AI in enterprise management: determinants of purchase intention among CEOs without AI experience

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Abstract

Purpose – This study introduces a novel model of AI adoption focused on purchase intention by CEOs with no prior AI experience – a key shift from traditional usage-based approaches. It addresses how executives make strategic investment decisions under uncertainty, emphasizing trust and perceived value over readiness factors.
Design/methodology/approach – Survey data from 252 CEOs were analyzed using PLS-SEM and necessary condition analysis (NCA). The model evaluates the effects of security, perceived value, response costs, organizational compatibility and facilitating conditions, explaining 73.7% of purchase intention variance ($R^2 = 0.737$).
Findings – Security and perceived value emerged as the strongest drivers of AI purchase intention, while response costs act as a significant deterrent. Although facilitating conditions and organizational compatibility are relevant, their impact is secondary at the pre-adoption stage. The model also identifies perceived value and organizational compatibility as necessary – but not sufficient – conditions for adoption.
Originality/value – This research makes three key contributions: (1) it reconceptualizes AI adoption as a staged strategic process centered on purchase intention; (2) it applies upper echelons theory to explain how CEOs' lack of AI experience shapes their cognitive evaluations of risk, cost and strategic value during early-stage adoption decisions, offering a novel context for its use in AI adoption research and (3) combines PLS-SEM and NCA to identify both drivers and prerequisites for early-stage AI investment.

Keywords Artificial intelligence, Purchase intention, CEO, Strategic management executive decision-making, Technology adoption
Paper type Research paper

1. Introduction

Artificial intelligence (AI) has emerged as one of the most influential technologies in the transformation of the contemporary business landscape (Thakur, 2024). Owing to its ability to replicate human capabilities such as information processing, complex problem-solving, and decision-making, AI has become an essential tool for organizations seeking to optimize their operations and enhance competitiveness (Huang and Rust, 2021). Technologies such as machine learning, computer vision, and natural language processing are generating new opportunities to transform data management, business processes, and human resource management within organizations (Brauner *et al.*, 2025; Mariani *et al.*, 2022).

The functional benefits derived from the application of AI in the business domain are well-documented. Among them are the efficient processing of large volumes of data that enhances decision-making (Hussain, 2024), the automation of operational tasks across various

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sectors (Wang *et al.*, 2023), and improvements in customer service quality (Sampson, 2021). Additionally, AI reduces the burden of repetitive work for employees, enabling them to focus on higher value-added activities, thereby increasing productivity and competitive advantage (Enholm *et al.*, 2022; Vial *et al.*, 2023).

Beyond these functional gains, AI's strategic value is recognized across industries such as healthcare (Gupta *et al.*, 2023; Johnson *et al.*, 2023), finance (Bhatnagr *et al.*, 2024; Rahman *et al.*, 2023), legal services (Garlyal *et al.*, 2024; Singhal *et al.*, 2024), manufacturing (Monroy-Osorio, 2024), supply chain management (Di Vaio *et al.*, 2023; Singh *et al.*, 2024) and marketing (Makhlooq and Al Mubarak, 2024; Maldonado-Canca *et al.*, 2024a), where it contributes to long-term competitiveness and innovation. Its implementation enables data-driven decision-making, agile response to market changes, and the development of new business models (Ahuja, 2024). Despite this momentum, the adoption of AI also entails a range of economic, organizational, cultural, and technological challenges (Yang *et al.*, 2024). Major barriers include high initial investment costs (Prasad, 2024), the need for adequate technological infrastructure, and the shortage of specialized talent (Brauner *et al.*, 2025; Oldemeyer *et al.*, 2024). Moreover, organizational adaptation requires not only resources but also agile structures and corporate cultures open to innovation (Neumann *et al.*, 2024). Data security and privacy, along with cybersecurity-related risks, also raise concerns, particularly among executives with no prior experience in advanced technologies (Mahmud *et al.*, 2022).

Despite these challenges, the adoption of AI tools is increasingly widespread among both large enterprises and small and medium-sized enterprises (SMEs), prompting growing interest in its potential impact (Chatterjee *et al.*, 2022; Lu *et al.*, 2022). While large organizations tend to integrate these technologies more deeply, SMEs often face financial and technical constraints that limit adoption (Khan *et al.*, 2023; Mikalef *et al.*, 2023; Yang *et al.*, 2024). Therefore, this study includes a sample comprising small, medium, and large organizations, offering a broad and comparative view of AI acquisition perception across different organizational contexts.

Within this process, the role of Chief Executive Officers (CEOs) is critical (Verdú-Jover *et al.*, 2023). They lead resource allocation, promote innovation, and steer digital transformation strategies (Hsu *et al.*, 2019; Rahman *et al.*, 2021). However, not all CEOs possess the technical knowledge necessary to comprehend the strategic potential of AI (Szopiński, 2016). This lack of familiarity may manifest in two ways: (1) a general lack of understanding of AI, its functionalities, and its strategic implications (Fornazarič, 2023; Sjöberg and Schill, 2023), or (2) a lack of experience in investment decision-making and digital transformation processes specifically related to AI-based technologies (Kim and Kim, 2022; Rane *et al.*, 2024).

Nevertheless, not all CEOs have the same prior experience with technology. In this study, "lack of prior AI experience" is defined as the absence of direct exposure to AI-based tools, which does not necessarily imply a complete lack of digital literacy. That is, a CEO may be proficient in digital tools (e.g. enterprise software, CRM systems, data management, or cloud computing) without having been involved in the adoption of AI tools within their organization. This distinction is key, as strategic decision-making regarding AI requires a different evaluative process, one that emphasizes long-term value, risk mitigation, and strategic alignment over day-to-day usability (Mazorenko and Kaitanskyi, 2024).

Existing theoretical frameworks on technology adoption—such as the Technology Acceptance Model (TAM) (Davis *et al.*, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003), and the Theory of Planned Behavior (Ajzen, 1991)—have primarily focused on usage intention, particularly among end-users or digitally literate organizational members. However, these models do not fully capture the strategic decision-making processes that occur at the executive level, especially among non-technically experienced CEOs (Ho *et al.*, 2024; Ndubueze *et al.*, 2024; Rautiainen, 2017).

In contrast, this study addresses a critical research gap by focusing on AI purchase intention—a construct that is theoretically and psychologically distinct from usage intention. While usage intention reflects operational engagement, purchase intention reflects a strategic commitment that involves higher levels of uncertainty, financial risk, and alignment with long-term business objectives (Iqbal *et al.*, 2024; Mukhopadhyay, 2024).

This study is conducted in Spain, a country where AI adoption among firms remains limited despite growing institutional and market pressure. According to the National Observatory of Technology and Society (2023), only 8% of Spanish companies had adopted AI as of the latest report—comparable to the EU average but well below countries like Denmark (24%), Portugal (17%), and Finland (16%). This reflects a significant growth potential and highlights the importance of understanding the enablers and barriers to AI adoption in this national context. Spain's business landscape, characterized by a high concentration of SMEs and moderate digital maturity, offers a relevant setting to explore how CEOs with limited exposure to AI navigate early-stage technology investment decisions.

Given this theoretical and empirical gap, this study aims to explore how CEOs with no prior experience using AI tools evaluate the risks, costs, and strategic benefits associated with AI acquisition. Specifically, it examines which organizational, economic, cultural, and technological factors influence their intention to invest in AI technologies. This leads to the core research question guiding the study: what shapes executive-level decision-making in the early stages of AI adoption when direct experience with AI tools is absent? To address this, we develop a conceptual model that synthesizes economic, organizational, cultural, and technological dimensions to explain how these CEOs evaluate AI investments.

2. Literature review and theoretical framework

2.1 Artificial intelligence and managerial decision-making

AI has become a strategic pillar of digital transformation, playing a key role in process optimization, data-driven decision-making, and enhanced operational efficiency (Khan *et al.*, 2024). Its capacity to automate repetitive tasks, analyze large volumes of data in real time, and generate predictive models has driven its adoption across a wide range of industries (Bedué and Fritzsche, 2022; Yang *et al.*, 2024). However, its impact is not uniform, as it depends on each organization's technological readiness and firm size (Maldonado-Canca *et al.*, 2024a).

One of the most evident benefits of AI is its ability to automate processes, thereby improving productivity and reducing operational costs (Andayani *et al.*, 2024). In sectors such as manufacturing and construction, the deployment of intelligent robotics and predictive maintenance has optimized workflows, minimized downtime, and maximized resource utilization (Wong *et al.*, 2024). In supply chains, AI has enhanced inventory management and demand forecasting, helping to prevent stock shortages and surpluses (Al-Amin *et al.*, 2024). These applications enable firms to operate with greater agility, particularly in volatile markets where resource management efficiency is a key competitive factor (Kumar *et al.*, 2024; Zulkarnain *et al.*, 2025).

