI on customer experience was the most tangible effect identified by the company's leadership (P1), with 23 codifications. The adoption of AI has enhanced agility, accuracy, and personalization in user interactions. Key applications include generative AI chatbots and operational copililots that improve response time and clarity. E2 noted that the tool analyzes customer data to identify the main issues, reflecting increased customer intelligence (Gallouj & Windrum, 2009).

These tools reduce friction by offering contextualized responses and anticipating needs, thereby reinforcing the customer experience as a strategic priority (Dwivedi et al., 2023). Even in the pilot stages, AI features such as intelligent search and FAQs within the Super App show promise. As E9 mentioned, We have been studying AI to simplify the customer's journey.

AI is evolving from a task processor to a relationship enabler, aligned with the idea of user-centered decision-making (Balakrishnan & Dwivedi, 2024). Hyper-personalization based on user behavior has become a key differentiator. As E9 emphasized, We can truly be more assertive. E8 added: The app is being developed for personalized versions, while E7 highlighted AI's role in boosting service efficiency (Liang et al., 2025). Thus, AI emerges as a strategic pillar aimed at transforming customer relationships.

Challenges of structure, culture, and technological integration

The study shows that digital transformation barriers require coordinated strategies to maintain competitiveness (P2). While AI adoption is expanding and considered strategic, significant technological, organizational, and cultural challenges remain (Kane et al., 2017; Tadeu et al., 2024).

The lack of a consolidated data architecture hinders AI scalability (ABC, 2023). Participant E2 noted that there was a barrier in data structuring, with Participants E5 and E3 citing weak infrastructure and data volume issues. Financial constraints were mentioned less frequently but remained relevant (E1).

Culturally, digital acculturation is considered key to success, yet challenges persist. E7 stated, Our challenge is to create an environment where people understand the benefits, while E2 pointed to the gap between interest and application, stating, People want to join but do not know how.

Interviewees also described mixed attitudes, ranging from fear and mistrust to unrealistic expectations. As E8 observed, People go through insecurity, while E2 added, Some think it can do everything.

In response, the company is working to overcome these barriers and develop a scalable and sustainable foundation for strategic AI implementation.

Development of digital and AI competencies

The interviews highlighted that ongoing training and adaptation are crucial for sustaining innovation and efficiency (P3). AI expansion is linked to building digital competencies and literacy, reinforcing dynamic capabilities as competitive advantages (Hess et al., 2020; Vial, 2019).

Technological transformation relies on human development through governance, acculturation, and education. As E5 emphasized, Teach, teach, teach. Structured initiatives include training programs, learning communities, and practical activities. E7 noted, We invested heavily at first in training, and E6 added, They focused on certifications and preparation.

Leadership plays a key role in fostering this culture, with training programs from middle to top management (E9) promoting engagement and continuous learning (Bonnet & Westerman, 2020). A critical skill is discerning when AI is necessary and when simpler automation is sufficient. E3 stated, The main capability is seeing what really requires AI, and E5 added, AI needs people who know the problem.

Skills such as exploration and questioning are also vital. For example, E9 said, In AI, it is essential to know how to ask, and E8 said, It is about being curious. Overall, digital competency development is part of a broader strategy for preparing employees for complex, innovation-driven environments.

Perceptions on the use and potential of AI

The interviews showed that digital transformation and operational restructuring are viewed as vital for market survival and growth (P4). Leaders express a desire to become a sector benchmark, as E1 stated, We want to be a company that uses this technology differently.

While AI's potential is recognized, it remains in the early stages, requiring further testing and integration, as E4 and E6 noted. It is not seen as a magical solution, but as part of a broader ecosystem involving data quality, integration, innovation culture, and capability building, aligned with Tadeu et al. (2024).

This strategy aims to anticipate market trends and generate value, including revenue impact. As E9 stated: "*How can I use this to leverage myself, to sell better?*" AI use is expanding beyond customer service into marketing and product development, thereby enhancing user-centered transformation. E9 highlighted its cross-functional applicability, and E4 and E8 mentioned the gains in content creation and product impact.

AI is viewed as a strategic shift AI is treated as a value-creation driver. As E6 said, It's a paradigm shift, and E3 called it the next acceleration. The organization is building a smart digital ecosystem with a defined strategy and growing internal recognition of AI's potential and limits.

AI as a catalyst for digital maturity

The challenge of digital transformation transcends technological adoption and involves governance and organizational maturity (Tadeu et al., 2024). The data indicate that AI appears to have contributed to the perceived acceleration of the organization's digital maturity (P5), as expressed by E8: Artificial intelligence comes in as a partner to evolve digital maturity. This evolution results from the integration of AI into internal and external value flows, reflecting a strategic rather than a merely technical movement.

The statement by E1, You choose whether to operate as a traditional company or as a technology company, exemplifies this cultural shift, consistent with the perspective of Westerman et al. (2014), according to whom innovation must permeate the business model (Lago et al., 2026; Täuscher & Laudien, 2018) and organizational processes. The transformative role of AI aligns with authors such as Albino et al. (2023), who frame digital transformation as a driver of strategic and cultural change.

