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Artificial Intelligence: Understanding the determinants of adoption and intention to recommend the technology in the financial sector

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Resumo

O setor financeiro está a passar por uma transformação significativa devido à convergência dos avanços tecnológicos e à importância cada vez maior dos serviços financeiros. Esta tendência levou à adoção de tecnologias disruptivas, como a Inteligência Artificial (IA), para melhorar a prestação de serviços e responder às necessidades críticas. Apesar dos potenciais benefícios, a investigação sobre a aceitação da IA no sector financeiro continua a ser limitada. Este estudo propõe um modelo teórico inovador e abrangente que combina os modelos UTAUT2 e TAM, com a variável de intensão de recomendar a IA e dois moderadores pouco estudados na literatura, consciencialização e familiaridade, oferecendo informações valiosas sobre os fatores que influenciam a adoção e os efeitos moderadores sobre a intenção de recomendar. O modelo proposto foi testado empiricamente utilizando a modelação de equações estruturais (SEM) com dados de vários países. Os resultados sugerem que a utilidade percecionada, a facilidade de utilização percecionada e a confiança percecionada influenciam significativamente a atitude dos utilizadores. A motivação hedónica e a influência social surgiram como determinantes-chave da intenção de adotar a IA. O estudo também concluiu que a consciencialização moderou significativamente a relação entre a intenção de adotar e a intenção de recomendar. Esta investigação contribui para o ainda pouco estudado conhecimento sobre a adoção da IA no sector financeiro. As conclusões fornecem informações valiosas para as instituições financeiras que procuram implementar eficazmente soluções de IA e melhorar a aceitação dos utilizadores no sector.

Palavras-chave: Inteligência Artificial, Setor Financeiro, Adoção, FinTech

Abstract

The financial sector is undergoing a significant transformation due to the convergence of technological advancements and the ever-increasing importance of financial services. This trend has led to the adoption of disruptive technologies, such as Artificial Intelligence (AI), to enhance service delivery and address critical needs. Despite the potential benefits, research on the acceptance of AI within the financial sector remains limited. This study proposes an innovative and comprehensive theoretical model that combines UTAUT2 and TAM models, with an intention to recommend AI construct and two understudied moderators in literature, namely awareness and familiarity, offering valuable insights into factors influencing adoption and intention to recommend the technology. This model was empirically tested using structural equation modelling (SEM) with data from multiple countries. The results suggest that perceived usefulness, perceived ease of use, and perceived trust significantly influence user attitudes. Hedonic motivation and social influence emerged as key determinants of intention to adopt AI in the financial sector. The study also found that awareness significantly moderated the relationship between intention to adopt and intention to recommend. This research contributes to the yet understudied body of knowledge on AI adoption in the financial sector. The findings provide valuable insights for financial institutions seeking to effectively implement AI solutions and enhance user acceptance within the sector.

Key Words: Artificial Intelligence, Financial Sector, Adoption, FinTech

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List of Abbreviations

AI – Artificial Intelligence

ATU – Attitude towards use

AW – Awareness

FM - Familiarity

HM – Hedonic Motivation

ITR – Intention to Recommend

ITU – Intention to Adopt

ML – Machine Learning

PEU – Perceived Ease of Use

PR – Perceived Risk

PT – Perceived Trust

PU – Perceived Usefulness

SI – Social Influence

1. Introduction

The financial sector, as an indispensable cornerstone of the contemporary economy, has consistently undergone transformative shifts in response to technological advancements. In recent years, a notable surge in the integration of Artificial Intelligence (AI) into the financial domain has emerged (Hassani et al., 2020). Despite its growing presence, the comprehension of this phenomenon remains to be fully understood (Van der Burgt, 2019). Hailed as a transformative technology during the 2010s, AI is expected to surpass the significance of other technologies throughout the current decade (Hilpisch, 2020). More accurately, the financial services and FinTechs have witnessed disruptive transformation driven by the utilization of AI applications (Mamoshina et al., 2017). This work aims to investigate the intricate and dynamic landscape of AI adoption within the financial industry, exploring the ramifications, challenges, and possibilities associated with this technological revolution.

As the financial industry embarks on a new era, the utilization and implementation of AI present novel elements demanding thorough examination (Gerlich, 2023). Within the financial domain, AI-enabled technologies have permeated various strategic spheres, encompassing for example risk assessments, fraud detection and management, financial advice services, trading, financial management, and customer relationship management (Truby et al., 2020).

A multitude of factors propel the adoption of AI, including the relentless pursuit of a competitive edge, mounting regulatory hurdles, and escalating consumer expectations. These driving forces collectively have been incentivizing financial institutions to implement AI within their business (Van der Burgt, 2019).

Despite growing interest in Artificial Intelligence applications within the financial sector, a comprehensive understanding of its interaction with banking

services remains elusive. Notably, existing literature on the determinants driving AI adoption in this specific domain is relatively scarce. This underscores the critical need for in-depth research to illuminate the factors influencing bank integration of AI technologies. The present study seeks to address this gap in the current scholarship by investigating the key drivers of AI adoption within the financial sector. This work makes several contributions to researchers, contributing to the advancement of knowledge, by exploring and discussing direct implications for financial institutions and users.

Following this introduction, a further six chapters will be presented. We will start identifying the existing literature, divided into four main topics that are critical to understanding the topic, main challenges and opportunities involved, namely: Artificial Intelligence, the Financial Sector, the application of AI in the Financial Sector, and the existing approach models of technology adoption. In the second chapter, the research model and hypothesis formulation are presented, followed by the research methodology presentation in chapter three. Chapter four expands on the discussion of the results, followed by chapter five where are presented the main theoretical and practical implications, as well as future areas of study to pursue. The conclusions are presented in chapter six summarizing our work.

2. Literature Review

2.1 Artificial Intelligence

According to Hassani et al. (2020), Artificial Intelligence (AI) contains a wide range of meanings, making it impossible to identify a widely accepted scientific definition. This perspective is consistent with the finding of Legg & Hutter (2007), who offered an overview encompassing seventy different AI definitions, each reflecting a different point of view. Furthermore, Hassani et al., (2020) described

the concept as an intelligent system built to use and analyse data, as well as to do certain activities without programming. In contrast, Colom et al. (2010) defined AI as a broad cognitive skill that includes reasoning, problem-solving, and learning. Others say it is delineated as a machine's ability to perform cognitive functions typically associated with human minds (Theuri & Olukuru, 2022). AI is understood as being capable of performing cognitive intelligence, replicating, and enabling the augmentation and improvement of human cognitive capacities (Theuri & Olukuru, 2022). Machine Learning (ML) is one of the most pertinent areas of AI. As stated by Jo Pesch et al. (2022), ML comprises the capacity of machines to find patterns within large datasets. This technique is commonly used for automated risk evaluations. Theuri & Olukuru (2022) further categorize AI technology into two types: artificial machine intelligence, the computer performs tasks and makes decisions based on predefined rules and requirements, and machine intelligence, in which a computer uses self-improvement algorithms to improve its performance and capabilities with each task it handles.

AI's expansion throughout industries is having a huge impact in different spheres, namely at the social and economic levels. (Acemoglu & Restrepo, 2020). As a disruptive force, AI has helped to reduce the need for organizational resources such as operational support people (Almansour, 2023). Conversely, AI has a number of barriers, including ethical concerns (Almansour, 2023) and a lack of transparency (Vössing et al., 2022) all of which have been subjects of investigation in contemporary literature. There are several criticisms of artificial intelligence services in the current literature, citing limitations such as a lack of publicly accessible legitimate data and the costs involved with program maintenance and upgrading (Chen et al., 2018). In 2022, the European Commission introduced the Artificial Intelligence Act Proposal (AIA), establishing pivotal regulations (Wendehorst, 2021). Entities utilizing AI systems face obligations and risk assessment requirements outlined within the AIA. Notably, the AIA proposal categorizes AI systems as "high risks" if they have a

key role in ensuring safe working conditions, good health, and respect for fundamental rights within the European Union. From a financial perspective, AI systems used, for example for credit assessment, should be classified as high risk since they determine an individual's financial resources.