Beyond its impact on automation, AI has also enhanced managerial decision-making. Ogundeji *et al.* (2025) demonstrate how an AI-powered framework using machine learning and NLP improves financial planning and team productivity by processing large volumes of structured and unstructured data for real-time, evidence-based decisions. In industries such as finance and e-commerce, AI has improved fraud detection, risk assessment, and customer experience personalization (Gupta and Panigrahi, 2022). Particularly in dynamic sectors such as digital marketing, AI-based predictive analytics has proven to be a strategic asset for anticipating market shifts and optimizing commercial strategies (Islam *et al.*, 2024; Mariani *et al.*, 2022; Sullivan and Wamba, 2024).

Another area where AI has made a significant impact is in product and service innovation and personalization. The ability to analyze real-time data enables firms to tailor their offerings to customer needs, thereby improving satisfaction and loyalty (Okeke *et al.*, 2024; Pendyala and Lakkamraju, 2024). In marketing and customer relationship management, AI tools enhance the user experience through more personalized and dynamic interactions (Maldonado-Canca *et al.*, 2024b). A notable example is Amazon's personalization model, which illustrates how data-driven decision-making can strengthen long-term customer retention (Davidson and Rajeswari, 2025). However, a pronounced gap remains between large companies and SMEs in terms of AI adoption. While the former have progressively integrated these technologies, the latter face economic, technical, and organizational barriers that hinder implementation (Chatterjee *et al*., 2022; Oldemeyer *et al*., 2024; Daniel *et al*., 2020). These disparities highlight the need for tailored strategies that take into account firms' financial capacity and level of technological maturity (Maldonado-Canca *et al*., 2024a).

Although AI is widely recognized as a transformative technology, its adoption does not depend solely on technical performance or functionality, but also on strategic and organizational factors. In this context, executive leadership plays a critical role, as decisions concerning AI adoption involve not only the assessment of operational benefits but also the management of risks, implementation costs, and alignment with existing organizational structures (Oyekunle and Boohene, 2024). This issue becomes particularly relevant in the case of CEOs with no prior AI experience, who may face greater uncertainty during the evaluation and acquisition stages of these technologies (Cao *et al*., 2021; Dang *et al*., 2025).

However, AI adoption is not an automatic process, as investment in these tools is conditioned by a range of factors beyond technical performance. In particular, the purchase decision represents a critical stage in the digital transformation process, in which CEOs must carefully assess economic viability, technological security, and cultural compatibility before committing to acquisition (Zavodna *et al*., 2024). Unlike technology-experienced CEOs, who tend to view AI as a strategic investment, those without prior exposure are often more cautious in their evaluation, placing greater emphasis on factors such as security, organizational fit, and return on investment (ROI) before formalizing the purchase (Davenport and Ronanki, 2018; Zavodna *et al*., 2024).

2.2 Challenges in the acquisition of AI in organizations

Despite the undeniable benefits of AI in terms of efficiency, innovation, and competitive advantage, as outlined in Section 2.1, its adoption continues to pose a complex and multifaceted challenge for organizations. The decision to implement AI goes beyond mere technological feasibility (Maldonado-Canca *et al*., 2024a). Understanding these barriers is crucial for business leaders to design informed strategies that mitigate risks and facilitate effective AI integration (Zavodna *et al*., 2024). In addition to analyzing the challenges associated with AI adoption, this section explores the factors that lead some CEOs to completely reject the acquisition of such tools in their organizations.

Although the development of AI has reached a notable level of technical maturity, its adoption in organizational settings continues to face complex barriers that go beyond technological feasibility. Various studies have documented that the main obstacles are not limited to technical constraints, but also stem from economic, organizational, cultural, and strategic factors (Cubric, 2020; Hasani *et al*., 2023; Chatterjee *et al*., 2022; Zavodna *et al*., 2024). For instance, budget limitations in SMEs have been identified (Prasad, 2024), as well as poor alignment with business objectives (Booyse and Scheepers, 2024) and internal resistance driven by distrust in automated systems (Ivchyk, 2024). This evidence suggests that effective AI integration requires appropriate structural, cognitive, and cultural conditions. Accordingly, this section organizes the challenges into four interrelated dimensions—economic, organizational, cultural, and technological—to provide a structured and empirically grounded overview of the phenomenon.

2.2.1 Economic barriers. Financial constraints are a primary concern for executives when considering AI tools, as they require substantial investment with uncertain returns. Beyond software acquisition, costs extend to infrastructure, training, and ongoing operations (Agrawal *et al*., 2023; Mikalef *et al*., 2023). AI also entails a steeper learning curve and greater organizational adaptation, increasing hidden costs and delaying ROI (Davenport and Ronanki, 2018).

For SMEs, these concerns are amplified due to budget limitations and restricted access to funding (Zavodna *et al*., 2024). Larger firms can absorb long-term investments, while smaller ones often deprioritize AI to protect financial stability (Maldonado-Canca *et al.*, 2024a). Executives also worry about the risk of unmet expectations or integration issues (Mahmud *et al.*, 2023), leading many to adopt a "wait-and-see" approach (Cubric, 2020).

Costs do not end with implementation. Additional investments in data preparation, compliance, and system integration can exceed initial forecasts (Patel *et al.*, 2025). When executives perceive AI as high-risk and costly, they may delay adoption unless its business value is clearly demonstrated (Maldonado-Canca *et al.*, 2024a).

2.2.2 Organizational barriers. Organizational barriers are particularly relevant in this study, as the alignment between AI initiatives and internal processes strongly shapes the willingness of CEOs to commit to AI investment. This alignment has been shown to be a critical determinant in the adoption of digital technologies, particularly when top executives perceive a strategic fit between the technology and the firm's overarching orientation (Fretschner *et al.*, 2022). Resistance is further amplified when organizations lack prior exposure to AI, as uncertainty and perceived complexity increase executive aversion, especially in smaller firms (Maldonado-Canca *et al.*, 2024a). Ultimately, these organizational constraints often determine whether strategic intentions toward AI adoption materialize into concrete implementation efforts (Ivchyk, 2024).

Beyond financial constraints, a lack of organizational readiness also hinders AI adoption by top management (Zavodna *et al.*, 2024). Many firms lack a strategic framework for AI, leading to fragmented initiatives without executive support (Booyse and Scheepers, 2024). Implementation often requires interdepartmental collaboration, but rigid structures and bureaucracy slow or block progress (Hasani *et al.*, 2023).

Some CEOs remain skeptical of AI-driven decision-making, fearing a loss of control over strategic processes (Schwaeke *et al.*, 2024)—particularly in sectors traditionally reliant on human expertise (Maldonado-Canca *et al.*, 2024a). In high-risk industries like finance and law, legal and reliability concerns intensify this aversion (Gupta *et al.*, 2023). Firms with rigid structures and low compatibility with AI face added challenges, as integration often requires significant workflow transformation (Schwaeke *et al.*, 2025).

A further obstacle is the misalignment between AI initiatives and core business goals (Paiva, 2024). Without a solid business case, projects often lack executive backing and remain peripheral (Zavodna *et al.*, 2024; Booyse and Scheepers, 2024). Finally, AI implementation frequently disrupts talent management, requiring new roles and skills that generate internal resistance (Manoharan *et al.*, 2024).

2.2.3 Cultural barriers. Beyond structural and strategic challenges, resistance to AI is also rooted in organizational culture (Hasani *et al.*, 2023). Executives with limited exposure to digital technologies often show skepticism toward automated decisions, reinforcing aversion (Hendrawan *et al.*, 2024).

A well-known barrier is algorithmic aversion, where decision-makers distrust AI outputs due to limited transparency (Mahmud *et al.*, 2023). This intensifies with "black-box" systems, making it harder to understand decision logic and reducing willingness to delegate critical tasks (Cubric, 2020). To overcome this, AI vendors must offer not only technical reliability but also secure and trustworthy systems (Bedué and Fritzsche, 2022). In one study, 34.5% of managers who rejected AI cited overconfidence in their own abilities, and 20% preferred to retain control over decisions (Leyer and Schneider, 2021). These findings suggest that cultural, psychological, and leadership factors often underlie resistance to automation (Zhan *et al.*, 2024).

Fear of job loss and diminished influence also contributes to reluctance. Employees worry about automation, while executives fear losing strategic control (Booyse and Scheepers, 2024). In sectors where human expertise is central, traditional practices may resist change (Zavodna *et al.*, 2024).

Ethical and regulatory concerns—such as privacy, bias, and compliance—further inhibit adoption (European Parliament, 2023; Nishant *et al.*, 2024). Ensuring alignment with corporate values and laws poses a major challenge for CEOs, especially in highly regulated industries where legal and reputational risks are high (Gupta *et al.*, 2023; Booyse and Scheepers, 2024).

2.2.4 Technological barriers. From a technical perspective, AI adoption demands robust infrastructures, which many firms have yet to fully develop (Schwaeke *et al.*, 2024). A major challenge is integration with legacy systems, as existing software and hardware often prove incompatible with modern AI solutions (Hasani *et al.*, 2023). This leads to operational issues and higher implementation costs due to necessary upgrades or reconfigurations (Choi *et al.*, 2020).

