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Research paper

Determinants of AI Adoption Intention in Credit Risk Management: Evidence from Moroccan Banks

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Abstract

This research examines the behavioural intention of Moroccan banking professionals to integrate artificial intelligence (AI) into credit risk management. Utilizing an expanded Technology Acceptance Model (TAM), the study integrates five principal constructs: perceived usefulness, ease of use, explainability, trust, and regulatory ambiguity. Data were collected from 131 credit risk professionals and examined by Partial Least Squares Structural Equation Modeling (PLS-SEM). The model explains 62.7% of the variance in behavioural intention. The results show that perceived usefulness is the most important factor in adoption, while explainability, trust, and ease of use were not statistically significant. Regulatory ambiguity showed a significant positive effect on behavioural intention, highlighting the importance of the regulatory environment in shaping AI adoption decisions. These findings indicate that in the Moroccan banking sector, performance value and legal frameworks are prioritized over usability or transparency. The study provides actionable insights for policymakers and financial organizations aiming to facilitate AI integration in environments sensitive to compliance.

Keywords: *Artificial Intelligence; Behavioural Intention; Credit Risk Management; Regulatory Ambiguity; Technology Acceptance Model.*

1. Introduction

The banking sector, like many other industries, is undergoing rapid digital transformation driven by advancements in artificial intelligence (AI), machine learning, big data, and cloud computing. AI is increasingly positioned as a transformative force in finance, capable of reshaping how institutions assess risk, deliver services, and make strategic decisions. Over the past few years, the implementation of AI technologies across sectors has surged, with the number of organizations engaging in active AI projects rising from one in twenty-five to one in three (Alhadidi et al., 2020). According to Europe Business School, AI refers to the ability of a system to understand and interpret external data, learn from it, and apply that knowledge flexibly to achieve specific goals (Zemankova, 2019). Guo (2021) describes AI as a technological research field that seeks to simulate and extend human intelligence, while Dilek et al. (2015) highlight both its scientific and problem-solving dimensions.

In the banking sector, artificial intelligence has achieved considerable prominence, particularly in domains such as fraud prevention, customized services, and risk assessment. According to Alsmadi et al. (2022), artificial intelligence and machine learning are now regarded as fundamental elements of contemporary financial systems, fostering enhancements in operational efficiency and decision-making. The incorporation of AI into risk management procedures signifies a broader transition from conventional methods to more predictive and data-oriented approaches. Among the different classifications of financial risk, credit risk continues to be one of the most essential and influential. It signifies the potential for loss resulting from a borrower's failure or refusal to fulfill contractual debt commitments (Moudgalya et al., 2022). For financial institutions, including banks, lenders, and insurance providers, assessing the creditworthiness of clients constitutes a fundamental function (Punniyamoorthy & Sridevi, 2016).

Historically, the process depended on statistical models such as linear and logistic regression. However, as borrower behavior grows more intricate and data sources become more varied, conventional models are progressively constrained in their predictive capabilities.

To overcome these challenges, AI-driven credit scoring models have been developed, providing adaptive, non-linear, and highly automated solutions. Nonetheless, many of these models are regarded as "black boxes" owing to the opacity of their decision-making mechanisms (Lange et al., 2022). In response, explainable AI (XAI) has been proposed as a means to enhance the transparency and interpretability of AI systems. Lange et al. (2022) created an interpretable artificial intelligence model utilizing data from Norwegian banks to forecast credit default risk. Their findings demonstrate that XAI can offer meaningful insights into factors such as credit balance fluctuations, outstanding loan ratios, and the duration of customer relationships. AI also assumes an increasing function in the management of operational risk. Gonçalves et al. (2022) highlight that operational risks, particularly during periods of economic decline, can be more effectively mitigated through AI-driven automation and real-time surveillance. However, their research also indicates that implementation obstacles, including scarce human resources and conflicting strategic objectives, continue to pose substantial barriers. Similarly, Milojevic and Redzepagic (2021) demonstrate that artificial intelligence and machine learning enhance performance across multiple banking risk areas, including market, liquidity, and credit risk. Their research advocates for a prudent yet systematic approach to adoption, harmonizing technological advantages with organizational preparedness. Mhlanga (2021) further emphasizes the significant impact of artificial intelligence and machine learning on credit risk assessment, especially in analyzing borrower behavior and predicting repayment ability. Although AI offers a promising pathway for revolutionizing credit risk management, its implementation raises regulatory and ethical considerations. Challenges including data privacy, algorithmic bias, and explainability are essential considerations when deploying AI within highly regulated industries such as banking. These issues are especially prominent in emergent markets, where regulatory frameworks are still developing and institutional capacities differ significantly.

In Morocco, the integration of artificial intelligence (AI) in the banking sector is still at an early stage, with a limited body of empirical research addressing its adoption. Existing studies have mainly examined general perceptions of AI or the broader impact of digital transformation (El Ouidani et al., 2023; Rechka & Kabbaj, 2024), without focusing on its use in specific, high-stakes areas such as credit risk management. This domain is particularly sensitive due to the opaque nature of AI models, stringent regulatory requirements, and the importance of institutional trust. Given the increasing pressure on Moroccan banks to enhance credit risk assessment especially in light of rising non-performing loans, a focused analysis is needed. To date, no study has systematically explored how AI is perceived and accepted for credit scoring using robust theoretical models such as the Technology Acceptance Model (TAM) in the Moroccan context.

This study addresses that gap by examining the cognitive, organizational, and contextual factors influencing banking professionals' intention to adopt AI tools for credit risk management, while extending TAM with variables such as explainability, trust, and regulatory ambiguity. A quantitative approach was employed using survey data collected from 131 Moroccan banking professionals, and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The model explains 62.7% of the variance in AI adoption intention. Among the five proposed constructs, perceived usefulness ($\beta = 0.408$; $p = 0.005$) and regulatory ambiguity ($\beta = 0.185$; $p = 0.041$) showed significant effects on intention. Trust and ease of use were marginally significant, while explainability did not show a significant influence. These findings provide several significant contributions. Initially, they emphasize the significant role of perceived usefulness as a primary factor influencing AI adoption in credit risk scenarios. Secondly, they emphasize the contextual significance of regulatory ambiguity, indicating that ambiguity in legal frameworks can serve as both an impetus and an obstacle to adoption. The minimal importance of explainability suggests that, within the Moroccan context, model transparency is not regarded as crucial for the adoption of AI. This may be attributed to banking professionals' increased dependence on institutional control mechanisms rather than their own technical comprehension of AI systems illustrating a trade-off between transparency and perceived value in contexts where institutional trust supersedes the necessity for personal interpretability. This study provides context-specific insights for banks, regulators, and technology providers seeking to enhance AI adoption in credit risk management within Moroccan financial institutions.