The construction of a solid AI governance framework was mentioned in 14 second-order codes and is evidenced by E6: We organized artificial intelligence as one of the strategic pillars of the year. Concrete actions, such as internal communities, knowledge paths, and thematic forums, strengthen the integration of AI into decision-making and daily operations. Participant E7 emphasized the need for governance that can address all information security issues. E8 further highlighted the democratic nature of these initiatives: There has been teaching, training, and an effort to democratize these tools.

AI has been applied to reconfigure processes, automate decisions, improve services, and support the development of new products, indicating a transition from initial digitalization to a more advanced stage of maturity, as proposed by Westerman et al. (2014). This synergy is reinforced by E5: Complementarity from both a business and a technological perspective.

From a theoretical perspective, AI is treated as a catalyst for digital transformation (Vial, 2019) because of its potential for scalable personalization and intelligent automation. By applying AI at the strategic, tactical, and operational levels, an organization can develop dynamic capabilities (Teece, 2018. This connects to the idea of learning cycles (Chen et al., 2025), as emphasized by E3: AI only changes the numbers if we have actually gone through the previous transformation.

This transformation includes the spontaneous adoption of agile methodologies, referenced in seven second-order codes. According to E3, the acculturation work and AI transformation today are 100% based on digital transformation. Agility, as pointed out by Albino et al. (2023), serves as the foundation for the effective adoption of AI.

Therefore, the accounts reveal a progressive movement toward the strategic and conscious use of AI, indicating institutional advancement in digital sophistication. Technology is integrated into strategy, contributing to the reinvention of processes and value propositions. Thus, AI becomes more than a symbol of modernization; it is a driving force behind solid and sustainable organizational transformation (Kane et al., 2017).

Quantitative analysis

Before presenting the results of the CRITIC and WASPAS procedures, it is important to clarify the inferential scope of the quantitative analysis. Given the exploratory nature of the study and the limited number of respondents, the weights and rankings generated through multi-criteria decision-making methods should not be interpreted as statistically robust or generalizable measures of importance. Instead, they represent context-specific and perception-based structures that reflect how decision criteria and strategic alternatives are comparatively salient within the analyzed organizational setting (Miyashita & Pinochet, 2025). Accordingly, the quantitative component is used to illustrate, structure, and contrast managerial interpretations rather than to establish causal relationships or inferential claims.

The quantitative phase was conducted using a multi-criteria instrument applied asynchronously via an electronic link, following the completion of semi-structured interviews. This approach aimed to accommodate the time constraints of participating executives, ensuring the feasibility of data collection. To maximize the response rate, four follow-up rounds were conducted, resulting in six valid respondents. The objective was to capture participants' perceptions regarding the comparative salience of five strategic alternatives for adopting Artificial Intelligence (AI) in organizational processes: (A1) full implementation, (A2) partial implementation, (A3) acquisition of ready-made and/or outsourced solutions, (A4) internal development, and (A5) hybrid development (Thakkar, 2021). The analysis considered seven decision criteria: implementation cost, deployment time, operational efficiency, technological complexity, internal capacity building, organizational risk, and strategic alignment. Data were initially processed using the CRITIC method to define the weights of the criteria, followed by the application of the WASPAS method to rank the alternatives.

Weight generation using the CRITIC method

The choice of the CRITIC method for criteria weight generation reflects a concern for analytical transparency rather than claims of methodological superiority. While equal weighting could have been adopted, such an approach implies an assumption of equivalent salience across criteria, which represents a form of implicit arbitrariness when empirical perceptions suggest differentiated salience. Similarly, researcher-assigned weights would introduce normative judgment and potential bias, shifting the analytical focus from managerial perceptions to theoretical or authorial preferences. In contrast, CRITIC derives weights from the internal structure of the data by combining dispersion and inter-criteria correlation, allowing the identification of criteria that contribute relatively more discriminative information while reducing redundancy. Given the exploratory and interpretive nature of the study, CRITIC was employed as a more defensible and transparent weighting strategy among the available alternatives, without implying the statistical robustness or generalizability of the resulting weights.

The WASPAS method was selected as the decision aggregation technique because it balances additive and multiplicative logics within a single analytical framework. By integrating summation- and product-based mechanisms, WASPAS reduces the dominance of extreme values that may disproportionately influence rankings in purely additive or multiplicative approaches. This characteristic is particularly relevant in studies relying on perceptual data and small samples, where extreme evaluations may reflect contextual salience, rather than stable preference structures.

Importantly, the use of WASPAS in this study does not imply inferential ambitions or claims of methodological superiority. Instead, WASPAS is employed as a decision-structuring tool that supports the systematic comparison of strategic alternatives by organizing perceived trade-offs in a transparent and analytically coherent manner. Within the interpretivist and exploratory mixed-methods design adopted in this research, WASPAS complements qualitative insights by enhancing comparative reasoning rather than producing generalizable rankings or robust statistical conclusions.