2.2 Financial sector

As asserted by Lalwani & Lalbeg (2022), emerging from the rise of technology, digital banking offers a new way to manage finances. In today's digital age, we believe that embracing this transformation is crucial for banks, as the transition towards cashless transactions becomes increasingly inevitable. This transition is bringing relevant benefits to the financial sector, particularly in the realm of costs, combating money laundering and corruption. Still and all, the cashless economy reduces the risk of any consequence related to carrying physical currency, like loss of cash or robberies. (Kumari & Khanna, 2017). With only one click, users may execute basic banking tasks such as money transfers, bill payments or statements without having to visit a physical bank location. When making purchases, people usually choose digital wallets over cash as a safe payment method, opting for the perceived security benefits of digital payments. In clients' terms, convenience is the primary motivator to utilize digital banking mechanisms, while banks may also benefit from cost savings and exceptional service. (Lalwani & Lalbeg, 2022). Despite the exponential rise of digital banking, a significant proportion of consumers remain hesitant to adopt it. Scholars attribute this to various factors, but it is a consensus that banks have to raise trust among consumers to drive significant adoption of digital banking (Jadil et al., 2021).

Mobile banking, a key component of the digital banking ecosystem, further enhances user experience by removing barriers to access (Payne et al., 2021). A study developed by Maynard (2020) exhibits that in 2024 there will be an amount of 3.6 billion digital banking users (which include both e-banking and mobile

banking), a 1.2 billion increase from 2020. This expansion can be attributable to the rise of smartphone users and Internet customers (Kumar et al., 2023). Lyman (2015) has documented the global proliferation of digital financial services, with implementations reported in over 80 countries. This expansion has facilitated financial inclusion for millions who were previously excluded or underserved by traditional financial institutions. Consequently, these individuals are transitioning from cash-based transactions to a digital financial ecosystem offering a diverse range of services, including payments, transfers, access to credit and insurance products, investment opportunities, and secure savings mechanisms. All in all, in this paradigm, banks are strongly encouraged to integrate artificial intelligence into their digital and mobile platforms, particularly those focused on the collection, storage, and analysis of client data (Payne et al., 2021).

2.2.1 AI's Applications

In the ever-evolving financial landscape, the integration of AI has ignited a wave of transformative change in several areas for example, Customer Relationship Management, Fintech and Robots Advisors, Credit Risk Assessment, Anti-Money Laundering and Stock Price Analysis.

2.2.1.1 Customer Relationship Management

The concept of Customer Relationship Management (CRM) regards increasing customer satisfaction by analysing accurate information about customers, hence boosting business competitiveness (Idzikowski et al., 2019). CRM is designed to maximize long-term customer value by orienting the company operations, marketing, and customer service toward client relationship management and supporting information technology (IT) systems (Chang, 2014). Furthermore, CRM's fundamental goal is to retain current customers by enhancing their loyalty

and attracting new clients, ultimately leading to improved profitability (Hansotia, 2002). In recent years, several banks have expressed their commitment to fostering and managing deeper interactions with their clients with the aim of maximizing customer equity. This entails developing and sustaining effective customer connections to enhance overall customer satisfaction (Yao and Khong, 2011). Customers represent one of the most crucial assets of a financial organization, thus their engagement must be continuously protected and improved. Everyone can understand that it is critical for banks to satisfy the changing needs and wishes of their customers (Almansour, 2023).

In contradistinction to conventional digital technologies, AI exhibits a unique capability for customer service personalization. By leveraging intricate algorithms, AI can tailor services to individual users and generate predictions autonomously. Furthermore, AI interfaces possess the ability to communicate, interact, and deliver customer service, all while functioning independently (Wirtz et al., 2018). Regarding the study of Basha et al. (2020), there are some factors positively related to customer satisfaction in digital banking, which in turn is strongly related to Artificial Intelligence. Notably, ease of use, service quality, content understanding, and security play a crucial role.

The contemporary financial services landscape is characterized by evolving consumer demands. Customers increasingly prioritize convenience and speed in their financial services (Lytvyn et al., 2024). To navigate this dynamic environment, financial institutions must strategically leverage technological advancements to ensure their service offerings remain aligned with these evolving consumer expectations (Semenog, 2020). Banco Santander in Brazil exemplifies the potential of AI-powered CRM with its virtual assistant "Gente" (meaning "people"). This chatbot addresses inquiries and requests, eliminating the need for human interaction in many cases. This innovative feature enables faster and more efficient customer service, offering 24-hour availability and the resolution of straightforward issues within minutes. For more intricate problems,

the chatbot seamlessly transitions consumers to human assistance (Conta-Corrente, 2020).

2.2.1.2 FinTech and Robot Advisors

Werth et al. (2023) emphasize technology as a critical success factor for FinTechs, and contemporary technology is inextricably linked to AI adoption and integration. The application of Artificial Intelligence in the corporation's daily operations extends beyond customer service. For instance, Machine Learning technologies facilitate risk prediction and monitoring. This form of robotics, based on Big Data analysis, is helpful in various aspects, such as detecting fraud, monitoring transactions, and managing data (Hasan & Hoque, 2023).

The "robotic process automation" (RPA) is another emerging technology impacting financial institutions. Financial robots and intelligent automation tools offer high capacity, repetitive processing capabilities, and accuracy. These robots have significantly boosted digitalization and automation of various financial services, attracting academic interest (Ren & Weng, 2019). Financial giants like Deloitte and PwC are actively deploying RPA financial robots. While adoption has reached over 32% of financial applications (Li, 2020), potential risks exist. Li (2020) also highlights the lack of research on managing the risks associated with implementing RPA in complex financial processes, demanding high accuracy. Therefore, while RPA offers benefits, it requires further development and careful implementation within institutions. By incorporating these technologies, financial institutions can improve their credit risk management processes, leading to more informed lending decisions, enhanced efficiency, and potentially reduced risks. However, it is crucial to acknowledge the limitations and potential drawbacks of these emerging technologies and continuously strive for improvement in their implementation and regulation.

It's important to notice that the most impacted area of FinTechs is in the realm of services. Among the recent innovations, robo-advisors are attracting attention

due to their unique features that set them apart from traditional services. (Belanche et al., 2019). It is expected that services with AI-driven services such as robo-advisors will gradually replace human jobs in future years. This shift necessitates careful integration to achieve sustainable success, as customers transition from interacting with human employees to robotic services (Issa et al., 2023). Therefore, companies are progressively embracing AI to reshape how businesses engage with customers. AI-enabled FinTech can revolutionize the financial system by addressing various social, sensory, cognitive, and emotional issues that people face while engaging with financial institutions. Cognitive behaviour displays observation, critical thinking, and problem-solving, as well as interactions with service functioning and accessibility. Happiness, excitement, fury, and hate are all expressed through emotional components. (Arora et al., 2023). FinTechs leverage sophisticated financial services and AI-driven innovation to enhance operational efficiency and productivity across critical industries. In this context, Almansour (2023) highlights the crucial role of personnel expertise and skillsets for effective AI utilization, given FinTechs' reliance on data-driven algorithms.

2.2.1.3 Credit Risk Assessment

Credit risk, defined as the potential for a borrower to default on their financial obligations, is a critical concern for financial institutions. This risk stems from two primary sources: external macroeconomic factors and the borrower's internal operating conditions (Hu & Su, 2022). Credit risk can manifest in various forms, such as credit default risk, concentration risk, country risk, and counterparty risk (Bhattacharya et al., 2022). Contemporary Financial institutions are increasingly leveraging artificial intelligence (AI) and machine learning (ML) to assess borrowers' creditworthiness and associated risk profiles, informing lending decisions (Jáuregui-Velarde et al., 2024). Bussmann et al. (2020) propose an explainable AI model for credit risk analysis, specifically within peer-to-peer

lending platforms. Their findings suggest that AI can elucidate borrowers' credit scores and predict their future behaviour, albeit with regulatory implications concerning transparency and consumer protection. Moreover, Chakraborty and Joseph (2017) highlight the applications of machine learning in risk assessment. They emphasize the importance of understanding mortgage contract development for financial institutions' balance sheet management. ML algorithms can also forecast existing customers' buying patterns, enabling more precise advisory services.