Data quality and availability are also critical (Vannuccini and Prytkova, 2023). Firms without large, structured datasets face obstacles in deploying AI models effectively (Cubric, 2020). Fragmented or biased data can result in inaccurate outputs, reducing executive trust in AI-driven decisions.

Cybersecurity is another growing concern. Executives worry about data breaches, unauthorized access, and cyber threats, as AI systems often process sensitive information (Gupta *et al.*, 2023). SMEs are especially vulnerable due to weaker cybersecurity infrastructure (Bhalerao *et al.*, 2022).

Lastly, the shortage of AI-specialized talent remains a key barrier. Successful implementation requires expertise in machine learning, data analytics, and governance—skills many firms struggle to attract or retain (Maldonado-Canca *et al.*, 2024a). This challenge is more acute in emerging markets and low-digitization sectors, where competition for talent is high and training investment remains low (Zavodna *et al.*, 2024).

2.3 Theoretical background

This study adopts a multi-theoretical perspective to reflect the complexity of AI purchase decisions at the executive level. Unlike technology usage decisions at the operational level, purchasing decisions by CEOs involve the evaluation of strategic fit, risk perception, organizational alignment, and personal managerial traits. Therefore, each theory integrated into the model addresses a distinct cognitive or structural barrier, enabling a more comprehensive understanding of the determinants of purchase intention.

The incorporation of new technological tools, such as AI, into organizations is a complex process that depends not only on perceptions of usefulness and ease of use—as posited by traditional technology adoption models such as the TAM (Davis *et al.*, 1989) and the UTAUT (Venkatesh *et al.*, 2003)—but also on strategic investment decisions. In particular, the adoption of AI for organizational decision-making is conditioned by managers' willingness to trust algorithmic systems and delegate certain decisions to them, as a lack of trust and perceived loss of control may hinder implementation (Brink *et al.*, 2024).

For CEOs with little experience in AI, the decision-making process is even more uncertain. They must not only assess whether the technology justifies its cost and aligns with business strategy, but also overcome psychological barriers such as algorithmic aversion and a lack of trust in such systems (Brink *et al.*, 2024). In this context, understanding how CEOs without prior AI experience make decisions regarding AI acquisition requires theoretical frameworks that explain how risks, benefits, and costs associated with investments in emerging technologies are evaluated.

To this end, Prospect Theory and Expectancy-Value Theory offer complementary yet distinct insights. Prospect Theory (Kahneman and Tversky, 1979) posits that decision-makers are risk-averse in uncertain contexts and tend to overvalue potential losses when outcomes are ambiguous. Applied to AI adoption, this theory suggests that CEOs unfamiliar with AI may overestimate the financial, operational, and organizational risks involved. This is captured in our model through the construct "Response Costs," which reflects the perceived effort, difficulty, and hidden costs of acquiring and implementing AI solutions. These perceptions align with the predictions of Prospect Theory, as the novelty and opacity of AI tools can amplify risk aversion in decision-making. Recent studies in Human-Computer Interaction support this view, showing that algorithmic systems can magnify existing cognitive biases and influence decision-making under uncertainty (Boonprakong *et al.*, 2025).

Complementing this, Expectancy-Value Theory (Fishbein and Ajzen, 1975) explains how individuals make decisions based on a rational evaluation of the expected benefits weighed against perceived costs. Within this study, the theory underpins the construct "Perceived Value," which captures the CEO's belief that the benefits of adopting AI—such as increased efficiency, competitive advantage, or improved decision-making—outweigh its monetary and organizational costs. This theory is central to our model, as it provides a cognitive framework through which CEOs without technical backgrounds assess the return on strategic investments in emerging technologies (Chen and Tajdini, 2024).

Together, Prospect Theory and Expectancy-Value Theory explain how CEOs evaluate the trade-offs inherent in adopting AI: Prospect Theory accounts for the cognitive biases and risk aversion heightened by uncertainty, while Expectancy-Value Theory explains the rational cost-benefit analysis behind perceived value. Their combined application clarifies how the psychological and economic dimensions of executive decision-making interact, particularly in high-risk, low-familiarity contexts such as AI acquisition.

In addition, the Upper Echelons Theory (Hambrick and Mason, 1984) posits that strategic choices are not purely rational or objective, but are shaped by the cognitive base and values of top executives. This means that a CEO's professional background, prior exposure to technology, and personal attitudes toward innovation directly influence how new technologies are evaluated. In the specific case of AI adoption, the theory helps explain why CEOs without prior experience may perceive higher levels of uncertainty and risk, leading to greater reluctance to invest (Fornazarič, 2023; Chatterjee *et al.*, 2022). Their strategic decisions are not only informed by financial or technical data, but also by subjective filters—such as risk tolerance, innovation orientation, and perceived strategic fit. Upper Echelons Theory provides a foundational rationale for understanding purchase intention as a function of executive cognition, emphasizing that strategic choices reflect the values, experiences, and mental models of top executives rather than purely objective assessments (Bevilacqua *et al.*, 2025). In the context of AI adoption, this perspective is particularly salient: implementation decisions often depend less on organizational readiness and more on how CEOs cognitively frame the risks and potential of emerging technologies (Zheng *et al.*, 2024). This connection is especially relevant in early-stage adoption contexts, where uncertainty is high and benchmarking is limited, making individual executive characteristics—such as openness to innovation or risk tolerance—critical determinants of strategic action (Burkhard *et al.*, 2023).

Each remaining theory in the model addresses a different barrier to adoption. Organizational Compatibility is linked to Innovation Diffusion Theory (Rogers, 2003), which highlights the importance of aligning new technologies with existing processes and structures. Technological barriers are captured through Facilitating Conditions, based on UTAUT (Venkatesh *et al.*, 2003), which emphasize the enabling role of infrastructure and technical support. Cultural barriers are represented by Security, grounded in Perceived Risk Theory (Featherman and Pavlou, 2003), which explains how concerns about data privacy, system transparency, and trust in automation affect adoption intentions.

In light of this theoretical framework, purchase intention (PI) emerges as a key factor, as it reflects the willingness of CEOs to acquire new tools—even in the absence of prior knowledge about their functioning (George, 2004; Pavlou and Fygenson, 2006). The literature has shown that PI is a reliable predictor of technology adoption behavior, particularly in contexts where strategic decision-making involves evaluating multiple sources of uncertainty (Febriani *et al.*, 2022). However, in the case of CEOs with no prior experience in AI, purchase intention becomes even more critical, as lack of familiarity with the technology can heighten risk perception and influence the cost-benefit evaluation (Mahmud *et al.*, 2022; Chatterjee *et al.*, 2022). According to Kelly *et al.* (2023), while purchase intention represents a crucial step in the investment decision process, its conversion into actual adoption depends on contextual factors such as organizational compatibility and perceived security.

By assigning each theoretical framework to a specific decision-making domain—economic (Prospect and Expectancy-Value), organizational (Innovation Diffusion), technological (UTAUT), cultural (Perceived Risk), and strategic cognitive (Upper Echelons)—the model achieves conceptual clarity and avoids redundancy.

2.4 Theoretical hypotheses

2.4.1 Facilitating conditions. Facilitating conditions (FC) refer to the extent to which CEOs believe they have the resources and organizational support needed to adopt and use AI in their firms (Trang, 2021). These include infrastructure, access to skilled personnel, and readiness to support technology use (Gupta *et al.*, 2024; Jameel *et al.*, 2023).

Although prior research links FC positively with technology adoption, their influence may vary depending on organizational maturity and leadership perception. In firms with low digital readiness, FC may not translate into purchase behavior if seen as insufficient or misaligned with strategy (Purwantini *et al.*, 2024; Übellacker, 2025). Some studies show FC positively impacts AI adoption when CEOs believe their infrastructure can support implementation (Cao *et al.*, 2021; Pozzo *et al.*, 2024), while others find no significant effect, underscoring contextual variability (Jameel *et al.*, 2023). However, existing literature has not yet explored this relationship specifically among CEOs with or without prior AI experience. Therefore, we propose the following hypothesis:

H1. Facilitating conditions positively impact the intention to purchase AI tools by CEOs with no prior AI experience.

2.4.2 Organizational compatibility. Organizational compatibility (OC) refers to the extent to which a technology aligns with an organization's values, needs, and internal processes (Rogers *et al.*, 2014). In the AI context, this construct includes the technical readiness to integrate AI into existing systems and workflows (Eliseo *et al.*, 2025), as well as the degree to which such tools support strategic alignment with business goals (Schwaeke *et al.*, 2025).

Empirical research has consistently demonstrated that compatibility with organizational infrastructure and culture is a significant predictor of technology adoption. For example, Kishore and McLean (2007) found that organizational alignment directly influences the infusion of IT innovations in large firms. Similarly, Frambach and Schillewaert (2002) highlighted that compatibility with existing values and operational routines is a key determinant in organizational decision-making processes related to new technologies.