Initially, the responses obtained through the multi-criteria instrument were processed as follows. Textual labels such as 'less important' and 'very important,' used to indicate the level of importance corresponding to scores 1 and 7, respectively, were removed, retaining only the numerical values. Next, the average score provided by the six respondents was calculated for each alternative and its corresponding criteria. The initial data were then normalized, considering both the beneficial attributes and the scale of the non-beneficial attributes, resulting in the normalized decision matrix (Table 5). Second, the correlation of the criteria was performed to obtain the weights (Table 6).

Table 5. Normalization of the original decision matrix data.

	Criteria						
Alternatives	C1	C2	C3	C4	C5	C6	C7
A1	0.0000	0.2000	0.8889	0.0000	1.0000	0.0000	1.0000
A2	0.3077	0.0000	0.8889	0.7500	0.7143	1.0000	0.7500
A3	0.5385	0.3000	1.0000	1.0000	0.0000	1.0000	0.0000
A4	1.0000	1.0000	0.0000	0.7500	1.0000	0.8000	0.5000
A5	0.4615	0.4000	0.1111	1.0000	0.5714	1.0000	0.5000

Note. Developed by the authors.

Table 6. Correlation matrix of the criteria and calculation of coefficients and weights.

(ρ_{jk})	C1	C2	C3	C4	C5	C6	C7
C1	**1.0000**	0.8532	-0.6703	0.6094	-0.0549	0.5591	-0.5685
C2	0.8532	**1.0000**	-0.7947	0.1938	0.2902	0.0857	-0.2594
C3	-0.6703	-0.7947	**1.0000**	-0.3096	-0.3933	-0.2347	0.0312
C4	0.6094	0.1938	-0.3096	**1.0000**	-0.6548	0.9685	-0.8001
C5	-0.0549	0.2902	-0.3933	-0.6548	**1.0000**	-0.5764	0.8425
C6	0.5591	0.0857	-0.2347	0.9685	-0.5764	**1.0000**	-0.6842
C7	-0.5685	-0.2594	0.0312	-0.8001	0.8425	-0.6842	**1.0000**
(1 - ρ_{jk})	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
C1	0.0000	0.1468	1.6703	0.3906	1.0549	0.4409	1.5685
C2	0.1468	0.0000	1.7947	0.8062	0.7098	0.9143	1.2594
C3	1.6703	1.7947	0.0000	1.3096	1.3933	1.2347	0.9688
C4	0.3906	0.8062	1.3096	0.0000	1.6548	0.0315	1.8001
C5	1.0549	0.7098	1.3933	1.6548	0.0000	1.5764	0.1575
C6	0.4409	0.9143	1.2347	0.0315	1.5764	0.0000	1.6842
C7	1.5685	1.2594	0.9688	1.8001	0.1575	1.6842	0.0000
(c_j)	5.2720	5.6313	8.3714	5.9929	6.5468	5.8819	7.4386
(w_j)	**0.1168**	**0.1248**	**0.1855**	**0.1328**	**0.1450**	**0.1303**	**0.1648**

Note. Developed by the authors.

Finally, the criteria were interpreted according to their CRITIC-based weighting structures within the analyzed context. Operational Efficiency (C3) displayed the highest informational contribution in the decision matrix (18.55%), indicating comparatively greater discriminative power and lower redundancy than the remaining criteria. In contrast, Implementation Cost (C1) showed the lowest informational contribution (11.68%), suggesting that it added comparatively less non-redundant information to the evaluation structure in this specific context. From an interpretive standpoint, these results suggest that managers assigned greater salience to efficiency-related considerations than to cost-related concerns when assessing AI adoption alternatives (Table 7).

Table 7. CRITIC-Based weighting structure of decision criteria in the studied context.

Criteria		Rank	%
Operational efficiency	C3	1	18.55%
Strategic alignment	C7	2	16.48%
Internal capabilities and capacity building	C5	3	14.50%
Technological complexity	C4	4	13.28%
Organizational risks	C6	5	13.03%
Implementation time	C2	6	12.48%
Implementation cost	C1	7	11.68%

Note. CRITIC weights represent the relative informational contribution of each criterion in the decision matrix, which is derived from criterion variability and inter-criterion non-redundancy. However, they should not be interpreted as direct measures of intrinsic managerial importance. Source: Developed by the authors.

Ranking of alternatives using the WASPAS method

To apply the WASPAS method, the initial attributes were normalized (Table 8) to identify the benefit and cost criteria. Only then was it possible to calculate the total relative importance $Q_i^{(1)}$ based on the WSM method (Table 9) and $Q_i^{(2)}$ for the WPM method (Table 10), assigning the weight values w_i generated by the CRITIC method.

Table 8. Normalization of the original decision matrix data.

	C1	C2	C3	C4	C5	C6	C7
A1	0.6579	0.7576	0.9750	0.8947	1.0000	0.8387	1.0000
A2	0.7353	0.7143	0.9750	0.9714	0.9444	1.0000	0.9730
A3	0.8065	0.7813	1.0000	1.0000	0.8056	1.0000	0.8919
A4	1.0000	1.0000	0.7750	0.9714	1.0000	0.9630	0.9459
A5	0.7813	0.8065	0.8000	1.0000	0.9167	1.0000	0.9459

Note. Developed by the authors.

Table 9. Weighted Additive Scores (WSM).