2.2.1.4 Anti-money Laundering

Anti-money laundering (AML) is a term used to describe the efforts combating the "attempt to conceal the proceeds of illegal activities by disguising them as legal earnings" (Kuzmenko et al., 2023). In recent times, some banks have been fined by legal authorities, due to deficiencies in their controls over money laundering (Chen et al., 2018). When engaging with high-risk clients, banks must put in place efficient systems, controls, and procedures to manage the risk. As Jullum et al., (2020) stated, there are, at least, three primary concerns about the current anti-money laundering systems: i) the simplicity of rule-based systems; ii) the huge number of false alerts and iii) the difficulty of maintaining the rules as a living document that adapts to changing circumstances.

AI-based approach to AML proved to be more time and cost-effective. Regardless of their level of automation and sophistication, these AI services can offer AML services, like KYC (know your customer) and transaction monitoring (Kindylidi, 2022). Machine learning algorithms are being studied and used to automatically recognize abnormal patterns in massive volumes of financial data. In AML cases, there are normally two different solutions: supervised and unsupervised. (Chen et al., 2018). Supervised techniques involve algorithms that learn from labelled examples in a training set, for example, "Normal or Suspicious". The algorithms build a model to classify new, unlabelled data in a

testing set into predefined label categories. On the other hand, unsupervised techniques use algorithms in group data without any prior labels. These groups, called clusters, are formed based on characteristics or patterns within the data (Chen et al., 2018). HSBC Holdings, a leading global financial that has effectively leveraged artificial intelligence providers to augment its anti-money laundering (AML) efforts and capabilities. Utilizing sophisticated data mining techniques to identify patterns within the bank's extensive historical data, was able to improve the detection of anomalies that may be indicative of money laundering activities. This real-time analysis enables HSBC to proactively halt transactions before fraudulent activities can materialize. The AI-driven solution has significantly reduced the occurrence of false positives, which are transactions flagged as fraudulent but are not fraudulent. This reduction in false positives is a crucial achievement, as these erroneous alerts can impose substantial costs on the bank, including fines and reputational damage (Kharpal, 2023).

2.3 Literature Theoretical Models

2.3.1 Extended unified theory of acceptance and use of technology (UTAUT2)

Venkatesh et al. (2003) examined eight key theories in depth and produced the unified theory of acceptance and use of technology (UTAUT). This model proposes that four constructs have a direct influence on use behaviour and behavioural intentions (performance expectancy, effort expectancy, social influence and facilitating conditions). Since its first design in 2003, UTAUT has been used to explain technology adoption in organizational contexts, however, it was extended to the acceptance and use in a consumer context (Venkatesh et al., 2012). UTAUT2 added three constructs to the main theory (hedonic motivation, price value and habit).

2.3.2 Technology Acceptance Model (TAM)

The TAM (Davis, 1989) is a theory for understanding user adoption of technology, including artificial intelligence. This model has explanatory power in predicting customers' desire to use emerging technology as well as actual use (Lim & Zhang, 2022). The original TAM was built considering the outcomes of two extrinsic motivations – Perceived Usefulness and Perceived Ease of Use. Despite that, Venkatesh & Davis (2000) put forward an improved model by incorporating seven additional variables (subjective norms, voluntariness, image, job relevance, result demonstrability, output quality and experience) resulting in a purported 20% increase in the model's explanatory power compared to the original, as per findings by (Wu et al., 2011).

2.3.3 Diffusion of Innovation (DOI)

The DOI theory adds by assessing innovations and the success of their transmission through a more accurate indicator of consumer behaviour (Rogers, 2003). According to research on innovation dissemination, innovation is a critical component (Zhao & de Pablos, 2011), and human innovativeness is also an essential aspect in affecting the results of technology adoption (Yi et al., 2006).

2.3.4 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (an expanded version of the Theory of Reasoned Action) has been widely utilized in the recent literature to understand, explain, and predict many sorts of behaviour (Machaka-Mare et al., 2023). According to the TPB, attitude, subjective norms, and perceived behavioural control all have a direct impact on behavioural intention, as well (Ajzen, 1991). Perceived behavioural control can be defined as the sense of availability of the abilities, opportunities, and resources required to carry out the behaviour under discussion (Kumari & Devi, 2023).

2.3.5 Task Technology Fit (TTF)

In the realm of information systems (IS) and technology management, the Task-Technology Fit (TTF) model stands as a foundational theoretical framework. Propounded by Goodhue & Thompson (1995) and further refined, the TTF model posits that technology adoption hinges on the alignment between the inherent properties of the technology and the specific demands of the tasks individuals or organizations seek to accomplish (Goodhue & Thompson, 1995). This implies that even if users perceive a technology to be highly advanced, they may refrain from adopting it if they perceive it as ill-suited for the tasks at hand (Zhou et al., 2010).

3. Research Model

Based on the recognition that existing literature has not yet fully understood the factors that drive AI adoption and how these elements interrelate to influence individual choices regarding AI adoption, particularly in the financial sector. This study leverages a combination of two well-known models, the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Technology Acceptance Model (TAM), as seen in Fig. 1, with an Intention to Recommend construct and the moderation of Awareness and Familiarity' important variables. The actions of these moderators can significantly impact the learnability and formation of user communities surrounding technological adoption. The choice of UTAUT stems from its established strength in predicting information technology acceptance, as noted by Martins et al. (2014) who viewed it as one of the most comprehensive models available in the literature. The inclusion of TAM, alongside UTAUT2, is explained by its strong predictive power regarding technology use. Additionally, its determinants offer clarity for

system developers, facilitating their incorporation during system requirement analysis and development stages (Lee, 2009).

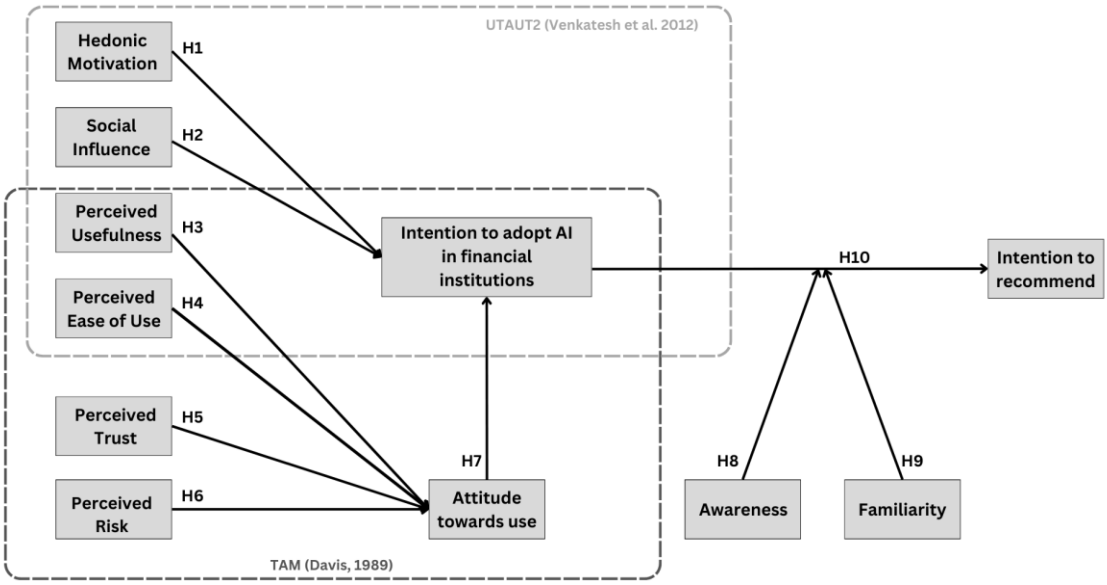

Figure 1- Proposed Research Model

Perceived Usefulness and Perceived Ease of Use are included in the area of both models because, as stated by Venkatesh et al., (2003), Perceived Usefulness (TAM) is equivalent to the Performance Expectancy (UTAUT) and Perceived Ease of Use (TAM) is equivalent to Effort Expectancy (UTAUT).