This relationship is particularly relevant in contexts of low prior exposure, where CEOs may hesitate if AI is perceived as incompatible with existing structures or decision-making logic (Maldonado-Canca *et al.*, 2025). Perceived misalignment can lead to resistance, even when sufficient resources are available (Ivchyk, 2024). In contrast, high organizational compatibility fosters a sense of continuity, reducing perceived disruption and increasing purchase intention (Agrawal *et al.*, 2021; Prasad, 2024).

H2. Organizational Compatibility positively impacts the intention to purchase AI tools by CEOs with no prior AI experience.

2.4.3 Security. Security (SC) is a critical factor in AI adoption, particularly when handling sensitive data (Habbal *et al.*, 2024). It directly impacts purchase intention by fostering trust in the technology (Siagian *et al.*, 2022). For CEOs with no prior AI experience, security concerns—such as data misuse, regulatory breaches, or reputational damage—often outweigh functionality (Gupta *et al.*, 2024). Previous studies confirm this relationship: Dimitriadis and Kyrezis (2010) found that perceived security significantly influences adoption intentions in technology-enabled services, while Shropshire *et al.* (2015) demonstrated that perceived usefulness and ease of use of security software affect behavioral intent. Security framing, including guarantees and certifications, can shape executive perceptions (Dean *et al.*, 2024; Kappel, 2024), and systems like AI-enabled CRMs help reduce data-handling risks (Chatterjee *et al.*, 2022). Despite this, fears of unauthorized access and breaches persist (Gupta *et al.*, 2023). Accordingly, we propose the following hypothesis:

H3. Security positively impacts the intention to purchase AI tools by CEOs with no prior AI experience.

2.4.4 Perceived value. Perceived value (PV) refers to the overall assessment decision-makers make by weighing expected benefits against associated costs, risks, and efforts (Zeithaml, 1988). It is a recognized driver of purchase intention in technological contexts (Al-Debei and Al-Lozi, 2014; Wang *et al.*, 2018). Empirical studies confirm that perceived value significantly influences adoption decisions, particularly through utilitarian and economic dimensions. In digital innovation, this effect persists even when moderated by uncertainty or limited experience (Wang *et al.*, 2018).

In the context of AI, CEOs without prior exposure often rely on vendor framing—such as projected ROI or testimonials—when assessing value (Maldonado-Canca *et al.*, 2024a). However, high perceived value alone may not suffice, as concerns about feasibility, alignment, or trust can counterbalance it (Shank *et al.*, 2021; Zavodna *et al.*, 2024). This study examines whether perceived value remains a significant predictor of AI purchase intention among CEOs lacking prior experience. Based on this, we propose the following hypothesis:

H4. Perceived Value positively impacts the intention to purchase AI tools by CEOs with no prior AI experience.

2.4.5 Response costs. Response costs (RC) refer to the perceived burdens of adopting a technology, particularly in terms of financial investment, security risks, and compliance efforts (Milne *et al.*, 2000; Al-Emran *et al.*, 2021). In AI adoption, this includes upfront and operational costs (Agrawal *et al.*, 2023), as well as efforts to meet regulatory standards (Johnston and Warkentin, 2010). Concerns about vulnerabilities and their impact on AI efficiency also influence executive decisions (Raddatz *et al.*, 2020).

In high-uncertainty contexts—especially among CEOs with no prior AI experience—such costs may be magnified by unfamiliarity (Dang *et al.*, 2025). Unclear investment scopes, hidden expenses, or regulatory ambiguity can elevate perceived risk (Kochkina *et al.*, 2024).

Prior research confirms that response costs negatively affect technology adoption, creating strong barriers (Ameen *et al.*, 2020; Al-Emran *et al.*, 2021). High initial costs and uncertain ROI remain major hurdles (Agrawal *et al.*, 2023). While AI promises efficiency, it often entails hidden costs tied to maintenance and compliance, complicating adoption decisions (Pandey *et al.*, 2021). Accordingly, we propose the following hypothesis:

H5. Response costs negatively impact the intention to purchase AI tools by CEOs with no prior AI experience.

2.5 Research model

Based on this theoretical foundation and the challenges identified in Section 2.2, this study proposes a model based on five key variables that aim to explain the decision-making process of CEOs regarding AI investment (see Table 1).

Recent research highlights the importance of these factors in executive decision-making. For example, a study by IBM (2023) found that although 69% of CEOs acknowledge the benefits of AI, only 29% believe their teams possess the necessary competencies for effective adoption. Similarly, Deloitte (2023) reports that more than two-thirds of CEOs make AI investment decisions without fully assessing its organizational impact, emphasizing the need to account for perceived value and security risks in such decisions.

Moreover, the literature suggests that a lack of familiarity with AI increases uncertainty and delays adoption in small and medium-sized enterprises (Chatterjee *et al.*, 2022). This is consistent with Prospect Theory, which posits that individuals with greater aversion to uncertainty tend to avoid investments perceived as risky (Kahneman and Tversky, 1979). However, according to the Upper Echelons Theory (Hambrick and Mason, 1984), a firm's strategic decisions reflect the experience and profile of its top executives. Recent studies have shown that CEOs with prior experience in technology are more likely to evaluate AI

Table 1. Theoretical mapping of AI adoption barriers and research constructs

Barriers (Section 2.2)	Proposed model variables	Theoretical foundation
Economic barriers: High investment costs, uncertain ROI, financial risk in SMEs	Response costs Perceived value	Expectancy-Value Theory (Fishbein and Ajzen, 1975), Prospect Theory (Kahneman and Tversky, 1979)
Organizational barriers: Lack of adequate infrastructure, poor strategic alignment, internal resistance	Organizational compatibility	Innovation Diffusion Theory (Rogers, 2003), TAM (Davis *et al.*, 1989)
Cultural barriers: Algorithmic aversion, distrust in AI, fear of automation	Security	Perceived Risk Theory (Featherman and Pavlou, 2003)
Technological barriers: Lack of specialized talent, integration issues with legacy systems, cybersecurity risks	Facilitating conditions	UTAUT (Venkatesh *et al.*, 2003)

Source(s): Authors' own work

investments positively, whereas those without such experience perceive higher risks and exhibit lower purchase intention (Fornazarič, 2023; Chatterjee *et al.*, 2022). This distinction is crucial, as uncertainty surrounding AI investments may be shaped by a CEO's familiarity with digital technologies and their ability to interpret long-term strategic benefits.

For all these reasons, the proposed model approaches AI purchase intention from a strategic and financial perspective, distinguishing itself from earlier models focused primarily on usage intention. Unlike end-users, CEOs must consider long-term implications, including organizational compatibility (Hasani *et al.*, 2023), implementation costs (Choi *et al.*, 2020), security concerns (Zhan *et al.*, 2024), and strategic alignment (Schwaeke *et al.*, 2024). Figure 1 illustrates the proposed model, including the previously described assumptions.

2.6 Literature review protocol

To ground the model in solid theoretical foundations, a structured and deliberately focused literature review was conducted, aimed at identifying the most relevant and recent contributions on the adoption of artificial intelligence in organizational contexts, with

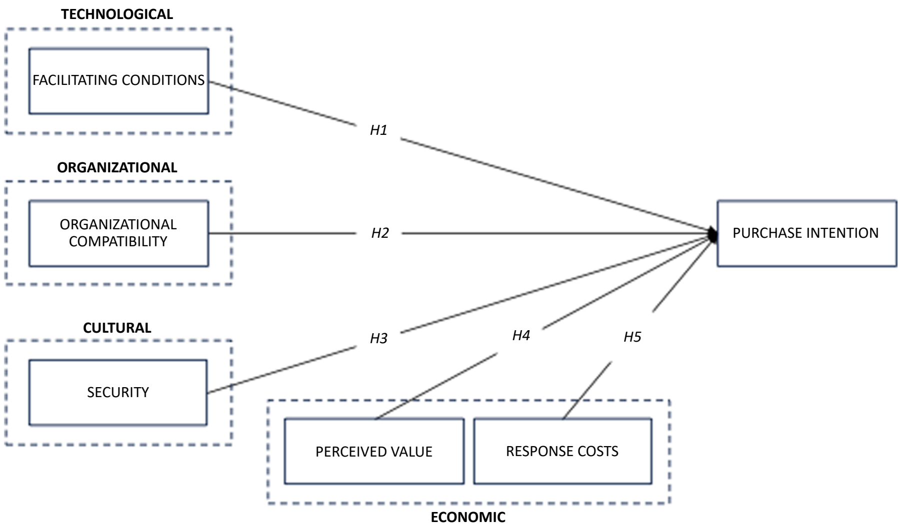

Figure 1. Research model. **Source:** Authors' own work

particular emphasis on decision-making processes by executives. Although it was not a systematic review in the strict sense, the procedure adhered to academically rigorous criteria. The literature search was carried out primarily in the Scopus and Web of Science databases, supplemented by queries in Google Scholar to locate recent studies still in the publication process. The search strategy was based on Boolean combinations of predefined keywords, such as: "*Artificial Intelligence*" *AND adoption,* "*AI*" *AND* "*purchase intention,*" "*Technology acceptance*" *AND* "*executives*" *OR* "*CEO,*" "*Decision-making*" *AND* "*emerging technologies,*" *and* "*Organizational barriers*" *OR* "*AI enablers*".