	C1	C2	C3	C4	C5	C6	C7	WSM
A1	0.0768	0.0945	0.1808	0.1188	0.1450	0.1093	0.1648	0.8902
A2	0.0859	0.0891	0.1808	0.1290	0.1370	0.1303	0.1604	0.9125
A3	0.0942	0.0975	0.1855	0.1328	0.1168	0.1303	0.1470	0.9041
A4	0.1168	0.1248	0.1437	0.1290	0.1450	0.1255	0.1559	0.9407
A5	0.0913	0.1006	0.1484	0.1328	0.1330	0.1303	0.1559	0.8922
w_i	0.1168	0.1248	0.1855	0.1328	0.1450	0.1303	0.1648	

Note. Developed by the authors.

Table 10. Weighted Multiplicative Scores (WPM).

	C1	C2	C3	C4	C5	C6	C7	WPM
A1	0.9523	0.9660	0.9953	0.9853	1.0000	0.9773	1.0000	0.8817
A2	0.9647	0.9589	0.9953	0.9962	0.9917	1.0000	0.9955	0.9055
A3	0.9752	0.9697	1.0000	1.0000	0.9691	1.0000	0.9813	0.8993
A4	1.0000	1.0000	0.9538	0.9962	1.0000	0.9951	0.9909	0.9369
A5	0.9716	0.9735	0.9595	1.0000	0.9875	1.0000	0.9909	0.8879
w_i	0.1168	0.1248	0.1855	0.1328	0.1450	0.1303	0.1648	

Note. Developed by the authors.

A variation in the lambda (λ) value was applied, conducting the analysis with λ = 0, 0.25, 0.50, 0.75, and 1. This sensitivity analysis allows for the verification of whether changes in lambda toward 0 or 1 (corresponding to the WPM or WSM, respectively) affect the final ranking of the alternatives.

Table 11 presents the results of the WASPAS method applied to alternatives A1–A5 using the weights derived from CRITIC method. It displays the WSM and WPM scores, as well as the aggregated WASPAS values for different λ levels (0 to 1), indicating the variation in the combination of the two methods. The final ranking of alternatives remained stable across all λ values, consistently highlighting A4 (Internal Development) as the highest-ranked alternative and A1 (Full Implementation) as the lowest-ranked.

Table 11. WASPAS method output according to the generalized criterion (λ).

Alt.	$Q_i^{(1)}$ WSM	$Q_i^{(2)}$ WPM	(λ = 0)	Rank	(λ =0.25)	Rank	(λ = 0.5)	Rank	(λ = 0.75)	Rank	(λ = 1)	Rank
A1	0.8902	0.8817	0.8817	5	0.8838	5	0.8859	5	0.8880	5	0.8902	5
A2	0.9125	0.9055	0.9055	2	0.9073	2	0.9090	2	0.9107	2	0.9125	2
A3	0.9041	0.8993	0.8993	3	0.9005	3	0.9017	3	0.9029	3	0.9041	3
A4	0.9407	0.9369	0.9369	1	0.9378	1	0.9388	1	0.9398	1	0.9407	1
A5	0.8922	0.8879	0.8879	4	0.8890	4	0.8901	4	0.8911	4	0.8922	4

Note. Developed by the authors.

The results were organized around five propositions formulated based on the literature on digital transformation, artificial intelligence (AI), and digital maturity, particularly in the context of organizations in emerging countries. The analysis combined qualitative and quantitative evidence using the CRITIC and WASPAS methods, offering an integrated view of the critical factors for AI adoption. Table 14 presents the Integration of Propositions, Evidence, and Practical Implications.

Table 12. Ranking of alternatives in order of priority.

Alternatives		Rank
Internal Development	A4	1
Partial Implementation	A2	2
Ready-Made Solutions/Outsourcing	A3	3
Hybrid Development	A5	4
Full Implementation	A1	5

Note. Developed by the authors.

Exploratory sensitivity analysis across MCDM methods

An exploratory sensitivity analysis was conducted by applying multiple compensatory multi-criteria decision-making (MCDM) methods, namely WSM, WPM, TOPSIS, MOORA, COPRAS, PROMETHEE II, and WASPAS, to the original decision matrix using the same CRITIC-derived weights. The cost and implementation time were treated as cost-type criteria, whereas the remaining criteria were modeled as benefit-type criteria. The objective of this analysis was not inferential validation but rather to examine the stability of the salience ordering of alternatives under different aggregation logics (Kao, 2010).

Table 13. Sensitivity analysis of alternative rankings across MCDM methods.

Alternative	WSM	WPM	WASPAS	TOPSIS	MOORA	COPRAS	PROMETHEE
In-house development	1	1	1	3	1	1	2
Partial implementation	2	2	2	2	2	2	1
Off-the-shelf solutions / Outsourcing	3	3	3	1	3	3	3
Full implementation	4	4	4	4	5	4	5
Hybrid development	5	5	5	5	4	5	4

Note. Developed by the authors.

To evaluate the robustness of the rankings obtained from the multi-criteria decision-making methods, a sensitivity analysis based on rank correlation measures was performed using Spearman's rho (ρ) and Kendall's tau (τ) coefficients. These non-parametric statistics allow for the assessment of the degree of concordance among the rankings produced by different methods, providing insights into the stability of decision outcomes.