From the UTAUT2, five variables were included in our model, namely Hedonic Motivation, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioural Intention. Building upon Baptista & Oliveira's (2015) argument, Price value was not included since in financial services users often perceive banking services as free of charge or not incurring in channel specific fees. Given the high penetration of smartphones and computers of the target population, which serve as one of the predominant gateways to access financial services, the variable Facilitating conditions were not included in the model. This exclusion reflects the assumption that conditions such as technical support or online help are unlikely to be a significant barrier or supporter to the

technology adoption within this specific context. Habit was also not included since Artificial Intelligence as we know it today, it is still a relatively new technology, and people have not yet used it extensively enough to form a habit. Supported by the same fact, that AI is not yet a reality nowadays in most of the financial sector (Gansser & Reich, 2021), the use of behaviour construct was also not included within the theoretical model.

Hedonic Motivation (HM) is described as the satisfaction or pleasure derived from using technology, and it has been found to have a significant impact in deciding technological acceptance (Brown & Venkatesh, 2005). Individual's enjoyment and positive experiences with technology significantly influence people's openness to adopting new technologies. (Lowry et al., 2013). By analysing prior research, Moorthy et al. (2019) demonstrate that Hedonic Motivation interaction significantly impacts technology adoption.. Thus, the following hypothesis has been constructed:

H1*. Hedonic Motivation positively influences the intention to adopt AI-enabled financial applications and services.*

Social Influence (SI) is the extent to which consumers perceive others (e.g., family and friends) believe they should use a particular technology (Venkatesh et al., 2012). Recent research underscores the growing prominence of social influence as a significant factor impacting users' intention to accept and adopt technological innovations (Faqih & Jaradat, 2021). Studies suggest that social pressure from specific reference groups, such as tech-savvy peers or privacy-conscious family members, can influence customers' intentions to adopt new technologies (Zhou et al., 2010). Thus, the following hypothesis has been constructed:

H2. *Social Influence positively influences the intention to adopt AI-enabled financial applications and services.*

Perceived Usefulness is understood as the degree to which an individual believes that using a specific technology will enhance their job performance (Venkatesh et al., 2003). In compliance with Compeau & Higgins (1995), people are more likely to accept new technology if they see good benefits from it. Thus, the following hypothesis has been constructed:

H3. *Perceived Usefulness positively influences the attitude toward the use of AI-enabled financial applications and services.*

Perceived Ease of Use is defined as "the degree of ease associated with the use of the technology" (Venkatesh et al., 2012). Research consistently highlights the pivotal role of perceived effort in technology acceptance, demonstrably influencing users' decisions (Nguyen et al., 2023). Miltgen et al. (2013) suggest that perceived ease of use contributes to a more accurate prediction of users' intention to adopt new technologies. In the framework of this study, ease of use might refer to the user's perception of the ease with which they can perform banking tasks or access financial services within AI technology. Thus, the following hypothesis has been constructed:

H4. *Perceived Ease of Use positively influences the attitude towards the use of AI-enabled financial applications and services.*

Perceived Trust holds significant importance in studies related to technology (de Visser et al., 2016). Perceived trust encompasses user's subjective assessment of how trustworthy, reliable, and secure they perceive a technology or system can be, which, in turn, affects their willingness to use and their attitude towards it (Roca et al., 2009). According to researchers, trust is a critical step toward social acceptance of new technologies, such as Artificial Intelligence (Wu et al., 2011). As a result, perceived trust may serve to improve future usage of AI banking

services over time (Payne et al., 2018). Thus, the following hypothesis has been constructed:

H5. *Perceived trust positively influences the attitude towards the use of AI-enabled financial applications and services.*

Perceived Risk is typically defined as a feeling of uncertainty about the potential negative repercussions of adopting a product or service (Featherman & Pavlou, 2003). Risk may be classified into numerous categories, including privacy, financial, social, temporal, and performance risk (Lee, 2009). Users' intent to communicate information and execute transactions, and consequently use AI's financial features, are reduced when they perceive risk (Pavlou et al., 2003). Thus, the following hypothesis has been constructed:

H6. *Perceived risk negatively influences the attitude towards the use of AI-enabled financial applications and services.*

Attitude is an individual's view and appraisal of a given conduct (Belanche et al., 2022). In essence, it reflects a generated emotional condition towards a specific technology (Rabaa'i & ALMaati, 2021). As proposed by de Luna et al. (2019), Attitude towards use includes behavioural (preference for technology usage), affective (emotional reaction to technology), and cognitive (individual beliefs, experience about technology) components and all of them directly influence intention to adopt. Thus, the following hypothesis has been constructed:

H7. *Attitude towards use positively influences the intention to adopt AI-enabled financial applications and services.*

Awareness, from the customer perspective, is, as stated by Sathye (1999), a key aspect of any acceptance of an innovative technology. In this context, awareness refers to the understanding and recognition of the potential risks and benefits of using AI financial services. On the other hand, awareness can also be defined as

the ability to make an appropriate assessment of sources of information or ideas (from the internet or social interactions) (Nurbarani & Soepriyanto, 2022). Drawing on the work of Howcroft et al. (2002), the lack of knowledge of online banking services and their benefits are considered reasons for consumers' reluctance to use online banking services offered by banks. The same may be applied regarding the use of AI. Thus, the following hypothesis has been constructed:

H8. *Awareness moderates the relationship between the intention to adopt and the intention to recommend, in such a way that the relationship will be stronger among people with higher levels of awareness.*

Familiarity can be described by the level of knowledge and experience that users have with various forms of technology (Fütterer et al., 2023). Mäenpää et al. (2008) asserted that variances exist in the attitude of customers and their intentions based on their varying levels of familiarity with AI. Users with a higher level of familiarity with such innovations will gain firsthand experience, will value such technology in terms of its usefulness, develop more positive attitudes toward them because they have more knowledge about the practical value of this technology, and will recommend a technology more often when they have an in-depth knowledge of its characteristics (Castaneda et al., 2007). However, customers who are less familiar with AI make more decisions based on subjective standards (Belanche et al., 2019). Thus, the following hypothesis has been constructed:

H9. *Familiarity moderates the relationship between the intention to adopt and the intention to recommend, in such a way that the relationship will be stronger among people more familiar with the AI.*

4. Methodology and Data

The choice of the research method normally is not determined by the research scope but by the research purpose. Considering the nature of the investigation, trying to understand the factors that may influence the use of AI technology financial sector, we choose to follow a quantitative methodology of research. The target population was the adult population, over 18 years old, who have one or more banking accounts and use any kind of financial services. No restrictions were imposed based on participants' country of residence. This is intended to promote a geographically representative sample, encompassing individuals from diverse contexts and potentially capturing variations in financial service usage across different settings. Minimum educational attainment requirements were also not enforced. This inclusivity allowed for the participation of individuals with varying levels of formal education, reflecting the broad spectrum of users within the target population of financial service consumers.

Based on the fact that survey instruments had typically been used in studies of technology adoption (Venkatesh et al., 2003), we constructed an online survey hosted on a well-known platform (Google Forms). The survey was developed in the English language using adapted items from existing literature. Measurement items for Perceived Usefulness, Perceived Ease of Use, and Familiarity were adapted from Belanche (2019); items for Perceived Risk were adapted from Featherman & Pavlou (2003); items for Perceived Trust were adapted from Payne et al. (2018) and Susanto et al. (2016); items for Social Influence and Hedonic Motivation were adapted from Venkatesh et al. (2012); items for Awareness were adapted from Al-Somali et al. (2009) and Rehman et al. (2012); items from attitude towards use were adapted from Payne et al. (2018) and Al-Somali et al. (2009); items for Intention to use were adapted from Park & Joon Kim (2013); finally, items for intention to recommend were adapted from Oliveira et al. (2016). Each

item was measured using a Likert scale ranging from 1 (totally disagree) to 7 (totally agree). The questionnaire was created in English and then translated into Portuguese, by a native-speaking and translated back into English, by another person, to ensure consistency.