The inclusion criteria focused on peer-reviewed articles published between 2019 and 2025, although foundational theoretical works—such as the TAM, UTAUT models, or Prospect Theory—were also considered regardless of publication date, due to their conceptual relevance. Both empirical and theoretical studies were selected, provided they addressed topics related to artificial intelligence adoption, purchase intention, technological decision-making, and executive leadership, as well as those exploring barriers and enablers in organizational settings. In contrast, publications that did not focus on the organizational level or that dealt exclusively with user-technology interaction were excluded, as were studies that did not offer a direct theoretical contribution to strategic investment decisions in AI.

The selection of studies was carried out through an in-depth reading of the full texts in order to assess their theoretical and empirical relevance to the study's focus. The articles were grouped around four key thematic barriers—economic, organizational, cultural, and technological—and subsequently linked to specific theoretical frameworks (see Table 1). This process enabled the integration of multiple conceptual approaches—such as Prospect Theory, Expectancy-Value Theory, Innovation Diffusion Theory, the UTAUT model, Perceived Risk Theory, and Upper Echelons Theory—into a unified model aimed at understanding the purchase intention of AI technologies by CEOs with no prior experience.

3. Research methods

3.1 Survey design and development

The variables used in this study were adapted from previous research to ensure validity and consistency in measurement (Davis *et al*., 1989; Mcafee and Brynjolfsson, 2012). A 7-point Likert scale was employed, where 1 represents "do not agree at all" and 7 "strongly agree", to measure 22 items related to the study variables, including purchase intention as the dependent variable. Purchase intention was measured using a four-item scale adapted from Song and Zahedi (2005), a widely recognized measure in technology adoption research. These items assess the likelihood and willingness of CEOs to acquire AI tools for their companies. The full set of items used in the questionnaire is presented in the Annex. All measurement items were adapted from validated scales used in previous studies to ensure content validity and conceptual alignment. The original sources for each construct—Facilitating Conditions, Organizational Compatibility, Security, Perceived Value, Response Costs, and Purchase Intention—are detailed in the Annex (see "Measurement Scales" table).

To mitigate common method bias, we included four additional questions following the recommendations of Kock (2015) and Kock and Lynn (2012), ensuring the absence of measurement bias (see Table 2).

The questionnaire included a detailed explanation of what AI tools are and what they are not, with practical examples of common AI solutions. This ensured that participants correctly understood the context of the questions and avoided misconceptions about the technologies under evaluation.

3.2 Pilot test

Before launching the final survey, we conducted a two-phase pilot test, following the recommendations of Venkatesh *et al*. (2003). First, the questionnaire was reviewed by senior

Table 2. VIF extracted from the constructs to test the CMB

Variables	VIF
Facilitating conditions	1.429
Organizational compatibility	2.288
Purchase intention	1.848
Security	1.986
Perceived value	2.043
Response costs	1.065
CMB_Variable	

Source(s): Authors' own work using SmartPLS 4.0

researchers in artificial intelligence and business technology to ensure its theoretical adequacy and clarity. Then, a pilot test was conducted with 20 CEOs, which allowed us to verify the comprehension of the questions and make necessary adjustments to improve the clarity and accuracy of the measurement instrument. This process ensured that the items were appropriate for the specific context of CEOs with no prior AI experience, reducing the risk of ambiguous responses.

During this phase, one item initially included in the "Response Costs" construct—"We will need to frequently update the AI tools implemented in our business processes"—was removed. Feedback from experts indicated that this item was conceptually redundant with broader operational cost elements already covered in RC1 and could introduce semantic ambiguity. Its exclusion enhanced the internal consistency and interpretability of the construct.

3.3 Data collection

Data collection was conducted between August 2023 and May 2024 using a combination of methods, including online distribution via email and WhatsApp, follow-up phone calls to encourage participation, and face-to-face surveys during business meetings. Given the study's focus on CEOs with no prior experience in AI, a rigorous two-step screening process was implemented to ensure the validity of the sample.

First, the initial question of the survey explicitly asked participants whether they had previously used or implemented AI tools in their companies. Only those who responded "No" were allowed to proceed with the questionnaire. To further validate these responses, a follow-up question required participants to name any AI-based tools they were familiar with. If a respondent demonstrated familiarity with AI tools beyond a general awareness, their survey was excluded from the final sample.

A total of 451 CEOs were initially contacted, and after applying these selection criteria, 252 responses were validated for analysis. To ensure that the sample was representative of Spain's business landscape—where SMEs constitute over 95% of firms (INE, 2024)—stratified sampling was used, taking into account company size and industry. This methodological approach not only ensured the inclusion of a diverse range of businesses but also strengthened the reliability of the findings by accurately capturing the perspectives of executives unfamiliar with AI technologies.

To determine the minimum sample size required, we conducted an *a priori* power analysis using G*Power 3.1. We selected the statistical test for multiple linear regression (fixed model, single regression coefficient), two-tailed, assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a statistical power of 95% ($1-\beta = 0.95$). Although the theoretical hypotheses specify expected directions (positive for H1–H4 and negative for H5), a two-tailed test was chosen as a conservative approach, commonly used in empirical research to detect effects in either direction.

The analysis indicated that a minimum sample of 89 participants was required to detect significant effects of one independent variable, controlling for four others. Our final sample of 252 CEOs exceeds this threshold, ensuring sufficient power to detect even smaller effects with statistical confidence.

3.4 Respondent profiles

The final sample consisted of 252 CEOs from Spanish companies of varying sizes and industries (see Table 3). This diversity was intentional to capture heterogeneity in AI adoption across different organizational structures, as firm size influences financial capacity, technological readiness, and perceived value of AI (Chatterjee *et al*., 2022).

To ensure representativeness, we employed a stratified sampling approach based on company size, followed by snowball sampling to reach additional executives. This combined method is widely used for elite, hard-to-reach populations, where random sampling is often unfeasible. As Mendez (2020) highlights, when properly guided, snowball sampling can outperform classical techniques in executive research.

A total of 451 CEOs were contacted, and 252 validated responses were obtained after applying the inclusion criterion of no prior experience with AI tools. This corresponds to a response rate of 55.8%, consistent with prior executive-level AI adoption studies, which report rates between 20 and 60% (Oldemeyer *et al*., 2024).

4. Data analysis

4.1 Measurement model

To evaluate the model using PLS-SEM, we first verified the reliability and validity of the constructs. Additionally, an exploratory multigroup analysis by industry revealed that Perceived Value had a significantly stronger effect on Purchase Intention in service-sector firms ($\Delta = 0.322$; $p = 0.020$). This finding underscores the strategic relevance of perceived value in intangible service contexts, where AI adoption decisions may depend more on expected strategic benefits than operational readiness.

Following established criteria (Henseler *et al*., 2015; Roldán and Sánchez-Franco, 2012), all outer loadings exceeded the 0.7 threshold, except for item RC3 (0.697), which was retained due to its theoretical relevance and because it did not compromise the internal consistency of the construct. As noted by Hair *et al*. (2021), loadings slightly below 0.7 may be acceptable when composite reliability and AVE values remain above the recommended thresholds.

All constructs demonstrated strong reliability—Cronbach's alpha and composite reliability coefficients surpassed Nunnally's (1978) recommended threshold of 0.7—and convergent validity, with AVE values above the 0.5 cutoff (Straub *et al*., 2004), as detailed in Table 4.

Table 3. Number of CEOs by company size

Company size	Sample
0 employees (self-employment)	37
From 1 to 9 workers	110
From 10 to 49 workers	67
From 50 to 249 workers	23
From 250 to 499 workers	9
More than 500 workers	6
Total sample	*252*

Source(s): Authors' own work

Table 4. Factor loadings, composite reliability and convergent validity

	Outer loadings	Cronbach's alpha	Composite reliability (Rho_A)	Composite reliability (Rho_C)	Average variance extracted (AVE)
FC	0.740–0.879	0.842	0.854	0.895	0.681
OC	0.907–0.954	0.931	0.944	0.956	0.879
PI	0.963–0.969	0.975	0.975	0.982	0.931
SC	0.997–0.998	0.996	0.996	0.997	0.993
PV	0.898–0.943	0.934	0.935	0.953	0.835
RC	0.697–0.923	0.786	0.949	0.861	0.677

Source(s): Authors' own work using SmartPLS 4.0

A G*Power analysis confirmed sample adequacy ($n = 252$), exceeding the minimum of 92 participants required for an expected effect size of $f^2 = 0.15$ with $\alpha = 0.05$ and power = 0.80 (5 predictors).