1.1. Research objectives and questions

This study seeks to explore the behavioural dynamics that influence the adoption of artificial intelligence (AI) in credit risk management within the Moroccan banking sector. While AI holds strong potential to improve risk assessment accuracy and operational efficiency, its successful adoption depends on how end users, particularly credit risk professionals, perceive its value, usability, trustworthiness, transparency, and regulatory clarity. To address this objective, the study investigates the following research questions:

RQ1: What are the key perceptual factors that influence Moroccan credit risk managers’ intention to adopt AI in credit risk management?

RQ2: How do perceived usefulness, perceived ease of use, explainability, trust, and regulatory ambiguity shape the intention to adopt AI technologies in this context?

In answering these questions, the research extends the classical Technology Acceptance Model (TAM) by incorporating additional context-relevant variables namely, explainability, trust, and regulatory ambiguity to better capture the complexities of AI adoption in a highly regulated and risk-sensitive environment. This study includes five principal sections. The first section presents the research topic and emphasizes the existing gap that the study aims to fill. The second section offers a comprehensive analysis of the literature and delineates the theoretical framework supporting the research. The third section delineates the methodology, encompassing the sampling strategy, questionnaire formulation, and data analysis techniques. The fourth section elucidates and analyzes the principal findings. The fifth section presents the conclusion, addresses the study's limitations, and suggests directions for future research.

2. Literature Review

2.1. Credit risk

Credit risk constitutes a fundamental component of banking operations, as it is intrinsically linked to the financial intermediation function executed by deposit-taking institutions (Saunders and Cornett, 2011). This practice, which transforms short-term assets into medium- or long-term loans, subjects banks to the risk of borrower or counterparty defaulting on their financial obligations (Hull, 2018). Numerous authors endeavored to delineate the parameters of this risk. Heem (2000) characterizes it from a banking perspective as "the risk of the client defaulting on a financial obligation, typically the repayment of a loan." Henri Calvet (1997) characterizes counterparty risk as "the risk of loss resulting from the default of a debtor to whom the credit institution is owed a receivable." These definitions underscore the fundamental nature of credit risk: a unilateral violation of a contractual obligation that may lead to financial loss. Credit risk pertains to the probability of a partial or complete payment default, whether intentional or unintentional, leading to a financial loss for the institution. The determination is chiefly influenced by two factors: the borrower's creditworthiness, typically assessed through credit ratings, and the loan's duration. When this risk materializes, it may threaten not only the bank's short-term profitability but also the integrity of its asset portfolio and, ultimately, the institution's long-term financial stability. Risk exposure can be evaluated through two complementary dimensions. The initial component, termed the idiosyncratic component, pertains to borrower-specific attributes including financial structure, profitability, governance, payment behavior, and default history. This research is generally detailed and depends on internal data or behavioural scoring frameworks. The second component is systemic, comprising macroeconomic factors that may affect the overall level of default risk. These determinants include interest rate trends, inflation, the economic cycle, asset price volatility, and financial imbalances (Altman & Saunders, 1998; Laeven & Valencia, 2013).

These two dimensions interact closely and define the vulnerability of credit portfolios, both at the microeconomic level and across the financial system as a whole. From a theoretical standpoint, the conceptualization of credit risk finds its roots in the seminal work of Akerlof (1970), who introduced the notion of information asymmetry as a source of market failure, through the now-classic “market for lemons” example. This idea was further developed by Stiglitz and Weiss (1981), who demonstrated that banks’ inability to perfectly assess borrowers' true risk profiles gives rise to two major distortions: adverse selection, where the riskiest borrowers are paradoxically the most likely to seek credit; and moral hazard, which refers to changes in borrower behavior after receiving financing. In this regard, Freixas and Rochet (2008) argue that financial institutions exist not only for operational efficiency but also to address the information failures inherent in capital markets. Banks act as informed intermediaries, internalizing the costs of evaluation and monitoring. Diamond (1984) formalizes this role through his delegated monitoring theory, whereby banks reduce information asymmetries and optimize lender-borrower relationships by pooling monitoring costs and conducting rational screening. From a regulatory standpoint, this situation is governed by strict standards, particularly those established by the Basel Committee, whose central mission is to strengthen the robustness and resilience of the global banking system. It does so by requiring institutions to cover credit risk recognized as a direct threat to financial stability through minimum capital adequacy requirements. These theoretical foundations have made it possible to understand credit risk not merely as an isolated or random failure but as a structural phenomenon stemming from persistent economic and informational frictions, leading to the progressive development of tailored risk management methods. The growing significance of this risk in modern economies fully justifies efforts toward tighter regulatory oversight and methodological advancement. This dynamic is clearly reflected in the evolution of non-performing loans (NPLs) observed in Morocco over the past decade, as illustrated in the chart below. Evolution of non-performing loans (in billions of dirhams) by borrower category between 2014 and 2024.

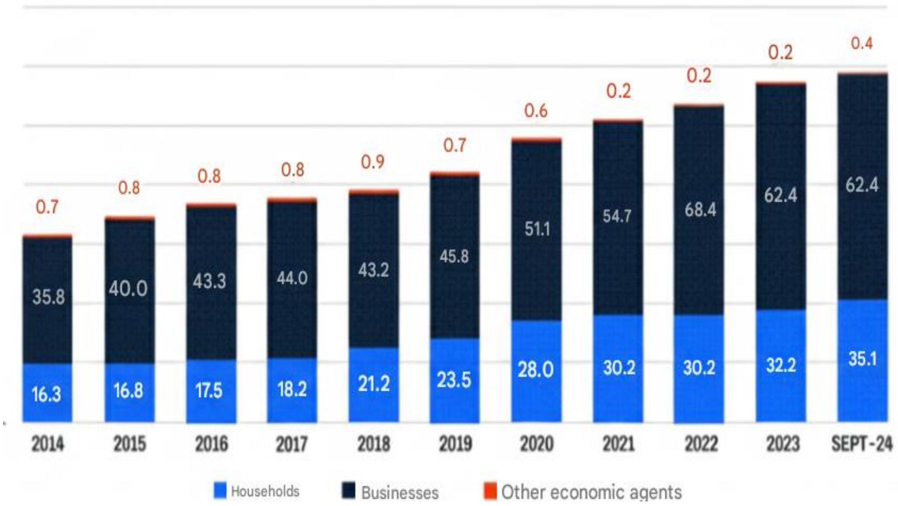

Fig. 1: Trend in Non-Performing Loans (In Billions of Dirhams) by Type of Debtor between 2014 and 2024. Source: Le360, Based on Bank Al-Maghrib Data (Sembène, 2024).

In recent years, Moroccan banks have experienced a steady rise in non-performing loans (NPLs), reflecting mounting credit risk pressures. In response to this steady increase in defaults, Moroccan banks have gradually structured their credit evaluation frameworks, relying on increasingly rigorous and quantitative methodologies.

According to data from Bank Al-Maghrib, this trend illustrates the urgent need for more robust, data-driven tools to support risk assessment (Sembène, 2024). As a result, financial institutions have started to adopt more quantitative and rigorous evaluation models to improve their credit risk management frameworks. However, the successful integration of AI technologies will ultimately depend on understanding how Moroccan bankers perceive their relevance, usefulness, and risks. Without incorporating these perceptions, adoption efforts may fall short of their intended impact.