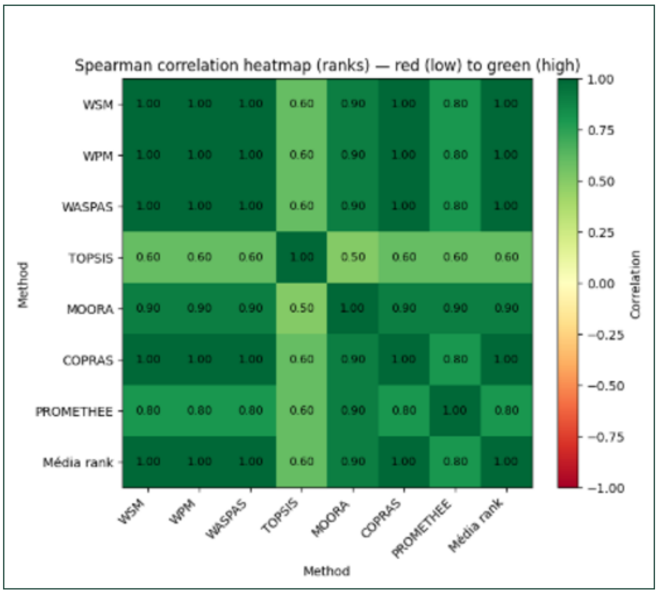
As reported in Table 13, the results indicate a high level of convergence among the WSM, WPM, WASPAS, and COPRAS methods. The pairwise correlations between these approaches reached ρ = 1.00 and τ = 1.00, indicating a perfect agreement in the ordering of alternatives. This strong convergence suggests that additive, multiplicative, and hybrid compensatory aggregation logics lead to equivalent rankings under the defined decision matrix and weight structure.

The MOORA method also demonstrated a high degree of alignment with this core group of methods, presenting correlation values of approximately ρ = 0.90 and τ = 0.80 (Table 13). These results indicate that, although minor positional differences exist, MOORA preserves the dominant preference structure identified by other compensatory methods.

In contrast, TOPSIS exhibited the lowest level of concordance with the remaining methods, with correlations of approximately ρ = 0.60 and τ = 0.40 compared to WSM, WPM, WASPAS, and COPRAS (Table 13). This divergence can be explained by the distance-based rationale of TOPSIS, which evaluates alternatives in relation to ideal and anti-ideal solutions rather than relying solely on compensatory aggregation, making it more sensitive to relative performance gaps among the criteria.

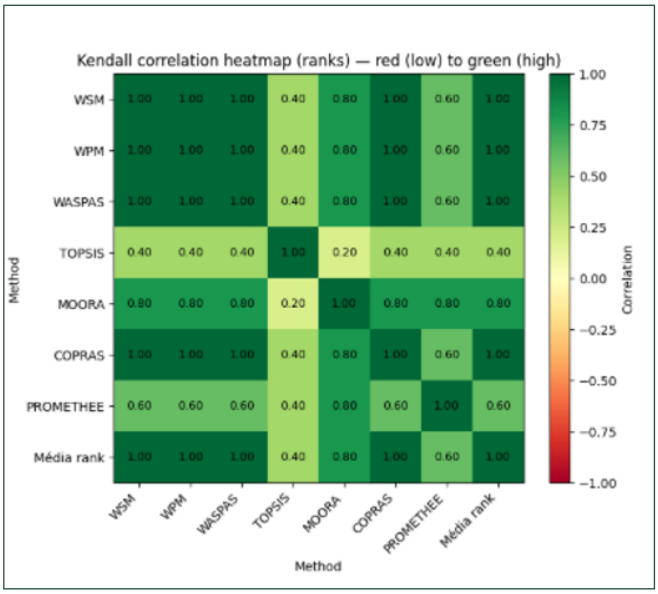
The PROMETHEE II method showed moderate to high agreement with the other approaches, with correlation coefficients of ρ = 0.80 and τ = 0.60 (Table 13). This pattern reflects the outranking nature of PROMETHEE, which incorporates pairwise preference comparisons and may capture subtle dominance relations that slightly alter the final ranking while maintaining its structure.

The correlation patterns discussed above are visually reinforced in Figure 4 and 5, which present the Spearman and Kendall correlation heatmaps, respectively. In both figures, the green-dominated regions highlight the strong convergence among most compensatory methods, whereas the lighter and yellowish tones associated with TOPSIS indicate comparatively lower levels of agreement. Importantly, no negative correlations were observed in either figure, confirming the absence of conflicting ranking structures across methods (Kao, 2010).



Source: Developed by the authors.

Figure 4. Spearman Rank Correlation Heatmap.



Source: Developed by the authors.

Figure 5. Kendall Tau Rank Correlation Heatmap.