The survey was pilot-tested amongst a group of 30 banking users, who were not included in the final data. Preliminary results showed that scales were reliable. The online survey was administered for three months, specifically from November 2023 until January 2024. The survey was actively disseminated across various social media platforms, such as LinkedIn, Facebook, WhatsApp, Instagram, and Survey Circle. To improve the research's visibility, the survey was re-shared on social media platforms, including LinkedIn (three times) and Facebook (twice), throughout the data collection period. Posts were carefully crafted to attract the attention of the target audience and generate interest in participating in the study. Direct messages were sent to a list of contacts, inviting them to participate and encouraging them to share the survey with their own contacts. At the end of the period, a total of 203 valid responses were collected.

The common bias was examined using Harman's single-factor test (Podsakoff et al., 2012) and the Marker Variable Technique (Johnson et al., 2011), confirming no significant common method bias in the data.

Table 1 - Descriptive statistics of respondent's characteristics

Variable	Category	Frequency	%
Gender	Male	126	62.4%
	Female	74	36.6%
	Prefer not to say	2	1.0%
Country of Residence	**Portugal**	158	78.2%
	EUA	17	8.4%
	Luxembourg	5	2.5%
	Italy	4	2.0%
	Qatar	4	2.0%
	Others	14	6.9%
Education	Bachelor's	87	43.1%
	Master's	71	35.1%
	Doctorate	1	0.5%
	Professional training	4	2.0%
	High-School	37	18.3%
	Prefer not to say	2	1.0%
Age	18-24	90	44.5%
	25-34	50	24.7%
	35-44	25	12.4%
	45-54	26	12.9%
	55-64	10	5.0%
	65 or over	1	0.5%

Analysing the comprehensive sample of 203 individuals, the data reflects a diverse and representative cross-section. The respondents are predominantly from Portugal (78%), with a significant minority from the United States (8.5%). There are also participants from Italy and Qatar (2%), France, Germany and Spain (1.5%), two participants from Poland (1%) and only one answer from the United Kingdom, the Netherlands and Belgium. The education attainment of the sample is relatively high, with 43.5% having completed a bachelor's degree, 35.1% having completed a master's degree, one respondent completed a PhD, and 18.2% having completed high school. The sample is also relatively young, with 44.9% of participants falling into the 18-24 age group, 24.6% in the 25-34 age group, and 12.3% in the 35-44 age group. In this sample, 69.5% belong to GenY and GenZ.

5. Data Analysis and Results

Structural Equation Modelling (SEM) constitutes a methodological approach for gauging causal relationships through the amalgamation of statistical data and qualitative causal hypotheses. Previous scholars have acknowledged SEM's potential in discerning between measurement and structural models, while also accounting for measurement error (Henseler et al., 2009). Within SEM, two primary methodologies exist: (i) covariance-based techniques and (ii) variance-based techniques. In the context of this study, we used a variance-based technique, namely the Partial Least Squares (PLS), supported by SmartPLS4 software (Ringle et al., 2022). PLS is deemed appropriate for this study for three main reasons: (i) the absence of prior testing of the research model in extant literature; (ii) the perceived complexity of the research model; (iii) the sample dimension is ten times greater than the maximum number of paths directed to a variable (Gefen & Straub, 2005). Following Anderson & Gerbing's (1988) criteria, the analysis was conducted in two steps: the measurement model, to assess the model's reliability and validity, followed by the structural model, to assess the structural relationship of the model. Details regarding both steps are presented as follows.

5.1 Measurement Model

The assessment of the measurement model encompassed an evaluation of the items' reliability, internal consistency, convergence validity, and discriminant validity.

Indicator reliability was ascertained based on the criterion that loading surpasses 0.7. All loadings, except AW4, satisfy the criteria, confirming a good indicator reliability of the instrument (Hair et al., 2017). Accordingly, the fourth

item for Awareness (AW4) was dropped. Internal consistency was gauged through the utilization of composite reliability and Cronbach's alpha. Examination of Table 2 reveals that all constructs demonstrate composite reliability, with Cronbach's alpha exceeding 0.7 in all instances (Hair et al., 2017), which suggests that the constructs are reliable.

The convergence validity was tested with the Average Variance Extracted (AVE), which should be higher than 0.5 (Hair et al., 2012). All constructs meet this criterion, as shown in Table 2.

Table 2 - Quality criteria and factor loadings

Construct	Reliability	AVE	Cronbach's Alpha	Item	Loadings	t-value
ATU	0.946	0.898	0.887	**ATU3**	0.941	76.95
				ATU4	0.954	155.48
AW	0.957	0.918	0.911	**AW1**	0.961	103.68
				AW2	0.955	97.11
FM	0.919	0.791	0.868	**FM1**	0.868	34.87
				FM2	0.898	39.37
				FM3	0.901	42.80
HM	0.958	0.883	0.934	**HM1**	0.937	80.57
				HM2	0.953	131.89
				HM3	0.929	65.54
PEU	0.922	0.747	0.887	**PEU1**	0.796	23.96
				PEU2	0.900	57.86
				PEU3	0.877	36.96
				PEU4	0.881	43.89
PR	0.927	0.809	0.887	**PR1**	0.870	11.17
				PR2	0.920	20.39
				PR3	0.907	20.57
PT	0.928	0.810	0.883	**PT1**	0.878	46.58
				PT2	0.912	71.13
				PT3	0.910	60.34
PU	0.946	0.854	0.914	**PU1**	0.903	49.95
				PU2	0.932	77.53
				PU3	0.937	72.86
SI	0.933	0.822	0.892	**SI1**	0.874	24.73
				SI2	0.916	49.66
				SI3	0.929	81.96

To analyse the discriminant validity, three different tests were applied and fulfilled. The first test was to analyse the Cross-Loadings, in which the loading of each indicator should be higher than all cross-loadings (Götz et al., 2010). To ensure this criterion, two items had to be excluded, namely ATU1 and ATU2 (see Annex 2). The Fornell-Larcker criterion was the second test, where the square root of all constructs' AVE should be greater than the correlation between the constructs (Fornell & Larcker, 1981). As seen in Table 3, diagonal values (square root of AVE, in bold) are greater than off-diagonal values (correlations between the constructs). All constructs fulfilled this criterion. Last, it was measured the heterotrait-monotrait (HTMT) ratio of correlations, where all values should be above 0.9 (see Annex C) (Henseler et al., 2015). Three items had to be eliminated to guarantee that this condition was met, namely ITR1, ITU1 and ITU2.

Table 3 - Fornell-Larcker criterion

	ATU	**FM**	**HM**	**ITR**	**ITU**	**PEU**	**PR**	**PT**	**PU**	**SI**
ATU	**0.948**									
AW	0.553									
FM	0.477	**0.889**								
HM	0.640	0.402	**0.940**							
ITR	0.554	0.322	0.520	**1.000**						
ITU	0.817	0.407	0.646	0.641	**1.000**					
PEU	0.679	0.513	0.509	0.529	0.676	**0.865**				
PR	-0.253	-0.076	-0.151	-0.077	-0.288	-0.075	**0.899**			
PT	0.748	0.327	0.650	0.528	0.724	0.551	-0.192	**0.900**		
PU	0.684	0.411	0.647	0.529	0.668	0.629	-0.138	0.691	**0.924**	
SI	0.559	0.323	0.586	0.458	0.588	0.442	-0.004	0.610	0.488	**0.907**

5.2 Structural Model and Hypotheses Testing

To preclude multicollinearity, it was imperative that, upon assessing the Variance Inflation Factor (VIF), all constructs fell within the threshold of 5 (Ringle et al., 2022), as seen in Table 4. The construct AW2 was eliminated to satisfy this criterion.