2.2. Model TAM

The Technology Acceptance Model (TAM), proposed by Davis (1986), is one of the most widely used theoretical frameworks for explaining the adoption of technologies in organizational settings. Based on the work of Fishbein and Ajzen (1975) on the theory of reasoned action, it posits that the intention to use a system is determined by two main beliefs: perceived usefulness, defined as the belief that the tool improves work performance, and perceived ease of use, understood as the degree of effort required to use the system.

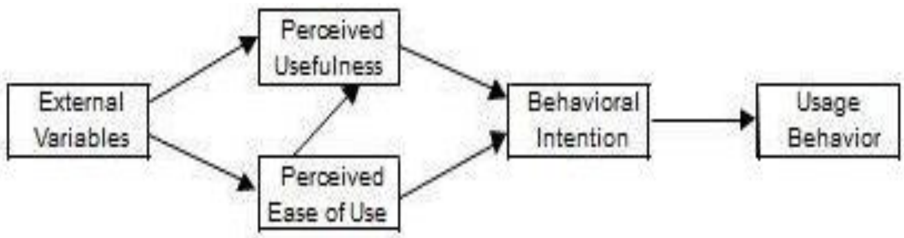

Fig. 2: Final Version of Technology Acceptance Model (TAM) (Venkatesh and Davis, 1996).

The figure illustrates the initial structure of TAM, in which these two main variables condition the intention to use, which is in turn influenced by external variables.

In the banking sector, where technology is introduced in highly regulated environments, several studies have confirmed the explanatory power of this model. Nath et al. (2013), through a survey of employees at public and private banks in India, emphasize that these two variables continue to play a decisive role in the acceptance of centralized information systems. Their study also proposes an extension of TAM through the introduction of contextual factors such as social influence, self-efficacy, and available technological resources, which indirectly affect perceptions of usefulness and ease of use.

Two notable developments of the original model have been proposed to overcome its limitations: TAM2 (Venkatesh & Davis, 2000), which incorporates social and cognitive variables (such as image, subjective norm, and outcome quality), and TAM3 (Venkatesh & Bala, 2008), which combines TAM2 with the determinants of ease of use from the anchoring and adjustment model (such as anxiety, playability, and self-confidence). These expanded versions offer a more comprehensive view of technology acceptance, particularly in complex professional contexts.

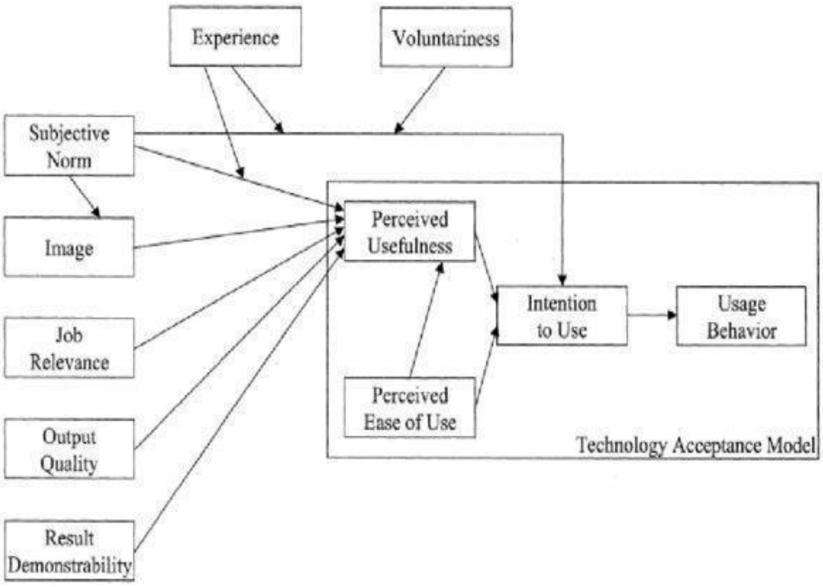

Fig. 3: Technology Acceptance Model (TAM 2) (Venkatesh and Davis, 2000).

TAM3 is currently the most detailed approach, integrating psychological, behavioural, and contextual levers that directly or indirectly influence perceived usefulness and perceived ease of use:

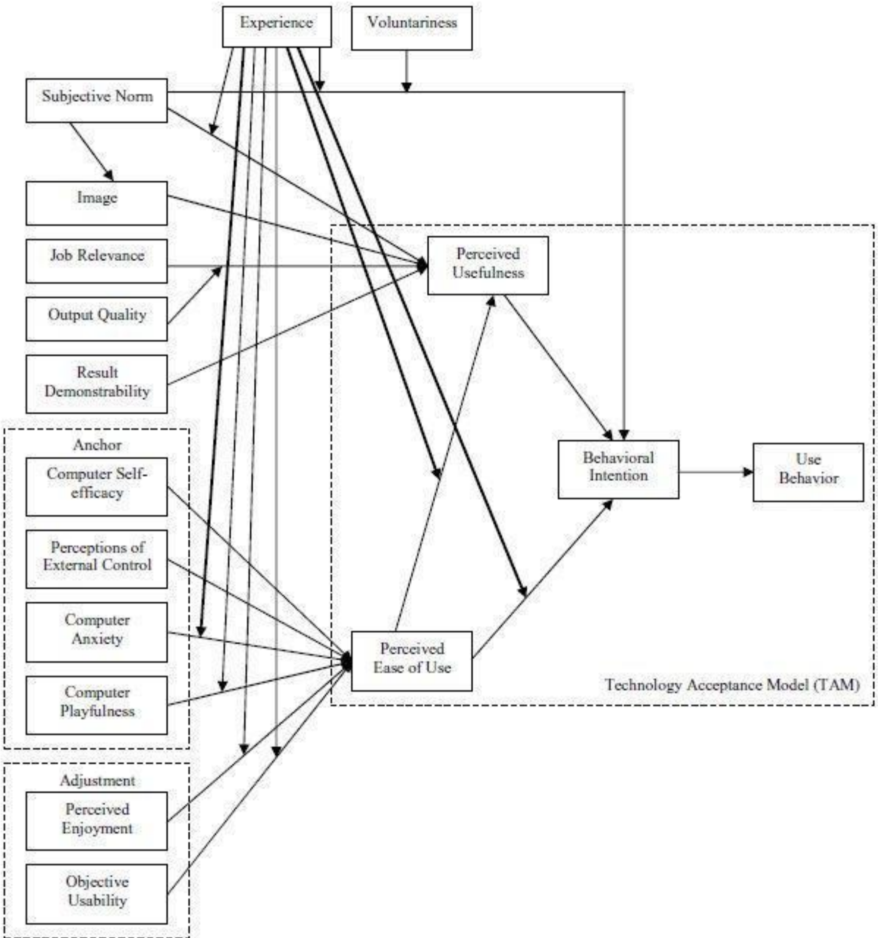

Fig. 4: Technology Acceptance Model (TAM 3) (Venkatesh and Bala, 2008).