Interpretive integration of quantitative evidence and propositions

Overall, the quantitative findings should be interpreted as analytically bounded insights that complement the qualitative analysis, rather than as independent evidence of causal relationships. The CRITIC-WASPAS results help clarify how managers in the studied subsidiary prioritize strategic alternatives under conditions of institutional constraints, limited digital maturity, and organizational complexity. Their contribution lies in enhancing analytical transparency and comparative reasoning within a mixed-methods interpretive framework rather than producing generalizable rankings or definitive measures of criterion importance.

The following propositions (Table 14) should be interpreted as analytical lenses, rather than causal claims. They aim to synthesize interpretive patterns observed in the case and support theoretical reflection rather than establish testable cause–effect relationships.

Table 14. Integration of propositions, evidence, and practical implications.

Proposition	Qualitative evidence	Quantitative support	Practical implication
P1. The adoption of Artificial Intelligence solutions is positively associated with increased customer satisfaction, establishing itself as one of the core objectives of digital transformation and maturity.	The interviewees emphasized AI-enabled improvements in customer service, personalization, response quality, and journey simplification. The qualitative analysis identified strong concentration in "improvement in customer experience" and "AI in customer service."	Operational Efficiency (C3) and Strategic Alignment (C7) displayed comparatively high salience in the CRITIC structure, supporting the view that managers associate AI adoption with service improvement and value delivery in this context.	Managers should prioritize AI applications that directly improve service responsiveness, personalization, and the quality of customer interaction.
P2. The existence of cultural barriers slows the implementation of AI and requires specific adaptive strategies to ensure its effectiveness.	The interviews revealed resistance to change, insecurity, unrealistic expectations of AI, and difficulties in organizational acculturation. Cultural and structural barriers have been repeatedly mentioned as implementation constraints.	Organizational Risks (C6) and Technological Complexity (C4) appeared among the comparatively salient criteria, indicating that managers recognize adoption barriers as relevant conditions that shape implementation.	AI adoption requires deliberate acculturation initiatives, internal communication, and adaptive implementation practices to reduce resistance and misalignment.
P3. Effective AI adoption requires continuous development of digital competencies, training, and change management to ensure innovation and operational efficiency.	Interviewees highlighted training, certifications, learning communities, leadership support, and practical capability building as essential for sustainable AI adoption.	Internal Capabilities and Capacity Building (C5) showed a comparatively high informational contribution, reinforcing the relevance of capability development within the studied decision context.	Firms should treat AI capability building as an ongoing organizational investment rather than a one-off technical requirement.
P4. In the analyzed organizational context, managers interpret changes in the operational model associated with digital transformation and AI adoption as relevant conditions that shape perceived competitiveness and organizational sustainability.	Managers associate AI with strategic repositioning, process modernization, ecosystem expansion, and improved competitiveness. Evidence suggests that AI is linked to broader operational and business model adaptations.	Strategic Alignment (C7) and Operational Efficiency (C3) were comparatively salient, indicating that managers evaluate AI not only in technical terms but also in relation to organizational competitiveness and long-term positioning.	AI initiatives should be connected to broader transformation goals, including process redesign, ecosystem integration and competitive repositioning.
P5. Within the studied subsidiary, managers perceive hybrid AI adoption strategies combined with internal capability development as viable pathways for addressing organizational risks and supporting digital transformation under emerging market constraints.	Qualitative material suggests a preference for balancing internal knowledge development with external support, especially in a context marked by capability gaps, infrastructure constraints, and organizational complexity.	The WASPAS ranking favored internal development, whereas qualitative evidence suggests that managers also value hybrid arrangements when they combine external expertise with internal learning, governance, and control.	Emerging market subsidiaries may benefit from hybrid AI strategies that combine external expertise with internal learning and governance development.

Note. Developed by the authors.

The propositions revisited in this section preserve the same analytical meaning established in the theoretical background and are interpreted here as context-bound lenses for understanding how AI adoption relates to digital transformation and digital maturity in the studied subsidiary. Rather than testing causal hypotheses, the analysis integrates qualitative evidence with MCDM-based comparative structuring to examine whether empirical material aligns with interpretive expectations derived from the literature. Overall, the results indicate that AI adoption in the case company is associated with customer-oriented value creation (P1), while remaining constrained by cultural and organizational barriers (P2), dependent on continuous capability development (P3), linked to perceived competitiveness and organizational sustainability through operational model adaptation (P4), and comparatively supported by hybrid strategies that combine internal capability building with selective external support (P5) (Kane et al., 2017; Teece, 2018; Vial, 2019).

Regarding Proposition 1, managers consistently associate AI adoption with improvements in customer satisfaction and experience, especially through faster service, greater personalization, and more contextualized interactions. In qualitative material, customer experience emerged as one of the most visible and concrete outcomes of AI use, particularly in customer-facing applications such as chatbots. This interpretation is also consistent with the comparatively high salience of Operational Efficiency (C3) and Strategic Alignment (C7) in the multi-criteria analysis, suggesting that, within the studied context, AI is perceived not merely as a back-office technology, but as an enabler of value creation in customer-facing processes and, therefore, as a relevant dimension of digital transformation (Liang et al., 2025). This finding is consistent with prior studies that emphasize the role of digital technologies in enhancing service quality, responsiveness, and customer-centered value creation in transformation processes (Albino et al., 2023; Dwivedi et al., 2023; Vial, 2019).