Table 4 - Variance Inflation Factor (VIF) test

	VIF		VIF
ATU3	2.738	**PEU4**	2.564
ATU4	2.738	**PR1**	2.913
AW1	3.337	**PR2**	2.972
AW3	3.337	**PR3**	2.157
FM1	2.135	**PT1**	2.158
FM2	2.380	**PT2**	2.811
FM3	2.337	**PT3**	2.722
HM1	3.937	**PU1**	2.647
HM2	4.437	**PU2**	3.687
HM3	3.640	**PU3**	3.731
ITR2	1.000	**SI1**	2.274
ITU3	1.000	**SI2**	2.870
PEU1	1.744	**SI3**	3.137
PEU2	3.060	**FM x ITU**	1.000
PEU3	2.801	**AW x ITU**	1.000

The assessment of the structural model and ensuing hypotheses testing hinges on the scrutiny of standardized paths. The significance levels of these paths were derived by employing the bootstrapping resampling technique with 5000 iterations of resampling (Chin, 1998). The results are summarized and presented in Figure 2.

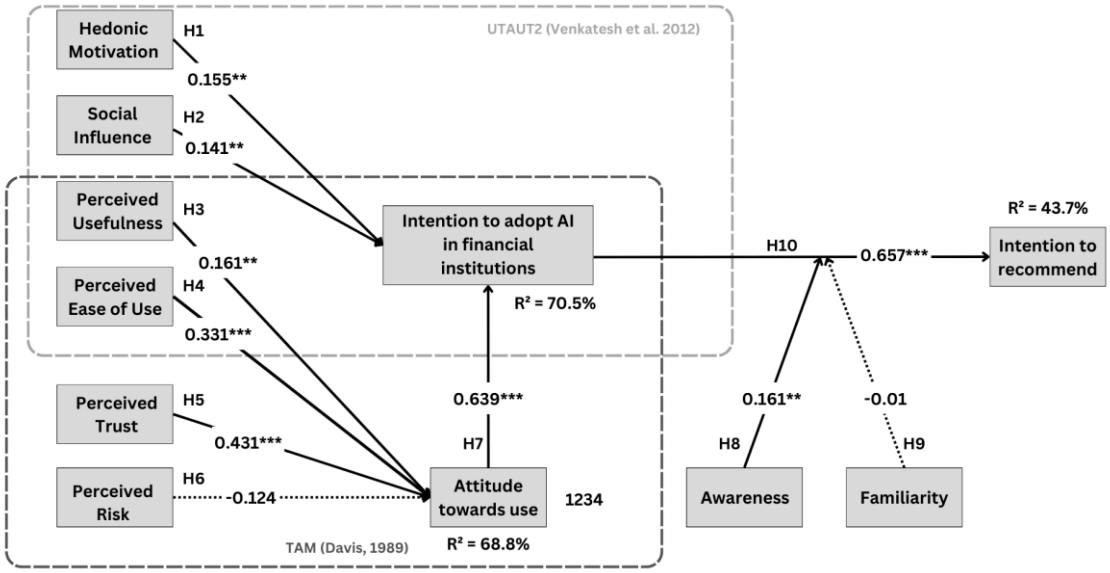

Figure 2 - Structural Model Results

The model demonstrated a commendable explanatory power, accounting for 68.8% of the variation in Attitude towards use, 70.5% in Intention to adopt, and 43.7% in intention to recommend.

Table 5 - Coefficient of determination values

	R^2	Adjusted R^2
ATU	0.688	0.682
ITU	0.705	0.700
ITR	0.437	0.423

Hedonic motivation and social influence emerged as statistically significant predictors of "Intention to adopt", both with p-values below 0.05. Furthermore, Perceived Usefulness, Perceived Ease of Use, and Perceived Trust were found to be statistically significant determinants of "Attitude Towards Use", with p-values under 0.05. These findings provide strong support for hypotheses H1, H2, H3, H4 and H5. The investigation further revealed a significant effect of Attitude towards use on Intention to adopt, validating hypothesis H7. Additionally, the positive association between the Intention to Adopt and the Intention to Recommend was statistically significant, supporting hypothesis H10. Awareness, with a p-value below 0.05, exhibited a moderating effect on Intention to Use and Intention to Recommend, substantiating hypothesis H8. However, the moderating effect of Familiarity failed to achieve statistical significance, rendering hypothesis H9 unsupported.

Table 6 - Structural Model Decision

Structural Paths	Path Coefficients	p-value	Conclusion
HM → ITU	0.155	0.043	**H1 Supported**
SI → ITU	0.141	0.029	**H2 Supported**
PU → ATU	0.161	0.020	**H3 Supported**
PEU → ATU	0.331	0.000	**H4 Supported**
PT → ATU	0.431	0.000	**H5 Supported**
PR → ATU	-0.124	0.002	**H6 Not Supported**
ATU → ITU	0.639	0.000	**H7 Supported**
AWxITU → ITR	0.161	0.030	**H8 Supported**
FMxITU → ITR	-0.01	0.876	**H9 Not Supported**
ITU → ITR	0.657	0.000	**H10 Supported**

6. Discussion

The proposed theoretical model stands out in its originality by seamlessly integrating the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), developed by Venkatesh et al. (2012) with the Technology Acceptance Model (TAM), introduced by Davis (1989), with the construct "Intention to recommend" (Oliveira et al., 2016) and augmenting it with two moderators, Awareness (Al-Somali et al. (2009), and Familiarity (Belanche et al., 2019). This novel framework provides a comprehensive perspective on the factors that influence AI adoption and recommendation in the financial domain.

6.1 Supported Findings

The research model explains 43.7% of variation in Intention to recommend artificial intelligence, 70.5% of variation in intention to use artificial intelligence and 68.8% of variation regarding attitude towards use. The research model empirically supported three significant relationships between attitude towards use and its antecedents: perceived usefulness, perceived ease of use, and

perceived trust. Additionally, two significant relationships were found between intention to adopt and its determinants: hedonic motivation and social influence.

6.1.1 TAM

A significant positive relationship was observed between attitude towards use and both perceived usefulness and perceived ease of use, with perceived ease of use exhibiting a stronger influence. The perceived Ease of Use relationship finding is consistent with several past studies (Sabir et al., 2023; Hashid & Almaqtari, 2024). This finding corroborates the notion of attitude's critical role in shaping intentions to adopt new technology-based services (Hernandez et al., 2009), such as Artificial Intelligence. Notably, empirical evidence consistently supports the enduring influence of perceived usefulness on attitude, persisting across both pre-adoption and post-adoption stages. Notwithstanding, the impact of perceived ease of use tends to attenuate in later phases of adoption (Davis, 1989; Karahanna et al., 1999).

Respondents consider perceived trust as one of the most important antecedents of attitude towards the use of AI, confirming prior studies (Payne et al., 2018; Sarkar et al., 2020). This study's findings however failed to establish a significant relationship between perceived risk and attitude towards use. This conclusion aligns with previous research conducted by Belanche et al. (2022) but runs counter to the results reported by Lara-Rubio et al. (2021). This result is also supported by the significance of Perceived Trust, as a heightened sense of trust in technology can engender a perception that its benefits outweigh the potential risks involved. The observed adoption patterns of Generation Y and Z (most respondents belong to these generations) may defy conventional assumptions about risk aversion. While these generations are often perceived as less inclined to take risks, they may actually possess an enhanced understanding of potential risks and a heightened awareness of the impact of technology. Their awareness

of artificial intelligence (AI) and its pervasive presence in society suggests that perceived risk may not be a significant factor in their decision-making processes.

6.1.2 UTAUT2

The hedonic motivation relationship finding is consistent with past research (Raman & Don, 2013; Venkatesh et al., 2012; Arora et al., 2023). Consequently, an individual's perceptions towards a technology demonstrably enhances when the technology is perceived as fostering enjoyment and entertainment. Moreover, the positive relationship between social influence and intention to use is consistent with findings from previous research (Venkatesh et al., 2003; Lee & Pan, 2023) and Kim et al (2009), concerning the effect of social influence on technology adoption.

This study also investigates the relationship between intention to adopt (ITU) and intention to recommend (ITR) AI within the financial sector. The empirical findings provide validation for the influence of ITU on ITR, thereby corroborating the results presented by Oliveira et al. (2016) and Venkatesh et al. (2012) and diverging from the conclusions drawn by Baptista & Oliveira (2015). The observed significance of this relationship strengthens the argument for a positive user propensity to recommend AI technology within the financial sector. This propensity is likely to manifest in social networks and other communication channels. The findings support the importance and relevance of incorporating the recommendation construct within this study and future research on new technology adoption, aligning with prior studies conducted by (Miltgen et al., 2013).