The bibliometric analysis conducted by Uula and Avedta (2023) confirms the strong presence of TAM in research on banking digitization, whether in mobile banking, online services, or artificial intelligence applications. However, the structural simplicity of the model, although advantageous from an empirical point of view, has been criticized for its inability to integrate variables related to organizational dynamics and professional appropriation logic. In this regard, Brangier et al. (2010) emphasize the need to move beyond an approach focused solely on stated intentions by incorporating determinants from the actual usage context, such as cognitive load, compliance standards, and institutional pressure.

In the context of the Moroccan banking sector, which is undergoing a digital transition, the TAM model remains an interesting basis for analyzing the adoption of artificial intelligence. That said, its application needs to be adapted to the reality on the ground. Indeed, in an environment where regulatory constraints are strong and technological trust issues are crucial, it is necessary to integrate variables such as trust in systems, understanding of algorithmic decisions (explainability), and clarity of the legal framework. In this regard, the work of Lahrach and Bentahar (2025) provides valuable insight: their study shows that perceived trust is the most decisive factor in the intention to adopt AI, far more so than perceived usefulness, which is nevertheless central to the TAM. This trust is based in particular on the quality of the data and the reliability of the systems used, highlighting the importance of rethinking the model to better align it with the realities of the Moroccan banking sector.

2.3. Conceptual model and hypotheses development

2.3.1. Determinants of the intention to adopt artificial intelligence

● Perceived Usefulness (UTI)

Perceived usefulness is a cornerstone of the Technology Acceptance Model (TAM) and refers to an individual's assessment of the extent to which a technological system enhances their job performance (Davis, 1989). Closely associated with concepts such as productivity, efficiency, and task optimization, it plays a decisive role in technological adoption processes. The study by Lee, Kozar, and Larsen (2003) underscores this, citing over 70 studies that identify a positive relationship between perceived usefulness and usage intention. When a tool is deemed relevant especially for its speed or decision-making support, users are more inclined to adopt it. This phenomenon has been widely observed in mobile banking services, where perceived convenience helps overcome users' initial reluctance (Chen & Hsu, 2006). Perceived usefulness is grounded in tangible benefits observed in practice. Davis (1989) identifies five key dimensions to evaluate it: task execution speed, support for daily functions, productivity improvement, enhanced efficiency, and overall performance gains. These criteria help determine to what extent a technology adds real value to a user's activity. In digital banking systems, this perception is often linked to the reliability of AI tools, especially for credit scoring, default prediction, and decision-making support (Nath et al., 2013; Baptista & Oliveira, 2015). In the context of our study, perceived usefulness emerges as a central driver for the acceptance of artificial intelligence technologies in Moroccan banks. It reinforces professionals' trust when associated with tangible gains in quality, speed, or decision-making accuracy. In this sense, Kabir et al. (2017) remind us that perceived usefulness remains one of the most commonly used antecedents in predicting the adoption of digital services, both at individual and organizational levels.

● Perceived Ease of Use (FAC)

According to Davis (1989), perceived ease of use (PEOU) refers to the extent to which an individual believes that using a system requires no significant effort or obstacles to accomplish a task. This variable holds a central position in the TAM model, alongside perceived usefulness, and significantly influences user attitudes and behavioural intentions toward technologies (Ekow Kelly & Palaniappan, 2022). It reflects how easy it is to interact with a system, regardless of prior experience. Venkatesh and Davis (2000) emphasize that in the case of mobile banking, adoption depends less on past usage and more on a technology's ability to provide immediate, accessible, and user-friendly solutions to functional needs. Several empirical studies confirm the positive impact of perceived ease of use on technology acceptance. For example, Amin, Rezaei, and Abolghasemi (2014) found that this perception strongly contributes to user satisfaction in mobile website usage. An interface considered intuitive not only enhances the user experience but also acts as a key lever for technology appropriation. This role becomes even more critical in contexts involving artificial intelligence or machine learning models. Uula and Avedta (2023) show that in the banking sector, interface simplicity and result clarity directly influence managers' acceptance of technological tools. Thus, PEOU is a decisive factor, not only by reducing cognitive barriers but also by facilitating the evaluation of perceived usefulness and, consequently, usage intention.

● Perceived Explainability (EXP)

In highly regulated environments like the banking sector, perceived explainability is an essential condition for the acceptance of AI-based technologies. It refers to the user's ability to understand and interpret the decisions generated by a system especially when such decisions have significant consequences, such as in credit granting or risk evaluation. This demand for transparency, central to explainable AI research (Guidotti et al., 2018), reflects the need to make technological decisions intelligible, thereby fostering trust and ensuring regulatory compliance. In this context, the concept of result demonstrability introduced by Moore and Benbasat (1991) offers complementary insight. It refers to the tangibility, observability, and communicability of system-generated outcomes, and plays a central role in shaping perceptions of usefulness. As illustrated in TAM2, if the positive effects of using a system are visible and easily attributable, users are more likely to consider it useful (Moore & Benbasat, 1991). Conversely, a high-performing yet opaque system may not be perceived as beneficial, thus hindering its adoption. Studies by Agarwal and Prasad (1997) confirm this dynamic, establishing a significant correlation between system explainability and usage intention. This connection aligns with the Job Characteristics Model (Hackman & Oldham, 1976; Loher et al., 1985), which highlights the importance of understanding concrete results to motivate engagement with a tool. In the Moroccan context, the demand for explainability takes on particular relevance. As AI solutions gain ground in banking risk management, Bank Al-Maghrib explicitly recommends greater transparency of algorithmic systems, especially in credit scoring. This reflects a governance logic in which the acceptability of technologies depends on their ability to produce understandable, traceable, and justifiable outcomes. Perceived explainability thus emerges as a critical variable at the intersection of technical, regulatory, and ethical concerns.