In relation to Proposition 2, the interviews repeatedly highlighted resistance to change, insecurity regarding AI, unrealistic expectations of its capabilities, and difficulties in translating interest in the technology into effective organizational use. These barriers were not treated as peripheral obstacles but as central conditions that affected the pace and depth of implementation. The quantitative component complements this interpretation by showing the comparative salience of Organizational Risks (C6) and Technological Complexity (C4), reinforcing the view that AI adoption depends not only on technical feasibility but also on cultural readiness and organizational alignment. This interpretation converges with studies showing that low digital maturity in developing contexts is often associated with weak training structures, infrastructural limitations and resistance to innovation (ABC, 2023; Tadeu et al., 2024; Yousaf et al., 2021).

This evidence is consistent with Proposition 3, according to which effective AI adoption depends on the continuous development of digital competencies, training, and change management. The case shows that internal learning initiatives, certifications, leadership-supported training, and practical experimentation are not marginal complements but part of the organizational infrastructure required for AI diffusion. This interpretation is reinforced by the relatively high informational contribution of Internal Capabilities and Capacity Building (C5) in the CRITIC structure, indicating that capability development is one of the most relevant dimensions in the decision context analyzed. In this sense, the findings suggest that digital maturity is sustained not only by technological acquisition but also by cumulative organizational learning and the development of internal competencies, which is consistent with the dynamic capabilities perspective and recent discussions on AI-enabled organizational transformation (Akter et al., 2022; Chen et al., 2025; Hess et al., 2020; Teece, 2018).

With respect to Proposition 4, managers linked AI adoption to broader changes in the operational model and perceptions of competitiveness and long-term organizational sustainability. In the empirical material, AI was associated with process modernization, strategic repositioning, ecosystem expansion, and the aspiration to strengthen the company's position within the mobility and payment ecosystem. This is theoretically relevant because it shows that, in this case, digital maturity is interpreted less as a static level of technological readiness and more as an adaptive organizational condition shaped by strategic reconfiguration. The comparative salience of Strategic Alignment (C7) and Operational Efficiency (C3) reinforces this interpretation, suggesting that managers evaluate AI not only in technical terms but also in relation to long-term positioning and organizational adaptability. This result is consistent with prior work that frames digital transformation as a strategic and organizational process involving business model adaptation, governance, and sustained value creation (Albino et al., 2023; Carvalho et al., 2021; Haefner et al., 2021; Vial, 2019).

Finally, Proposition 5 is partially supported by the convergence of qualitative and quantitative evidence. The WASPAS ranking identified internal development as the most salient alternative, while the qualitative material suggests that managers also value hybrid arrangements when they combine selective external expertise with internal learning, governance and strategic alignment. Rather than indicating a rejection of partnerships or outsourcing, these findings indicate a preference for arrangements that preserve internal knowledge accumulation while still benefiting from external support. In the context of a subsidiary operating under institutional and capability constraints, such arrangements appear to offer a more sustainable path for AI adoption and advancement of digital maturity. This interpretation is consistent with prior studies suggesting that AI implementation in constrained environments benefits from capability-building strategies that balance flexibility, control and learning (Hess et al., 2020; Ma et al., 2025; Yousaf et al., 2021).

From an ecosystem-level perspective, the results indicate that AI adoption does not operate only within the boundaries of a focal organization. The mobility and payment ecosystem analyzed in this study involves interactions among platform owners, users, commercial partners, technology providers, service operators, and complementary mobility-related services. This interpretation aligns with recent studies on mobility ecosystems and Mobility as a Service, which emphasize the integration of platforms, users, operators, payment systems, and service providers as central elements for inclusive and user-centered mobility solutions (Pagoni et al., 2026; Turoń, 2025). In this context, AI supports not only internal process optimization but also the orchestration of data, services, and interactions across organizational boundaries, reinforcing the role of digital technologies in reshaping business models, organizational capabilities, and value creation processes (Choudrie et al., 2025; Teece, 2018; Vial, 2019).

The relevance attributed to internal capabilities and hybrid development strategies suggests that digital maturity depends on the distribution and recombination of capabilities across the ecosystem. This finding is consistent with the literature on dynamic capabilities and digital transformation, which argues that organizations must integrate, build, and reconfigure internal and external competencies to respond to technological and market changes (Akter et al., 2022; Chen et al., 2025; Teece, 2018). In the specific case of AI adoption, this capability-based view becomes especially relevant because the effective use of AI depends not only on technological infrastructure but also on organizational learning, governance, employee training, data integration, and coordination with external partners (Dwivedi et al., 2023; Jie et al., 2025; Ma et al., 2025). Therefore, the findings extend the discussion beyond an intra-organizational view of digital transformation by showing that AI adoption in platform-based mobility contexts requires coordination mechanisms capable of aligning internal learning, external expertise, partner integration and user-centered value creation.