The extremely high factor loadings for Security (0.997–0.998) suggest unidimensionality and internal consistency. Given that CEOs tend to perceive security in binary terms ("it is secure" or "it is not"), such high alignment across items is theoretically coherent. As noted by Revelle and Condon (2025), this does not imply overfitting, particularly in constructs with low inherent variability.

Additionally, an exploratory multigroup analysis based on industry sector revealed that perceived value had a significantly stronger effect on purchase intention in service-oriented companies ($\Delta = 0.322$; $p = 0.020$).

4.2 Discriminant validity

Subsequently, discriminant validity was assessed using two established techniques: the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) detailed by Henseler *et al*. (2015). We show the more restrictive of the two in Table 5.

4.3 Structural model

The R-squared of the model is 0.742 while the adjusted R-squared is 0.737. In addition, for a deeper understanding of the structural model, the path coefficients with their *p*-values are reflected in Table 6.

Multicollinearity was assessed using the VIF (Variance Inflation Factor). As shown in Table 7, all VIF values are below 3.3, indicating no significant collinearity problems (Hair *et al*., 2021).

Table 5. Discriminant validity (heterotrait-monotrait ratio – HTMT)

	FC	OC	PI	SC	PV	RC
FC						
OC	0.509					
PI	0.605	0.711				
SC	0.467	0.672	0.791			
PV	0.588	0.816	0.782	0.676		
RC	0.206	0.118	0.304	0.194	0.265	

Source(s): Authors' own work using SmartPLS 4.0

Table 6. Evaluation of the structural model (path coefficients)

Hypothesis		Supported	Path	*p*-values
H1	Facilitating conditions > PI	Yes	0.147***	0.000
H2	Organizational compatibility > PI	Yes	0.129*	0.036
H3	Security > PI	Yes	0.447***	0.000
H4	Perceived value > PI	Yes	0.248**	0.001
H5	Response costs > PI	Yes	−0.125***	0.000

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$ (based on a bootstrap test with 10,000 samples)
Source(s): Authors' own work using SmartPLS 4.0

Table 7. Variance inflation factors (VIF)

	VIF
FC > PI	1.422
OC > PI	2.799
SC > PI	1.967
PV > PI	3.037
RC > PI	1.144

Source(s): Authors' own work using SmartPLS 4.0

In addition, when considering the overall model fit measure, the SRMR indicator was used, which proved to be particularly useful for PLS-SEM. This model yielded a value of 0.059, which is within the acceptable limits recommended by Henseler *et al.* (2015).

In conclusion, the five hypotheses of the proposed model were confirmed with significance. This model showed a very relevant explanatory power, namely 73.7%, exceeding the minimum standard of 10% proposed by Falk and Miller (1992). Finally, when evaluating the predictive capacity of our model, the Q^2 value represented in Table 8, reaffirms its predictive relevance.

4.4 Importance-performance map analysis (IPMA)

An Importance–Performance Map Analysis (IPMA) was conducted to assess the importance and performance of each construct in predicting Purchase Intention (Ringle and Sarstedt, 2016). Results in Figure 2 confirm that Security and Perceived Value are the most relevant predictors. However, both show performance levels below their relative importance.

This gap indicates strategic leverage points where targeted improvements could disproportionately enhance outcomes. For decision-makers and AI vendors, prioritizing enhancements in Security and Perceived Value may increase purchase intention—particularly in settings where trust and perceived value outweigh procedural readiness. In contrast, Facilitating Conditions, Organizational Compatibility, and Response Costs displayed limited importance in the model.

Table 8. Q^2 of the model

	Q^2predict	RMSE
PI	0.720	0.533

Source(s): Authors' own work using SmartPLS 4.0

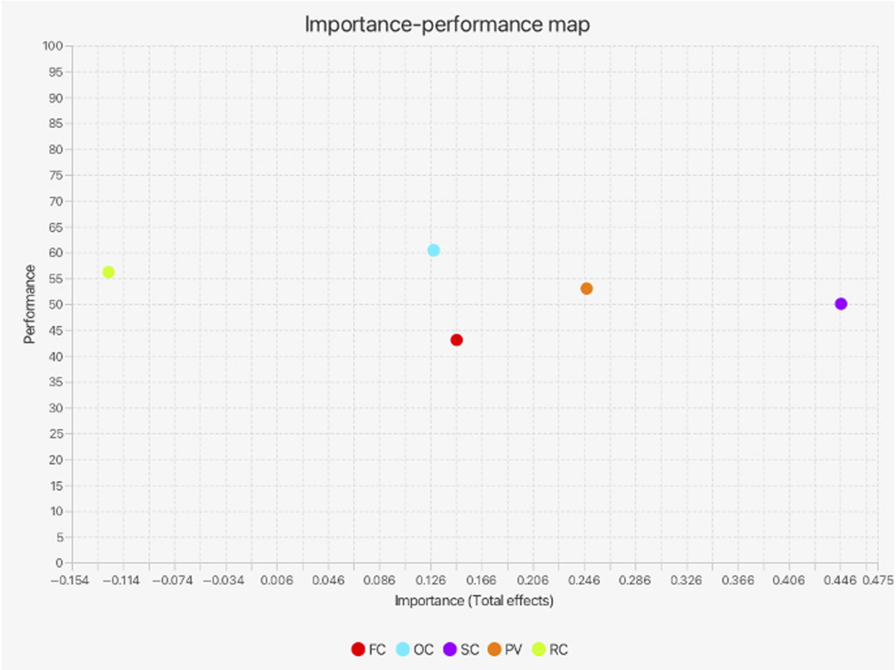

Figure 2. IPMA analysis. **Source:** Authors' own work using SmartPLS 4.0

4.5 Necessary condition analysis (NCA)

And continuing with the evaluation of the antecedents of the, Purchase Intention a necessary conditions analysis (NCA) was then performed to evaluate whether any variable is a necessary condition (without a certain result in this variable the dependent variable would not appear) by examining the size of the effect of necessity (d) and its statistical significance. The effect size is determined by dividing the area with no observations by the total area, resulting in a value between 0 and 1. Effect sizes are classified as small ($0 < d < 0.1$), medium ($0.1 \leq d < 0.3$), large ($0.3 \leq d < 0.5$), and very large ($d \geq 0.5$) (Dul, 2016). A commonly used threshold for necessity hypotheses is $d = 0.1$. For a necessity hypothesis to be valid, both the effect size and its statistical significance, which is usually assessed by the NCA permutation test (e.g. $p < 0.05$), must be confirmed. Table 9 presents the results, which indicate that Organizational Compatibility, Security and Perceived Value present mean and statistically significant effects.

Table 9. NCA analysis

	Original effect size	95%	Permutation *p*-values
LV scores – FC	0.039	0.037	0.041
LV scores – OC	0.276	0.069	0.000
LV scores – SC	0.130	0.035	0.000
LV scores – PV	0.266	0.061	0.000
LV scores – RC	0.034	0.129	0.834

Source(s): Authors' own work using SmartPLS 4.0

Once the significant effects of Organizational Compatibility, Security and Perceived Value were demonstrated, we proceeded to evaluate from which value they acted as bottlenecks, with Perceived Value being determinant when necessary, from the zero value of the Purchase Intention followed by Organizational Compatibility. Therefore, as can be seen in Table 10, both Perceived Value and Organizational Compatibility are important bottlenecks when calculating the Purchase Intention.

It is worth noting that Organizational Compatibility only emerges as a necessary condition from the 20th percentile of purchase intention onward, suggesting that CEOs tend to prioritize factors such as perceived value and security before considering organizational integration. This reflects common decision-making logic under uncertainty, where structural alignment follows once strategic benefits are recognized (Ali *et al*., 2024).

5. Discussion

The findings of this study underscore that AI purchase decisions among CEOs without prior experience are shaped not only by economic considerations but also by organizational alignment, cultural readiness, and technological trust. This supports earlier claims that AI adoption is not a purely rational process, but one filtered through personal heuristics and organizational conditions (Davenport and Ronanki, 2018; Fornazarič, 2023). The strong explanatory power of the model ($R^2 = 73.7\%$) and the absence of multicollinearity (VIF <3.3) confirm the robustness of the proposed framework for executive-level decision-making.