● Perceived Trust (CONF)

Trust refers to the belief one party has in the intentions and actions of another (Aldaabseh & Aljarah, 2021; Siagian et al., 2022). It goes beyond a mere feeling and is built across several dimensions, including ability, integrity, and benevolence of a system or actor (Benamati et al., 2010). To these traditional dimensions, Folake (2014) adds reputation, which proves to be an important antecedent of trust in the adoption of electronic services. In the technology adoption literature, trust has been successfully integrated into the Technology Acceptance Model. For example, Gu et al. (2013) and Jeong (2013) showed that trust positively influences the intention to adopt online banking services when combined with TAM constructs. Similarly, Al-Ajam and Nor (2013) found in Yemen that trust, alongside perceived relative usefulness and ease of use, determines the intention to use digital banking services. The concept of trust applied to technology has its roots in psychology and economics before being adapted to understand interactions in digital environments. Gefen et al. (2002) demonstrated that in e-commerce, the presence of ambiguity makes trust indispensable for transactions to occur. This observation is reinforced by Hansen et al. (2018) and Singh & Sinha (2020), who highlight the role of trust in adopting technologies in uncertain contexts, particularly on the Web. More broadly, trust positively influences user attitudes and behaviors toward technology. Empirical studies show that it affects the intention to use services such as mobile banking, regardless of demographic or cultural factors (Merhi et al., 2019; Shareef et al., 2018; Sigurdsson et al., 2018). Singh & Sinha (2020), Sharma (2019), and Hansen et al. (2018) note that trust has been studied across numerous domains from e-commerce to information systems and remains a major explanatory factor in user behavior. Additionally, Soderstrom (2009) identifies more than 29 types of trust, grouped into three categories: trust in technology, in the organization, and in individuals. In the specific case of the Moroccan banking sector, trust is a cross-cutting lever for technology adoption, especially AI-based ones. Research by Kesharwani & Bisht (2012) and Alalwan et al. (2017) shows that in digital banking environments, trust in systems plays a decisive role in usage decisions. In Morocco, such trust is often linked to users' prior experience with digital tools, the system's ability to manage algorithmic bias, and its compliance with regulatory standards. In a context where institutions must ensure the reliability, security, and transparency of technologies, strengthening trust becomes a key issue to facilitate the sustainable adoption of digital innovations.

- Perceived Regulatory ambiguity (FREG)

Perceived regulatory ambiguity refers to the ambiguity surrounding the laws and regulations governing the use of artificial intelligence (AI), particularly in sensitive domains such as credit risk management. In the Moroccan context, this ambiguity is heightened by the absence of a dedicated legal framework for AI in the banking sector. The only existing legislation is Law No. 09-08 on the protection of personal data, which, while essential, does not address more recent concerns such as algorithmic decision explainability, accountability of automated systems, or AI model governance. This legal gap creates a climate of hesitation and caution among financial institutions, which perceive a high risk in terms of compliance and reputation. As Ridzuan et al. note, the absence of appropriate regulation can lead to misconduct, raise ethical concerns, and result in loss of public trust ultimately undermining the potential benefits of AI-based innovations. Without clear regulatory oversight, intelligent systems such as banking chatbots used for transactions or customer support may operate outside the legal boundaries, exposing both users and institutions to unforeseen consequences. To ensure that technologies are safe, ethical, and beneficial, government support is essential. It not only protects citizens' rights but also enhances trust in automated systems, an indispensable condition for large-scale adoption (Ridzuan et al., 2023). In the financial sector, AI presents a major opportunity to improve service personalization, detect market anomalies, and prevent financial crises (Ridzuan et al.). However, without appropriate regulation, these innovations risk being hindered or misused. Regulatory ambiguity thus becomes a key contextual factor shaping AI adoption decisions in Moroccan banks, due to the lack of clear benchmarks on legal obligations, usage limits, and quality standards applicable to intelligent systems.
In line with the hypothetico-deductive reasoning adopted in this study, the conceptual model was developed based on a structured theoretical framework that combines contributions from established technology acceptance models (TAM) and the empirical specificities of the Moroccan banking sector. Each explanatory variable included in the model has been rigorously defined conceptually and justified in terms of its relevance to the studied context. Based on this theoretical and contextual foundation, the following hypotheses are proposed to model the relationships between risk managers' perceptions and their intention to adopt artificial intelligence tools:

- H1: The perceived usefulness of artificial intelligence positively influences risk managers' intention to adopt algorithmic tools.
- H2: The perceived ease of use positively influences the intention to adopt artificial intelligence tools.
- H3: The perceived explainability of artificial intelligence systems positively influences their acceptability and adoption in risk management processes.
- H4: Trust in artificial intelligence systems positively influences their adoption by risk managers.
- H5: Regulatory ambiguity surrounding the use of artificial intelligence significantly influences its adoption by credit risk managers.

Despite the extensive literature on technology adoption and credit risk management, several theoretical and empirical gaps remain. First, existing studies have primarily focused on general digital transformation or traditional scoring methods, with limited empirical evidence examining AI adoption specifically in credit risk management within emerging banking systems such as Morocco. Second, although the Technology Acceptance Model provides a robust framework for explaining technology adoption, prior research has predominantly emphasized individual-level cognitive determinants while underrepresenting institutional and regulatory influences, which are particularly critical in highly regulated financial environments. Third, the combined role of explainability, trust, and regulatory conditions in shaping AI adoption decisions in high-stakes financial contexts remains insufficiently theorised and empirically tested. Addressing these limitations, this study extends TAM by integrating context-specific institutional variables and provides empirical evidence on AI adoption in Moroccan banks, thereby contributing to both technology acceptance theory and the understanding of digital transformation in regulated financial systems.

3. Methodology

3.1. Study design and data collection

This study investigates the factors influencing Moroccan risk managers' behavioural intention to adopt artificial intelligence (AI) tools in credit risk management. It specifically explores how explanatory variables such as perceived usefulness, perceived ease of use, perceived explainability, trust, and perceived regulatory ambiguity shape technology adoption decisions in a banking context marked by growing digital transformation and increasing credit risk pressures. The research framework includes one key endogenous construct: the behavioural intention (BI) to adopt AI-based decision-support tools for credit risk assessment. The conceptual model consists of five main constructs: perceived usefulness (UTI), perceived ease of use (FACI), perceived explainability (EXP), trust (CONF), and regulatory ambiguity (FREG). The model proposes direct relationships between these five constructs and behavioural intention, as well as a set of hypotheses grounded in the extended Technology Acceptance Model (TAM) and contextualized within the Moroccan banking environment. To empirically test this model, the study targeted risk management professionals working in Moroccan banking institutions.
Data were collected through a self-administered electronic questionnaire, distributed via email and professional banking networks. The survey remained open for responses over a period of three months, from September to November 2025. Out of 147 total responses received, 16 were excluded due to incompleteness or non-eligibility (respondents not currently working in credit risk management), resulting in a final sample of 131 valid responses. This response rate reflects a strong engagement from the targeted professional community and provides a robust basis for statistical analysis.

Table 1 presents the demographic profile of the 131 valid respondents who participated in this study. The sample consisted predominantly of male participants (61%), while females accounted for 38% of the total. In terms of age distribution, the majority of respondents were between 25 and 34 years old (46.6%), followed by those aged 35 to 44 (32.1%). A smaller proportion fell within the 45 to 54 age group (11.5%), while respondents under 25 years and those aged 55 and above represented 9.2% and 0.8%, respectively. Regarding educational background, the vast majority held a master's degree (73.3%), with 16% holding a bachelor's degree and 10.7% a doctorate. As for professional experience, 44.3% of the participants had between 5 and 10 years of experience, 29.8% had between 10 and 15 years, 13.7% had less than 5 years, 10.7% reported 15 to 20 years of experience, and only 1.5% had more than 20 years. This distribution reflects a well-qualified and experienced respondent pool, suitable for assessing perceptions related to AI adoption in credit risk management.