The findings can also be interpreted in light of the CalmMobility paradigm, although there are important analytical limitations. Turoń (2025) proposed CalmMobility as a response to fragmented, accelerated, and poorly sequenced mobility transitions, emphasizing comprehensiveness, pacing–sequencing–inclusion, future readiness, citizen participation, and social embedding. From this perspective, sustainable mobility should not be understood only as technological modernization or infrastructure expansion, but as a coordinated and human-centered transition that aligns with innovation, governance, social acceptance, and long-term resilience. This view is also consistent with recent discussions on inclusive Mobility as a Service, in which digital platforms should support accessibility, integration, and user-centered value, rather than simply offering technological convenience (Pagoni et al., 2026).

In the case analyzed, AI adoption appears to contribute to some organizational conditions that may support this transition, particularly by reducing informational friction, improving service responsiveness, enabling personalization, and strengthening the integration between mobility and payment services. These elements are consistent with the company's movement from isolated payment automation toward a broader mobility ecosystem in which digital services, data-based decision-making, customer experience, and partner coordination become increasingly interconnected. However, the evidence does not allow claims about urban mobility transformation as a whole topic. Instead, the contribution is more modest and analytically bounded: AI adoption may help platform-based mobility organizations create internal and relational conditions that are compatible with CalmMobility principles, especially when technological innovation is combined with governance, capability development, ecosystem coordination, and user-centered service design (Hess et al., 2020; Ma et al., 2025; Pagoni et al., 2026; Turoń, 2025).

From a methodological standpoint, the integration of qualitative evidence and MCDM-based comparative structuring enhances the analytical transparency of the study by allowing managerial perceptions to be interpreted alongside the systematic organization of strategic trade-offs. However, this mixed-methods design should be understood as an analytical complement to the interpretive case study rather than as a mechanism for causal validation or statistical generalization. Consistent with the principles of analytical generalization, the findings are not intended to be statistically generalized to all subsidiaries or emerging market contexts. Instead, they offer transferable analytical insights into how AI adoption interacts with organizational culture, governance, and capability development, under institutional constraints. While the focal firm represents a relatively advanced and well-resourced case, the mechanisms identified, such as AI acculturation, governance alignment, and incremental capability recombination, may inform theory and practice in other subsidiaries facing similar structural tensions (Creswell & Plano Clark, 2018; Eisenhardt, 1989; Langley & Abdallah, 2011; Yin, 2018).

Beyond the internal organizational dynamics examined in this case, the findings may also be interpreted in light of broader socio-technical transitions in mobility. In this sense, the CalmMobility paradigm helps frame AI adoption not only as an internal digitalization effort but also as part of a wider transformation of mobility systems toward more integrated, intelligent, and context-aware service ecosystems. This perspective broadens the interpretation of the case by situating managerial perceptions of AI within an evolving mobility environment that extends beyond firm-level process optimization.

CONCLUSIONS

This study focused on how AI adoption interacts with digital transformation and digital maturity in a Brazilian subsidiary operating within a mobility and payment ecosystem. The findings show that AI adoption should not be understood as a linear or universally effective transformation driver. Instead, AI operates as a contingent catalyst of digital maturity, whose effects depend on governance structures, organizational acculturation, internal capability development, technological integration, and coordination with ecosystem actors.

This study contributes to the literature by offering a context-sensitive interpretation of AI-enabled transformation in emerging market subsidiaries. It also shows how MCDM techniques can be used within an interpretivist mixed-methods design as analytical tools to structure managerial perceptions rather than as instruments for statistical generalization or causal validation. From a practical perspective, the results suggest that organizations seeking to adopt AI should prioritize capability development, governance, and ecosystem coordination before pursuing extensive technological implementation.

Further studies should explore the CalmMobility paradigm empirically, assessing whether AI-enabled platforms contribute to more predictable, integrated, and human-centered mobility experiences beyond the organizational level.

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APPENDIX

Table 1. Comparison of Compensatory MCDM Methods for Alternative Ranking.

Method	Aggregation logic	Compensation treatment	Sensitivity to extreme values	Suitability for perceptual data	Suitability for small samples	Inferential scope	Main limitations
WSM (Weighted Sum Model)	Additive aggregation	Fully compensatory	High	Moderate	High	Non-inferential	May mask trade-offs and dominance effects
WPM (Weighted Product Model)	Multiplicative aggregation	Compensatory (product-based)	Very high	Low	Moderate	Non-inferential	Penalizes low scores disproportionately
WASPAS*	Integrated additive and multiplicative aggregation (WSM + WPM)	Fully compensatory (hybrid)	High to very high	Moderate	High	Non-inferential	Sensitivity depends on the balance between additive and multiplicative components; may inherit limitations of both WSM and WPM
TOPSIS	Distance to ideal solution	Partially compensatory	High	Moderate	Moderate	Non-inferential	Artificial ideal and anti-ideal solutions
MOORA	Normalization and difference	Partially compensatory	Moderate	Moderate	High	Non-inferential	Limited analytical flexibility
COPRAS	Proportional assessment	Compensatory	Moderate	Moderate	Moderate	Non-inferential	Less widespread theoretical adoption
PROMETHEE	Preference relations	Partially non-compensatory	Low	Low	Low	Non-inferential	Requires stable preference functions

Note. All methods listed are decision-support tools and do not provide statistical inference.*MCDM approach employed in the research.