5.1 The central role of security in trust formation

Among all factors, security emerged as the most influential determinant of purchase intention. Its high effect size ($f^2 = 0.394$) underscores CEOs' strong reliance on trust in contexts of low familiarity and high uncertainty. In line with Perceived Risk Theory (Featherman and Pavlou, 2003), decision-makers tend to avoid technologies perceived as opaque or unpredictable. This is especially true for generative AI tools such as ChatGPT or Midjourney, where concerns over hallucinated outputs, lack of transparency, and copyright ambiguity are widespread. Recent reports (e.g. IBM, 2023) show that such tools are often restricted in finance, healthcare, and legal sectors due to fears of data leakage and loss of control. These concerns are particularly salient among CEOs with no prior AI exposure, for whom security perceptions—not technical functionality—become decisive. This is consistent with findings by Mahmud *et al*. (2022),

Table 10. Bottleneck analysis

	LV scores – PI	LV scores – FC	LV scores – OC	LV scores – SC	LV scores – PV	LV scores – RC
0.000%	−1.819	NN	NN	NN	−2.009	NN
10.000%	−1.467	NN	NN	NN	−2.009	NN
20.000%	−1.115	NN	−1.968	NN	−2.009	NN
30.000%	−0.763	NN	−1.528	NN	−1.639	NN
40.000%	−0.410	NN	−1.528	NN	−1.465	−2.438
50.000%	−0.058	NN	−1.528	NN	−1.442	−2.438
60.000%	0.294	NN	−1.528	NN	−1.442	−2.438
70.000%	0.646	NN	−1.528	NN	−1.442	−2.438
80.000%	0.998	−1.540	−0.419	−0.002	−0.136	−2.438
90.000%	1.350	−0.977	0.251	−0.002	0.386	−2.438
100.000%	1.702	−0.977	0.251	0.205	0.603	−1.857

Source(s): Authors' own work using SmartPLS 4.0

who emphasize that trust-related factors dominate early-stage AI adoption in sensitive or highly regulated industries.

In line with this, algorithmic aversion emerges as a latent but critical barrier. As Cubric (2020) and Zhan *et al*. (2024) emphasize, executives often prefer familiar decision-making processes over AI-driven automation, particularly when systems operate as “black boxes.” The elevated scores for the Security construct and its unidimensional structure (loadings >0.99) reflect a binary trust logic: either the system is secure, or it is not. This reinforces that ethical and regulatory assurances, such as those promoted by the EU AI Act, are not merely compliance issues but act as proxy indicators of trustworthiness—particularly crucial for CEOs navigating AI for the first time.

5.2 Strategic framing and perceived value

Perceived value also played a central role in AI purchase decisions, consistent with Expectancy-Value Theory (Fishbein and Ajzen, 1975). CEOs were significantly more inclined to invest when AI was framed as offering clear strategic benefits—such as competitive advantage, market responsiveness, or ROI—rather than operational improvements alone. This mirrors recent findings by Wang *et al*. (2018) and Maldonado-Canca *et al*. (2024a), who showed that strategic framing of AI, rather than technical demonstrations, drives executive commitment in early adoption stages. Our multigroup analysis further supports this, showing that perceived value is especially critical in service-oriented firms ($\Delta = 0.322$; $p = 0.020$), where intangible benefits such as personalization and customer insights are core to the business model.

5.3 Conditional enablers: compatibility and facilitating conditions

In contrast, facilitating conditions and organizational compatibility, although statistically significant, had a more modest impact. These findings suggest that structural enablers are necessary but not sufficient for triggering purchase intention—a pattern echoed in prior studies where these variables acted as moderators rather than primary drivers (Purwantini *et al*., 2024; Jameel *et al*., 2023). The NCA reinforces this hierarchy: perceived value and security are indispensable antecedents, while organizational compatibility only becomes relevant beyond the 20th percentile of purchase intention.

This implies that CEOs must first be convinced of an AI tool’s strategic worth and safety before turning to logistical considerations. In this sense, compatibility and facilitating conditions do not initiate the adoption process but serve as critical enablers that determine whether and how the implementation can proceed. Their role is therefore conditional: they shape the feasibility and sustainability of AI integration once the intention has been formed—a sequencing that aligns with findings by Zavodna *et al*. (2024) and Ali *et al*. (2024).

5.4 The weight of risk: response costs in uncertain contexts

Response costs exhibited a significant negative effect, supporting Prospect Theory (Kahneman and Tversky, 1979). In uncertain scenarios, decision-makers overweight potential losses, particularly in financial and compliance domains. This pattern is well-established in AI adoption literature: SMEs and low-experience CEOs tend to delay investment when costs—both visible and hidden—are perceived as high (Agrawal *et al*., 2023; Dang *et al*., 2025). Our findings align with previous empirical evidence showing that financial ambiguity, unclear implementation scopes, and compliance burdens often outweigh functional appeal in early-stage decision-making (Cubric, 2020; Johnston and Warkentin, 2010). Crucially, these perceived costs are not merely financial calculations but are shaped by cognitive biases and risk heuristics specific to executives with limited technological exposure. This suggests that the impact of response costs extends beyond rational evaluation, connecting closely with the role of executive cognition and decision framing—an issue we explore in detail in the next section.

5.5 The role of executive cognition: toward an Upper Echelons perspective

The theoretical lens of Upper Echelons Theory (Hambrick and Mason, 1984) proves particularly useful in interpreting these results. The prominence of variables such as security and perceived value—over more “objective” indicators like infrastructure or staff readiness—highlights the importance of executive cognition, experience, and risk tolerance. As Bevilacqua *et al*. (2025) argue, strategic investment decisions are shaped as much by personal mental models as by technical feasibility. CEOs lacking prior exposure to AI are especially vulnerable to what Boonprakong *et al*. (2025) describe as *computational uncertainty amplification*—where the perceived opacity of a system intensifies preexisting biases and aversions.

Importantly, these findings call into question the applicability of traditional models such as TAM or UTAUT in executive settings. While those frameworks emphasize ease of use, perceived usefulness, and the role of facilitating conditions, they were primarily developed to explain technology acceptance among operational staff or general users. In executive-level decisions, however, purchase intention is less about user experience and more about strategic relevance, reputational risk, and long-term organizational fit. For instance, a CEO may dismiss a highly usable AI tool if it lacks alignment with strategic goals or raises reputational concerns—even if it scores high on usability metrics. This gap has been identified by Ho *et al*. (2024) and Ndubueze *et al*. (2024), who argue that the cognitive frameworks guiding high-level decision-makers demand distinct models tailored to strategic rather than operational concerns.

Exploratory patterns also suggest contextual nuances. While not statistically significant, large firms appear less influenced by facilitating conditions, likely due to pre-existing digital infrastructure. Conversely, smaller firms showed lower concern for organizational compatibility, prioritizing short-term value realization over long-term strategic alignment. These asymmetries suggest that tailored adoption strategies are necessary to align AI offerings with the maturity and constraints of different organizational segments (Chatterjee *et al*., 2022; Mikalef *et al*., 2023).

5.6 Contextual and ethical nuances

Finally, although ethical concerns were not explicitly modeled, they emerged implicitly through the security construct. As Nishant *et al*. (2024) and Gupta *et al*. (2023) argue, CEOs increasingly interpret security not only as data protection but also as compliance with ethical norms such as fairness, transparency, and algorithmic accountability. This dimension is likely to grow in importance as regulatory frameworks like the EU AI Act gain traction.

5.7 Theoretical contributions

This study makes substantial theoretical contributions to the literature on advanced technology adoption, particularly in the context of AI and executive decision-making. Its primary contribution is the development and empirical validation of a novel model that explains AI purchase intention among CEOs with no prior experience in this technology domain. Unlike traditional models—such as the Technology Acceptance Model (TAM; Davis *et al*., 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh *et al*., 2003)—which emphasize usage behavior, this research redirects attention to the pre-implementation stage, addressing a strategic phase that precedes actual adoption.

A central innovation of this model is the theoretical distinction between purchase intention and usage intention. While the latter has dominated technology acceptance studies, the former captures a higher-order strategic decision relevant to top executives navigating uncertainty. This distinction reflects the relevance of decision-making theories such as Prospect Theory (Kahneman and Tversky, 1979) and Upper Echelons Theory (Hambrick and Mason, 1984), emphasizing the cognitive filters and risk perceptions that shape early adoption behavior.

Additionally, this study repositions established constructs—such as facilitating conditions and organizational compatibility—within an executive context. Contrary to their traditional prominence in user-level adoption models, the findings reveal their secondary role at the purchase stage. Instead, security and perceived value emerge as dominant factors, reaffirming the role of trust and strategic alignment in the adoption of complex and uncertain technologies (Featherman and Pavlou, 2003; Bevilacqua *et al.*, 2025).

The integration of economic, organizational, technological, and cultural barriers into a unified conceptual framework further enhances the model's explanatory strength. Unlike earlier studies that address these dimensions in isolation, this research offers a holistic perspective that reflects the multifaceted nature of executive decision-making across firm sizes and sectors (Zavodna *et al.*, 2024).

Moreover, the application of NCA alongside PLS-SEM introduces a methodological advancement. By identifying perceived value and organizational compatibility as necessary—but not sufficient—conditions, the study captures the layered logic that characterizes strategic decisions under uncertainty. This dual analytical approach contributes to emerging calls for hybrid models that combine predictive and necessity-based logic in technology adoption research (Dul, 2016).