Table 1: Respondent Profile

Category	Details	Frequency (N)	Percentage (%)
Gender	Male	80	61.0%
	Female	51	38.0%
Age	Under 25 years	12	9.2%
	Between 25 and 34 years	61	46.6%
	Between 35 and 44 years	42	32.1%
	Between 45 and 54 years	15	11.5%
	55 years and above	1	0.8%
Education Level	Bachelor's degree	21	16.0%
	Master's degree	96	73.3%
	Doctorate	14	10.7%
Years of Experience	Less than 5 years	18	13.7%
	Between 5 and 10 years	58	44.3%
	Between 10 and 15 years	39	29.8%
	Between 15 and 20 years	14	10.7%
	More than 20 years	2	1.5%

3.2. The study variables and questionnaire

The measurement items used in this study were adapted from validated sources to ensure reliability and contextual relevance. Items related to UTI, FAC, and intention of adoption were derived from Venkatesh and Bala (2008). Explainability items were adapted from Venkatesh and Bala (2008) and Shin (2021), while trust-related items were taken from McLeod and Pippin (2012) and Lee and Song (2013). Regulatory ambiguity items were based on Dwivedi et al. (2021). The structured questionnaire consisted of four sections: general information, tools and techniques for credit risk evaluation, perceptions and impact of AI, and effectiveness and adoption of scoring models. All items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

3.3. Data analysis

This study applied a two-step structural equation modeling (SEM) approach to evaluate the validity of the proposed conceptual framework. In the first phase, confirmatory factor analysis (CFA) was conducted to assess the reliability, convergent validity, and discriminant validity of the measurement model. In the second phase, the structural model was tested using SmartPLS v.4 to examine the significance of the hypothesized paths between the constructs. The R^2 value was used to evaluate the explanatory power of the model. Figure 1 displays the research framework developed for this study.

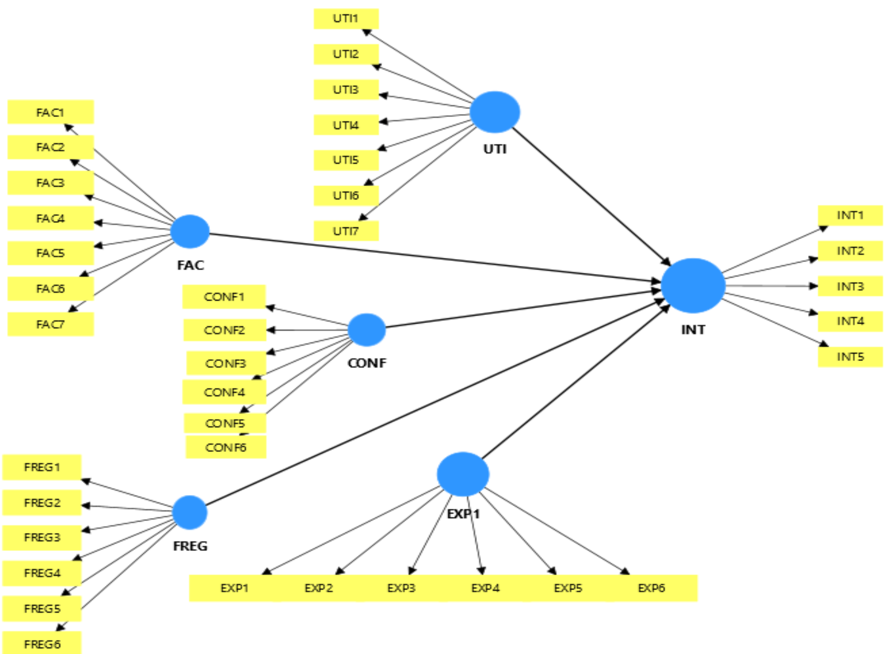

Fig. 5: Research Model.

4. Results

To ensure indicator reliability, outer loadings were first examined. In the initial analysis, several items displayed loadings below the recommended threshold of 0.70 (Hair et al., 2019), particularly within the FAC and CONF constructs. As a result, all indicators with loadings below 0.70 were excluded to improve the measurement quality. The refined model (Outer Loadings 2) retained only items with strong loadings (≥0.70), confirming the unidimensionality of constructs. This purification step enhanced both the internal consistency and convergent validity of the model, as evidenced by improved Cronbach's alpha, composite reliability, and AVE scores across all constructs. Cronbach’s Alpha values above 0.70 are generally considered acceptable, values above 0.80 are deemed good, and those exceeding 0.90 indicate excellent internal consistency (Hair et al., 2010). In this study, all constructs met the recommended thresholds for internal consistency (Cronbach’s Alpha > 0.70), composite reliability (ρC > 0.70), and convergent validity (AVE > 0.50), with the exception of the FAC construct. While FAC’s Cronbach’s Alpha and ρA fall slightly below the conventional cutoff, its AVE and ρC values remain above the acceptable threshold, justifying its retention in the measurement model following item purification.

Table 2: Construct Reliability and Convergent Validity Metrics (Cronbach’s Alpha, Composite Reliability, AVE)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CONF	0.832	0.847	0.900	0.750
EXP	0.733	0.739	0.845	0.646
FAC	0.553	0.561	0.817	0.690
FREG	0.878	0.879	0.908	0.622
INT	0.901	0.903	0.926	0.716
UTI	0.903	0.905	0.923	0.632

Discriminant validity was assessed using the Fornell–Larcker criterion, which compares the square root of each construct’s AVE with its correlations with other constructs. As shown in Table 2, all diagonal values (representing √AVE) exceed the corresponding inter-construct correlations, confirming adequate discriminant validity (Fornell & Larcker, 1981). For example, the square root of the AVE for CONF (0.866) is higher than its correlations with UTI (0.613), INT (0.639), and FREG (0.568). This demonstrates that each latent variable is empirically distinct and captures phenomena not represented by other constructs in the model.

Table 3: Discriminant Validity – Fornell–Larcker Criterion

	CONF	EXP	FAC	FREG	INT	UTI
CONF	0.866					
EXP	0.376	0.804				
FAC	0.509	0.312	0.831			
FREG	0.568	0.308	0.457	0.789		
INT	0.639	0.372	0.547	0.604	0.846	
UTI	0.613	0.351	0.492	0.557	0.719	0.795

The HTMT values presented in Table 3 were used to assess discriminant validity between the latent constructs. All HTMT values are below the recommended threshold of 0.85 (Henseler et al., 2015), indicating that the constructs exhibit adequate discriminant validity. This confirms that each latent variable in the model is empirically distinct from the others.

Table 4: Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)

	CONF	EXP	FAC	FREG	INT	UTI
CONF						
EXP	0.460					
FAC	0.744	0.451				
FREG	0.670	0.370	0.656			
INT	0.733	0.440	0.767	0.672		
UTI	0.703	0.433	0.693	0.621	0.791	

The R-square value for the dependent variable (INT) is 0.627, indicating that 62.7% of the variance in the intention to adopt AI is explained by the model. The Q²_predict value of 0.537 confirms strong predictive relevance. The RMSE (0.728) and MAE (0.507) also indicate acceptable prediction accuracy.