6.1.3 Moderators

The research model validated the moderating effect of Awareness on intention to use over intention to recommend. This result is consistent with the findings of earlier studies (Al-Somali et al., 2009; Howcroft et al., 2002; Rehman et al., 2012;

Sathye, 1999) and aligns with the initial hypotheses of this study. This significant correlation is unsurprising given the sensitive nature of the topic at hand – financial matters. Individuals naturally seek comprehensive information about a technology's intricacies, potential risks, and benefits before advocating for its adoption. The early adoption stage of AI in financial institutions undoubtedly contributes to user apprehension, prompting them to withhold endorsement until they acquire the necessary knowledge. Contrary to expectations, the moderating variable Familiarity failed to exhibit statistical significance. This outcome deviates from the findings reported by Belanche et al. (2019). One plausible explanation for this discrepancy is that the association between adoption, recommendation, and familiarity is rather tenuous. In essence, individuals may possess a basic understanding of AI but remain unconvinced that its advantages and effectiveness outweigh its drawbacks. It is noteworthy that this study delves into the financial domain, where user apprehensions are amplified owing to the substantial implications of financial decisions.

6.2 Implications for Research and Practice

The findings of this study have significant implications for researchers and practitioners alike. While the nationality and cultural background of the surveyed population may influence the study's conclusions, the inclusion of twelve different nationalities from developed countries with high levels of education and information access suggests that the findings have broader applicability in equivalent scenarios.

For researchers, this study offers a novel theoretical framework that integrates elements from two existing models, while also introducing two moderating variables in the relationship between AI adoption and recommendation behaviour. This proposed framework provides a valuable starting point for the theory and for future works. For practitioners, understanding the critical linkages between the study's constructs (trust, usefulness, ease of use, hedonic motivation,

social influence, and awareness) and the intention to use and recommend AI is crucial for developing effective and efficient strategies for implementing AI in financial institutions, especially in the traditional banks. By comprehending the motivations and forces that drive consumer decision-making in this domain, financial institutions can tailor their functionalities and marketing campaigns to align with the needs and preferences of their target audience. Such personalized approaches can significantly enhance the impact of AI tools, fostering greater acceptance and adoption among consumers.

Regarding the relevance of hedonic motivation, it is significant to note that risky, games, such as games of chance, evoke heightened levels of hedonic motivation due to the inherent pleasure and immediate rewards, such as discounts, associated with the current experience that primarily drive users to engage in these games (Lowry et al., 2013). In this regard, financial institution managers should strive to make their AI functionalities dynamic and foster feelings of pleasure, either through the prospect of rewards (through partnerships) or other gamification strategies. Conversely, financial institutions can capitalize on the persuasive power of social influence to enhance customer engagement and loyalty by prioritizing exceptional customer experiences, fostering referrals from existing clients, and actively utilizing social media platforms (Kingiri & Fu, 2020). Given the observed impact of awareness on the results, it is essential to emphasize the importance of disseminating information that instils comfort and confidence among the public regarding AI in financial services. Continuously sharing insights about the benefits, risks, and particularly the advantages of AI will project an image of transparency and trustworthiness towards consumers, leading them to be more likely to embrace and recommend AI-driven solutions, in the financial landscape.

6.3 Limitations and Future Research

The findings of the present study are subject to certain constraints, requiring further exploration in subsequent research endeavours. Firstly, although the demographic profile of the surveyed population complies with people from different nationalities, all nations represented share a comparable level of economic development. Given the pervasiveness of financial institutions across the globe, replicating this study with participants from developing countries, typified by limited access to high-quality information, would be instrumental in assessing the consistency of the observed trends. In a similar vein, exploring the adoption of AI-powered financial services among specific demographic groups, such as older individuals who may exhibit inherent apprehension towards digital services, warrants thorough investigation. This examination could be facilitated by incorporating the moderator construct "Age" into the research framework.

Despite the acknowledged potential importance of AI in FinTechs, research exploring its specific impact on personnel within FinTech startups remains scarce. Existing literature predominantly focuses on the broader financial industry or analyses specific AI applications within FinTechs, neglecting the unique employee perspective within these emerging companies. Moreover, future research could explore the integration of the Task-Technology Fit (TTF) model, or specific constructs from it, into the analysis of AI adoption in the financial services sector. This approach could provide valuable insights into the interplay between AI applications and the specific needs and requirements of consumers engaged in financial-related tasks. Furthermore, modifying the theoretical model to incorporate variables like gender or education would be highly beneficial for gaining a deeper understanding. On the other hand, as this service is intrinsically linked to the internet, and the emerging technological paradigm (Metaverse) is heavily reliant on artificial intelligence, examining

whether consumers exhibit consistent adoption factors in the realm of financial services, employing the metaverse, would be profoundly illuminating.

6. Conclusions

The application of artificial intelligence within the financial sector holds immense potential. By investigating the critical factors that influence the adoption of AI in financial services, we can establish a foundational framework to effectively promote its widespread use. Building upon prior research on AI adoption, this study employed an innovative model that integrated the UTAUT2 framework with the TAM model. Additionally, two moderators, Awareness and Familiarity, were incorporated to provide a more nuanced understanding of AI adoption behaviour. The empirical findings revealed both similarities and divergences from existing literature, highlighting the value of our extended model. Hedonic Motivation and Social Influence emerged as significant determinants of intention to adopt AI. Perceived Usefulness, Perceived Ease of Use, and Perceived Trust were identified as the primary drivers influencing users' attitudes towards AI use. Furthermore, the analysis demonstrated a moderating effect of Awareness on the relationship between intention to adopt and intention to recommend, while Familiarity did not exhibit a significant moderating effect. In achieving its objectives, this research has demonstrably contributed to the advancement of knowledge within the field. The inclusion of both Awareness and Familiarity as moderators within the proposed models presents a comprehensive framework for understanding how individual perceptions and prior exposure to AI influence recommendation intentions within the financial sector. By introducing these moderators, the study offers a more robust set of determinants for predicting intention to recommend,

emphasizing the importance of considering individual characteristics in the adoption process.

This research offers researchers an innovative theoretical framework with novel relationships that can guide future research endeavours. For practitioners in the financial services industry, understanding the critical factors influencing consumer awareness is paramount. This knowledge can be leveraged to design, refine, and implement AI-powered solutions effectively. While some financial institutions have already begun integrating AI into specific services, others can benefit from learning from these successful examples. By capitalizing on the growing public acceptance of AI technologies, the financial sector can usher in a new era of innovation and enhanced consumer experiences.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Gemini in order to translate and grammatically correct some information. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Annexes

Annex A – Survey

Construct		Item	Source
Social Influence (SI)	**SI1**	People who may exercise some influence on my behaviour think I should use AI-enabled banking applications and services.	(Venkatesh et al., 2012)
	SI2	People who are important to me think that I should use banking applications and services.	
	SI3	People whose opinions I value prefer that I use AI-enabled banking applications and services.	
Hedonic Motivation (HM)	**HM1**	Using AI-enabled banking applications and services is fun.	(Venkatesh et al., 2012)
	HM2	Using AI-enabled banking applications and services is enjoyable.	
	HM3	Using AI-enabled banking applications and services is very entertaining.	
Perceived Ease of Use (PEU)	**PEU1**	Learning to use AI-enabled banking applications and services would be easy for me.	(Belanche et al., 2019)
	PEU2	I would find it easy to manage my financial resources using AI-enabled banking applications and services.	
	PEU3	It would be easy for me to become skilful at using AI-enabled banking applications and services.	
	PEU4	I Would find AI-enabled banking applications and services easy to use.	
Perceived Usefulness (PU)	**PU1**	AI-enabled banking applications and services would improve my performance in managing my financial resources.	(Belanche et al., 2019)
	PU2	AI-enabled banking applications and services would improve my productivity.	
	PU3	AI-enabled banking applications and services would enhance my effectiveness.	
Perceived Trust (PT)	**PT1**	AI-enabled banking applications and services are trustworthy.	(Payne et al., 2018) (Susanto et al., 2016)
	PT2	AI-enabled technology provides financial services in my best interest.	
	PT3	AI-abled banking applications and services offer sincere and genuine financial services.	