Finally, the study's empirical focus on CEOs with no prior AI exposure fills a notable gap in the literature. Most adoption models overlook this critical population, yet these executives are central to shaping investment strategies in digitally maturing firms. The model's validation using data from 252 CEOs enhances both its theoretical robustness and practical relevance, laying the groundwork for future research into executive cognition and strategic AI investment.

5.8 Managerial contributions

The findings of this study offer several practical insights for stakeholders involved in AI adoption, especially within firms led by CEOs lacking prior experience with the technology. The most immediate implication is the central role of perceived security, underscoring the need to build trust through actionable and verifiable safeguards. Developers and vendors can build trust by emphasizing data protection guarantees, regulatory compliance (e.g. GDPR), and transparent algorithmic practices. Ethical assurances—such as adherence to the EU AI Act—serve not only regulatory purposes but also function as trust signals for executives evaluating high-risk technologies (Nishant *et al.*, 2024).

Another key implication concerns perceived value. Executives expect AI tools to deliver not only operational efficiencies but also strategic returns. Providers can address this by offering customized demos, ROI simulations, and case studies that align with each firm's priorities.

The negative influence of response costs highlights a frequent cognitive bias among non-technical executives: the tendency to overestimate complexity and underestimate their organization's readiness. To counter this, vendors should offer scalable pricing models—such as tiered plans based on usage volume or company size—that align the investment with each firm's actual needs and financial capacity. Additionally, they should design plug-and-play solutions with pre-configured dashboards or guided workflows, which minimize the learning curve and reduce reliance on specialized personnel. Pilot programs and free trials can also help lower perceived risk, enabling firms to experiment with limited deployment (e.g. within a single department) before committing to full-scale implementation. These initiatives, when complemented with integrated onboarding support—through interactive tutorials, live demos, or on-site workshops—facilitate smoother adoption and diminish resistance to change.

While security and value dominate the decision-making stage, facilitating conditions and organizational compatibility remain crucial for post-purchase implementation. Vendors must support clients in identifying integration points, adapting AI tools to pre-existing workflows, and overcoming internal bottlenecks that could hinder adoption.

The study's exploratory multigroup analysis suggests further managerial nuance. In large firms, facilitating conditions are perceived as less critical, likely due to their existing digital infrastructure. Conversely, small firms place lower emphasis on organizational compatibility, prioritizing ease of use and immediate value. This segmentation indicates that AI providers should tailor their strategies: simplifying deployment and emphasizing usability in SMEs, while stressing strategic alignment and scalability in larger firms.

5.9 Limitations and future research directions

This study offers important contributions but also presents limitations that open avenues for future research. The current sample focuses exclusively on CEOs with no prior AI experience. Future studies should broaden the scope to include executives with varying levels of technological familiarity and test whether such experience strengthens the impact of perceived value on purchase intention. Likewise, CEO traits (e.g. leadership style, risk aversion) and firm size could act as moderators—suggesting the hypothesis that CEO innovation aversion or perceived control may influence the role of perceived security.

The research was conducted in Spain, a context that may differ culturally or institutionally from other regions. Future cross-cultural studies could examine whether national cultural dimensions—such as uncertainty avoidance—moderate the influence of perceived security on AI purchase decisions.

Given the cross-sectional nature of the data, the findings represent a snapshot in time. A fruitful line of future research would be to conduct longitudinal studies tracking CEOs' attitudes and behaviors after direct exposure to AI—such as pilot program participation or post-implementation experiences. This would allow validation of whether such exposure strengthens the perceived value of AI tools and increases purchase intention over time.

Another limitation lies in the exclusion of individual CEO characteristics, such as leadership style, risk tolerance, or openness to change—factors that could influence decision-making processes regarding AI adoption. Future studies could explore whether these psychological traits—such as innovation aversion or perceived control—moderate the relationship between perceived security and purchase intention.

Although company size and sector were analyzed descriptively, future studies could conduct industry-specific analyses, particularly in highly regulated or data-sensitive sectors. It would be relevant to test whether the effect of perceived security is amplified in these contexts.

Finally, while this study used validated scales, the use of self-reported data may introduce biases such as overconfidence or social desirability. Future research could address this by combining quantitative methods with qualitative interviews or observational techniques to validate responses and uncover deeper motivations. In addition, researchers could test whether vendor support mechanisms—like free trials or ROI guarantees—reduce perceived response costs and positively moderate purchase intention.

6. Conclusion

This study offers a strategically grounded and underexplored perspective on how CEOs with no prior experience in artificial intelligence navigate complex AI acquisition decisions under conditions of uncertainty and limited familiarity. By introducing and empirically validating a multidimensional model grounded in economic, organizational, technological, and cultural perspectives, the research positions purchase intention as a distinct, strategic construct—clearly differentiated from traditional usage-based models such as TAM or UTAUT. This distinction is critical when analyzing executive decision-making under uncertainty, where trust and perceived strategic value override operational readiness or ease of use.

Rather than being driven by technical infrastructure, AI acquisition among non-technical CEOs is primarily influenced by intangible cognitive and psychological factors—most notably, trust in data security, ethical assurance, and confidence in the technology's long-term contribution to strategic goals. This reinforces the need for adoption frameworks that go beyond functionality and incorporate the subjective filters of top decision-makers, in line with the Upper Echelons Theory.

From a theoretical perspective, this study makes two key contributions. First, it integrates sufficiency logic (PLS-SEM) and necessity logic (NCA) to reveal not only which factors significantly influence decision-making, but also which are essential preconditions. Second, it challenges the assumption that structural enablers are primary drivers of adoption, highlighting instead the foundational role of security and perceived value. This dual approach enables a more nuanced understanding of how and when specific enablers act as bottlenecks in early-stage AI adoption—a hierarchy that must be recognized in both academic models and practical implementations.

These findings carry significant practical implications. For AI vendors, building executive trust through transparency and strategic value framing is more critical than demonstrating technical capabilities. Consultants must align interventions with the executive mindset, recognizing that trust and perceived benefit precede infrastructure investment. Policymakers should prioritize regulatory clarity and ethical safeguards—such as those outlined in the EU AI Act—to reduce perceived risks and accelerate adoption, especially among SMEs with lower digital maturity.

Future research should explore how CEO perceptions evolve after initial AI exposure, offering longitudinal insights into whether familiarity reduces uncertainty and strengthens strategic commitment. It should also examine how cross-cultural differences shape algorithmic trust, and how ethical guarantees influence adoption behavior across industries. By framing AI acquisition as a multidimensional, staged, and cognitively complex process, this study contributes to both theory and practice, laying the groundwork for more accurate and context-sensitive models of executive-level technology investment.

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(The Appendix follows overleaf)

Annex

Table A1. Measurement scales

Construct	Scale	References
Facilitating conditions	FC1: Our company has the necessary resources to implement AI tools in its processes FC2: Our company has the right knowledge to leverage AI tools to improve business processes FC3: The implementation of AI tools is compatible with existing systems and technologies in our company FC4: We have skilled personnel to manage and solve any AI-related challenge	Venkatesh *et al*. (2003)
Organizational compatibility	OC1: The use of AI tools is compatible with the processes in our company OC2: The use of AI is compatible with the way our company wants to operate OC3: The use of AI tools is compatible with the business strategy of our company	Davis *et al*. (1989), Moore and Benbasat (1991), Owen (2015)
Security	SC1: I am confident that the information I provide when using AI tools will be managed by appropriate processes SC2: I am confident that the private information I provide when using AI tools will be protected SC3: I believe that only legitimate parties will be able to access the information I provide using AI tools	Shin (2010, 2019)
Perceived value	PV1: I believe that AI tools can bring benefits to the business PV2: For me, the overall value of AI tools justifies their use PV3: AI tools can provide many advantages and conveniences for the enterprise PV4: I believe that the use of AI tools can really meet the needs of my organization	Parasuraman and Grewal (2000)
Response costs	RC1: Implementing AI tools in business processes is costly in both acquisition and operation RC2: We will need to frequently update the AI tools implemented in our business processes [DELETED] RC3: If security issues occur, they could affect the efficiency of the AI tools implemented in our business RC4: Complying with the security policies of AI tools would require a considerable investment of effort and time	Al-Emran *et al*. (2021), Johnston and Warkentin (2010)
Purchase intention	PI1: The likelihood of acquiring AI tools for my company is high PI2: The likelihood of purchasing AI tools for our organization is very likely PI3: My willingness to purchase AI tools is very high PI4: The likelihood that I will consider acquiring AI tools for my company is high	Song and Zahedi (2005)

Source(s): Authors' own work

Difference (others – services)	1-tailed (others vs services) *p*-value	2-tailed (others vs services) *p*-value
FC → PI	0.005	0.472
OC → PI	−0.159	0.107

(*continued*)

Table A1. Continued

Difference (others – services)	1-tailed (others vs services) *p*-value	2-tailed (others vs services) *p*-value
SC → PI	−0.132	0.188
PV → PI	*0.322*	*0.020*
RC → PI	0.093	0.114

Source(s): Authors' own work using SmartPLS 4.0

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