Table 5: R-Square, Adjusted R-Square, and Predictive Accuracy Metrics (Q², RMSE, MAE) for the Structural Model

	R-square	R-square adjusted
INT	0.627	0.612
Q²predict	RMSE	MAE
0.537	0.728	0.507

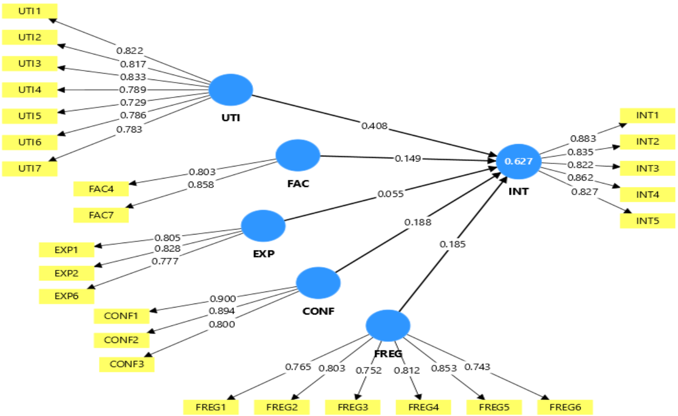

Fig. 6 : Research Model.

The structural model was assessed using path coefficient analysis. The results show that perceived usefulness (UTI → INT) has the strongest and statistically significant effect on behavioural intention (β = 0.408, p = 0.005), followed by regulatory ambiguity (FREG → INT) (β = 0.185, p = 0.041), both significant at p < 0.05. While trust (CONF → INT) and ease of use (FAC → INT) showed moderate effects (β = 0.188 and β = 0.149, respectively), their p-values (0.149 and 0.079) suggest that these relationships are not statistically significant at the 5% level. Explainability (EXP → INT) did not demonstrate a significant impact (β = 0.055, p = 0.325). These findings highlight the importance of perceived usefulness and the regulatory environment in influencing AI adoption intentions in credit risk management.

Table 6: Hypothesis Testing

Hypothesis	Relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	UTI -> INT	0.408	0.425	0.146	2.804	0.005	Support
H2	FAC -> INT	0.149	0.131	0.085	1.759	0.079	Not Support
H3	EXP -> INT	0.055	0.061	0.056	0.984	0.325	Not Support
H4	CONF -> INT	0.188	0.191	0.130	1.444	0.149	Not Support
H5	FREG -> INT	0.185	0.159	0.090	2.047	0.041	Support

5. Discussion and Implications

This study aimed to identify the main factors influencing Moroccan banking professionals' behavioural intentions to adopt artificial intelligence (AI) in the assessment of credit risk. The structural model was tested using data collected from 131 valid respondents and was based on the extended Technology Acceptance Model (TAM). The model explains 62.7% of the variance in behavioural intention, confirming a strong explanatory power.

The results support Hypothesis 1, showing that perceived usefulness (UTI) has a significant and positive influence on behavioural intention (β = 0.408, p < 0.01). This confirms that banking professionals are more inclined to adopt AI tools in credit risk management when they clearly perceive a benefit in improving task performance and decision quality. This finding reinforces the central role of perceived utility in shaping technology acceptance in professional and highly regulated environments, such as banking. Similar evidence was found by Hoque et al. (2025) in the context of Bangladeshi banks, where perceived usefulness emerged as the most influential driver of AI adoption among managers. Lim et al. (2025) reported that Generation Z's adoption of AI in banking is strongly associated with its perceived value in improving decision-making and service outcomes. In the Moroccan context, Rechka and Kabbaj (2024) highlighted that digital transformation in banks is largely accepted when perceived as adding concrete value to operational efficiency and customer engagement. These converging results across different geographical and institutional settings underscore the universal importance of perceived usefulness in facilitating AI integration within the banking sector.

Although the link remained directionally positive, Hypothesis 2, which proposed a positive association between behavioural intention to adopt AI and perceived ease of use (FAC), was not statistically significant (β = 0.149, p = 0.079). This implies that among experienced credit risk specialists, ease of use is not a determining factor in adoption intention, even though it may still affect impressions. Perceived ease of use may have a diminishing marginal effect in situations when users already have good technical or digital literacy, as is frequently the case with banking professionals. This is particularly true when strategic performance improvements take precedence over usability. These results are in line with earlier research by Rahman et al. (2023), who discovered that AI adoption intention in financial services was not significantly predicted by PEOU. However, perceived ease of use continues to be a significant factor in other user demographics or usage scenarios, such digital lending. According to Yadav and Shanmugam (2023), consumers' behavioural intention to embrace digital lending services was strongly impacted by simplicity of use, utility, and perceived security. This contrast demonstrates how user profile, technical maturity, and application environment may all affect how important ease of use is.

Similarly, Hypothesis 3, concerning the effect of perceived explainability (EXP) on intention, was not supported (β = 0.055, p = 0.325). This result is surprising given the growing emphasis placed on model transparency in AI systems. However, it may be explained by the fact that many respondents operate within institutional frameworks where interpretability is ensured at a procedural or organizational level, thus reducing the individual's perceived responsibility to fully understand AI-generated decisions. This finding aligns with recent empirical and meta-analytical evidence questioning the practical impact of explainability on adoption behaviours. Masciotra and Boudrias (2024), in an experimental study conducted in workplace settings, found that algorithmic explainability did not contribute to trust and, in some cases, even had a counterproductive effect on the intention to use AI. Their results suggest that providing explanations, even when technically accurate, does not necessarily enhance user confidence and may generate additional doubts or cognitive overload, thereby reducing adoption appeal. Similarly, a meta-analysis by Atf and Lewis (2025), synthesising findings from 90 studies, concluded that although explainability moderately improves trust, it is neither a dominant nor sufficient predictor of behavioural intention. Other determinants, such as perceived usefulness, perceived risk, and organisational readiness, tend to exert a stronger influence. These findings suggest that explainability, while normatively valuable, may play a secondary role in adoption decisions, particularly in professional contexts where decision accountability is shared or externally regulated. In highly regulated banking environments, model transparency may therefore function primarily as an organisational or compliance-related requirement rather than a direct individual-level driver of adoption intention. Consequently, explainability may influence adoption indirectly through mechanisms such as trust, perceived risk, or organisational governance rather than directly predicting behavioural intention.