Construct		Item	Source
Perceived Risk (PR)	**PR1**	Using AI-enabled banking applications and services would subject my account to potential fraud.	(Featherman & Pavlou, 2003)
	PR2	Using AI-enabled banking applications and services would put my privacy at risk.	
	PR3	AI-enabled banking applications and services might create problems with my bank account.	
Awareness (AW)	**AW1**	I have access to adequate information regarding using AI in financial services.	(Al-Somali et al., 2009) (Rehman et al., 2012)
	AW2	I have access to adequate information on the advantages of using AI in financial services.	
	AW3	I have access to adequate information on employing AI in financial services.	
	AW4	I never get enough information on how AI technology is being used in financial services.	
Familiarity (FM)	**FM1**	I have already used or studied any AI-enabled artificial intelligence system.	(Belanche et al., 2019)
	FM2	Throughout my life, I have had experience interacting with chatbots or robotics based on AI.	
	FM3	I am familiar with AI systems as a whole.	
Attitude towards use (ATU)	**ATU1**	AI-enabled banking applications and services are not intimidating.	(Payne et al., 2018) (Al-Somali et al., 2009)
	ATU2	I think that AI is essential, nowadays.	
	ATU3	I am confident that I can use AI-enabled banking applications and services.	
	ATU4	Overall, my attitude towards AI-enabled banking applications and services is positive.	
Intention to use (ITU)	**ITU1**	I am very likely to continue to use AI-enabled banking applications and services.	(Park & Joon Kim, 2013)
	ITU2	I intend to use AI-enabled banking applications and services as much as possible.	
	ITU3	I will continue to use AI-enabled banking applications and services if I have access to them.	
Intention to recommend (ITR)	**ITR1**	I will recommend to my friends to use AI-enabled banking applications and services if they are available.	(Oliveira et al., 2016)
	ITR2	If I have good experience with AI-enabled banking applications and services, I will recommend my friends to use them.	

Annex B – Cross-Loadings

Construct		ATU	AW	FM	HM	ITR	ITU	PEU	PR	PT	PU	SI	AW x ITU	FM x ITU
SI	**SI1**	0.501	0.542	0.317	0.535	0.412	0.475	0.404	0.091	0.503	0.421	0.874	-0.112	-0.158
	SI2	0.494	0.549	0.265	0.512	0.389	0.550	0.388	-0.051	0.548	0.415	0.916	-0.125	-0.050
	SI3	0.526	0.586	0.300	0.549	0.445	0.568	0.413	-0.037	0.601	0.489	0.929	-0.137	-0.060
HM	**HM1**	0.612	0.476	0.328	0.937	0.481	0.586	0.461	-0.144	0.588	0.583	0.560	-0.137	-0.061
	HM2	0.638	0.528	0.439	0.953	0.523	0.665	0.548	-0.162	0.648	0.656	0.566	-0.115	-0.047
	HM3	0.549	0.512	0.358	0.929	0.456	0.563	0.416	-0.117	0.594	0.580	0.524	-0.150	-0.026
PEU	**PEU1**	0.568	0.423	0.465	0.318	0.375	0.520	0.796	-0.050	0.401	0.451	0.373	-0.162	-0.252
	PEU2	0.619	0.419	0.424	0.491	0.517	0.635	0.900	-0.083	0.512	0.628	0.381	-0.147	-0.169
	PEU3	0.563	0.419	0.473	0.430	0.457	0.566	0.877	-0.043	0.485	0.558	0.382	-0.112	-0.167
	PEU4	0.594	0.349	0.415	0.513	0.476	0.610	0.881	-0.079	0.504	0.531	0.393	-0.117	-0.095
PU	**PU1**	0.618	0.417	0.341	0.539	0.498	0.622	0.601	-0.181	0.647	0.903	0.413	-0.142	-0.140
	PU2	0.620	0.445	0.384	0.631	0.485	0.624	0.585	-0.092	0.611	0.932	0.483	-0.225	-0.212
	PU3	0.657	0.465	0.412	0.624	0.484	0.608	0.558	-0.110	0.658	0.937	0.456	-0.171	-0.146
PT	**PT1**	0.660	0.500	0.265	0.544	0.454	0.639	0.528	-0.191	0.878	0.586	0.515	-0.077	-0.034
	PT2	0.672	0.450	0.249	0.585	0.477	0.668	0.500	-0.145	0.912	0.643	0.556	-0.160	-0.093
	PT3	0.688	0.585	0.367	0.626	0.494	0.649	0.461	-0.181	0.910	0.637	0.573	-0.122	-0.057
PR	**PR1**	-0.124	-0.054	-0.001	-0.044	0.026	-0.161	0.024	0.870	-0.125	-0.015	0.060	0.024	-0.204
	PR2	-0.247	-0.202	-0.029	-0.181	-0.101	-0.295	-0.016	0.920	-0.233	-0.135	-0.072	0.069	-0.146
	PR3	-0.262	-0.145	-0.138	-0.139	-0.086	-0.274	-0.159	0.907	-0.140	-0.167	0.031	0.102	-0.104
AW	**AW1**	0.537	0.961	0.486	0.524	0.378	0.553	0.483	-0.162	0.567	0.469	0.581	0.027	0.028
	AW3	0.523	0.955	0.413	0.507	0.351	0.512	0.406	-0.154	0.523	0.448	0.602	-0.033	-0.003
FM	**FM1**	0.381	0.447	0.868	0.294	0.260	0.317	0.376	-0.109	0.254	0.333	0.317	0.035	-0.038
	FM2	0.426	0.340	0.898	0.363	0.291	0.364	0.466	-0.060	0.298	0.396	0.209	-0.035	-0.183
	FM3	0.461	0.470	0.901	0.407	0.306	0.398	0.517	-0.039	0.316	0.366	0.336	0.038	-0.079
ATU	**ATU3**	0.941	0.492	0.479	0.546	0.517	0.726	0.648	-0.193	0.640	0.606	0.511	-0.186	-0.173
	ATU4	0.954	0.553	0.429	0.660	0.533	0.817	0.639	-0.282	0.771	0.686	0.546	-0.192	-0.112
ITR	**ITR2**	0.554	0.381	0.322	0.520	1.000	0.641	0.529	-0.077	0.528	0.529	0.458	0.012	-0.007
	ITU3	0.817	0.556	0.407	0.646	0.641	1.000	0.676	-0.288	0.724	0.668	0.588	-0.216	-0.114
	FMx ITU	-0.148	0.013	-0.114	-0.048	-0.007	-0.114	-0.196	-0.154	-0.068	-0.179	-0.094	0.532	1.000
	AWx ITU	-0.200	-0.002	0.014	-0.142	0.012	-0.216	-0.156	0.082	-0.133	-0.194	-0.138	1.000	0.532

Annex C – HTMT Ratio of Correlations

	ATU	AW	FM	HM	ITR	ITU	PEU	PR	PT	PU	SI	AW x ITU	FM x ITU
ATU													
AW	0.613												
FM	0.543	0.528											
HM	0.697	0.582	0.439										
ITR	0.588	0.398	0.344	0.536									
ITU	0.864	0.582	0.434	0.665	0.641								
PEU	0.766	0.517	0.582	0.553	0.561	0.717							
PR	0.261	0.164	0.088	0.146	0.084	0.286	0.090						
PT	0.841	0.633	0.371	0.714	0.562	0.771	0.623	0.208					
PU	0.756	0.524	0.460	0.698	0.554	0.699	0.697	0.136	0.769				
SI	0.627	0.685	0.369	0.642	0.485	0.620	0.499	0.079	0.684	0.539			
AW x ITU	0.212	0.033	0.044	0.148	0.012	0.216	0.165	0.076	0.141	0.203	0.146		
FM x ITU	0.159	0.017	0.121	0.050	0.007	0.114	0.210	0.178	0.072	0.188	0.104	0.532	