In contrast, Hypothesis 4, relating to perceived trust (CONF), did not yield a statistically significant effect on behavioural intention ($\beta = 0.188$, $p = 0.149$), although the relationship remained positive. This pattern suggests that, in the Moroccan banking context, trust may function less as a direct psychological driver of adoption and more as an institutionalised condition embedded in organisational controls. In highly regulated and risk-sensitive environments, decision-support technologies are typically deployed within formal governance structures (model validation, audit trails, internal control frameworks, compliance checks), which can reduce the extent to which individual users rely on their personal trust perceptions when forming adoption intentions. From an institutional perspective, adoption decisions are often shaped by normative and coercive pressures (e.g., compliance expectations, risk governance, internal policies), meaning that behavioural intention may be driven primarily by performance value (perceived usefulness) and regulatory context rather than interpersonal-style trust in the system itself. In this setting, trust may become a "background" requirement that is assumed once organisational safeguards are in place, producing limited incremental explanatory power at the individual level. This finding aligns with Ilias et al. (2026), who found that trust did not significantly influence Malaysian SMEs' intention to adopt e-invoicing within a compliance-driven framework, suggesting that organisational and normative forces can overshadow individual trust in regulated contexts. Similarly, Liew et al. (2025) reported that cognitive trust alone did not significantly predict adoption of banking voicebots, with emotional trust showing a stronger effect an important distinction because professional banking users may engage with AI tools primarily through cognitive/performance criteria rather than affective bonds. Conversely, our results diverge from Lim et al. (2025), who observed a significant effect of trust on Generation Z's intention to adopt AI in banking services, reinforcing that the role of trust is context-dependent and contingent on user profile, decision stakes, and organisational maturity. Overall, these results imply that trust may operate indirectly (e.g., through perceived usefulness, perceived risk, or perceived compliance) or may become more salient at later stages of diffusion when AI systems move from advisory tools to more autonomous decision-making. Future research should therefore test whether trust plays a mediating or moderating role, particularly under conditions of higher automation, weaker governance safeguards, or increased accountability placed on frontline users. Hypothesis 5 was supported, indicating that regulatory ambiguity (FREG) significantly and positively influences behavioural intention ($\beta = 0.185$, $p = 0.041$). The positive direction of this relationship suggests that, in the Moroccan context, regulatory ambiguity may be perceived less as a deterrent and more as a transitional condition that allows greater flexibility for experimentation with AI technologies. In the absence of fully codified AI-specific regulations, banking institutions may rely on internal governance mechanisms such as model validation procedures, audit trails, and compliance controls to manage uncertainty while pursuing technological innovation. From this perspective, regulatory ambiguity may simultaneously generate perceived risk and perceived opportunity, with the opportunity to innovate appearing to dominate at the intention stage.

This finding highlights the important role of the regulatory environment in shaping AI adoption decisions in financial institutions while also emphasizing the need for clearer legal frameworks regarding algorithmic decision-making, data governance, and model accountability, particularly in emerging markets such as Morocco. These findings are consistent with prior research emphasizing the importance of governmental frameworks in technology acceptance. According to Al-Hawamdeh and Alshaer (2022), the adoption of new technologies depends heavily on regulatory structures established by governments. Similarly, Wang et al. (2022) argue that policy support and legislative initiatives are essential to facilitate the diffusion and responsible use of emerging technologies. Alghamdi et al. (2020), Dora et al. (2021), and Pan et al. (2022) further reinforce this view by highlighting the pivotal role of government intervention in incentivising AI adoption through formalised laws, strategic guidelines, and institutional commitment. Collectively, these studies confirm that regulatory conditions play a decisive role in shaping technology adoption decisions, particularly in highly regulated sectors such as banking where risk aversion and compliance requirements are high. Although regulatory ambiguity may initially encourage experimentation, clearer institutional frameworks remain essential for the responsible and large-scale deployment of AI systems. Future research could further examine how regulatory clarity and organisational governance interact to shape adoption decisions over time.

From a theoretical perspective, this study extends the Technology Acceptance Model by demonstrating the importance of institutional and regulatory factors in highly regulated environments. The findings suggest that, in compliance-driven sectors such as banking, contextual determinants may play a role comparable to traditional TAM constructs. This highlights the need to reconsider technology acceptance models by integrating institutional and governance dimensions, particularly in emerging economies where regulatory frameworks shape technology adoption behaviour.

6. Conclusion

Artificial intelligence (AI) represents a major shift in credit risk management practices within the Moroccan banking sector. Its integration enables professionals to process large volumes of financial and behavioural data, enhance the precision of risk assessments, and support faster, data-driven decision-making. In a context where regulatory oversight and market expectations are increasingly demanding, AI is viewed not only as a tool for efficiency but also as a strategic asset to strengthen competitiveness and compliance. Nevertheless, its adoption raises critical challenges related to legal frameworks, algorithmic transparency, and the evolving balance between automation and human expertise.

This study investigated the behavioural intention of Moroccan banking professionals to adopt AI in credit risk analysis, using an extended Technology Acceptance Model (TAM). The results confirmed that perceived usefulness is the strongest determinant of adoption, reinforcing the importance of performance-based value in technology acceptance within highly regulated environments. This result is consistent with previous empirical evidence reported by Davis's (1989) original TAM paradigm, Hoque et al. (2025), Lim et al. (2025), and Rechka and Kabbaj (2024). Conversely, perceived ease of use and explainability did not significantly influence intention, suggesting that Moroccan practitioners prioritise operational efficiency over interface simplicity or system transparency. Trust, although positively associated with intention, was not statistically significant, potentially reflecting a reliance on institutional safeguards rather than personal confidence in AI tools.

Importantly, regulatory ambiguity was found to significantly influence AI adoption decisions, highlighting the central role of the regulatory environment in the Moroccan financial ecosystem. The absence of clear legal directives regarding AI-generated decisions, data governance, and model accountability shapes how credit risk professionals assess the risks and opportunities associated with AI implementation. This finding aligns with broader research emphasising the role of state-led frameworks and regulatory stability in supporting responsible technology diffusion, particularly in emerging markets.

This research contributes to the understanding of AI acceptance by providing context-specific insights from Morocco, a country undergoing rapid digital transformation in the financial sector. It underscores that successful AI integration depends not only on technological attributes but also on the clarity of institutional and regulatory arrangements. For Moroccan policymakers, regulators, and banking leaders, these findings underline the urgency of developing national guidelines and sector-specific standards to govern AI use in sensitive financial domains.

Despite its contributions, our study has some limitations. First, it relied on self-reported data collected at a single point in time, which may not capture evolving perceptions as AI tools become more embedded in banking workflows. Longitudinal research could provide richer insights into how attitudes shift with increased exposure and institutional maturity. Second, the study focused on direct structural relationships and did not explore mediation or moderation effects beyond those tested. Future research could investigate how organisational readiness, digital infrastructure, or policy awareness mediate the link between perceptions and adoption intention, particularly within the Moroccan banking context where technological disparities and compliance culture vary across institutions.

By extending the TAM to include trust, explainability, and regulatory ambiguity, this study offers a more nuanced and contextually grounded view of AI adoption in Moroccan banks. It opens new avenues for research and practice focused on the institutional enablers that shape how AI is received, evaluated, and ultimately adopted in complex, compliance-driven sectors.

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