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Artificial Intelligence:

Understanding the determinants of adoption and intention to recommend the technology in Mobile Stock Market Trading

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Master Thesis

NOVA Information Management School
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ARTIFICIAL INTELLIGENCE:

Understanding the determinants of adoption and intention to recommend the technology in Mobile Stock Trading

by

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Master Thesis presented as partial requirement for obtaining the Master’s degree in Information Management, with a specialization in Business Intelligence

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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ABSTRACT

As Artificial Intelligence continues to reshape the financial sector, providing numerous benefits and improvements, mobile stock trading is also becoming crucial for firms and individuals interested in investing. Both areas are playing an increasingly important role in the financial sector, reinforcing capabilities, empowering investors, and improving trading experiences. Nevertheless, the expeditious rise of AI in the financial sector has given rise to some ethical, security and privacy concerns, thus resulting in the need to study the determinants of adoption and intention to recommend such a disruptive technology regarding mobile stock trading. We advance the body of knowledge on this subject by exploring an almost unexplored area of research through the creation of an innovative research model, combining the well-known Delone and McLean information systems success model with the SOR theory. The data was collected in a south European country, in a quantitative study, analyzed using SEM - structured equation modeling. The results show that there is a direct strong relationship between perceived intelligence and perceived anthropomorphism, risk, cost, task technology fit and trust. Intention to use positively affects intention to recommend, satisfaction and net benefits. Understanding the main determinants of adoption of AI in the mobile stock trading sector is of extreme usefulness for practitioners, decision makers, and researchers, providing insights for user experience enhancement, revenue and efficiency increase, and cost reduction.

KEYWORDS

Artificial Intelligence; Mobile Stock Trading; Technology Adoption

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
MST	Mobile Stock Trading
SOR	Stimulus Organism Response
TTF	Task Technology Fit
IS	Information System
PLS	Partial Least Squares
SEM	Structural Equation Modeling

1. INTRODUCTION

The field of Artificial Intelligence is experiencing a rapid growth, holding the potential to transform and revolutionize the way we work and live, enhancing people's lives in numerous ways Berente et al. (2021). The rapid growth and implementation are a consequence of the acknowledgement of AI's disruptive power and benefits (Duan et al., 2019; Dwivedi et al., 2021). AI has been implemented in a vast collection of diverse domains, ranging from healthcare to the financial sector Collins et al. (2021). In fact, in the last years, we have witnessed an increase in the use and adoption of AI in the financial sector (Cao, 2020; Milana & Ashta, 2021). AI has made available to the financial sector the means to become more efficient, effective and reduce costs, by automating operations and drastically changing investment and trading activities (Buchanan, 2019; Goodell et al., 2021; Kruse et al., 2019; Manrai & Gupta, 2023). As found by G. Cohen (2022) high frequency machines account for 80% of all transactions in the stock market. These machines can incorporate a copious amount of information sources such as social media Ferreira et al. (2021), Internet, or internal data. A technology with such a disruptive power is a catalyst to change, but it does not initiate it by itself, resulting in the need for additional research in the field of AI adoption Atwal & Bryson (2021).

Mobile usage has spread globally due to its advantages such as the instantaneity, localization, and ubiquity (Gupta & Dey, 2023; Safeena et al., 2012). Mobile Stock Trading has disrupted the financial sector and is the fastest growing field within the sector Gupta & Dey (2023). Mobile Stock Trading applications use has been encouraged over the years with lower costs of various types Johri et al. (2023), when compared with other channels. Using it allowed investors to become more flexible, transparent and faster. Through the usage of mobile stock trading applications, investors can perform several tasks such as check stock performance, execute orders, analyze company information and conduct technical analysis (Chong et al., 2021; M. C. Lee, 2009). Moreover, the use of mobile stock trading applications also provided more convenient experiences while investing and performing other financial operations (Chong et al., 2021; M. C. Lee, 2009; Nair et al., 2022).

There is a lack of studies and research on AI adoption and the intention to recommend the technology on Mobile Stock Trading. Previous studies have shown scattered results requesting further research and validation. The main focus of previous studies was only to study the variable of adoption, producing a gap in the literature in regard to the post adoption variables such as the intention to recommend (Miltgen et al. 2013). A brief summary of some earlier research on AI and mobile stock trading adoption, their main theories and their respective findings, can be found in Appendix A. To the best of our knowledge, this is one of the first studies that focuses simultaneously on AI and Mobile Stock Trading combined with an intention to recommend the technology construct, thus filling a gap in the literature. There is a strong need for this study, since it has a great impact and disruptive power in not only the financial sector, but also people's lives. Considering the research gap, this study aims to identify the most important AI applications, techniques and benefits for the financial sector and in more detail for Mobile Stock Trading. This study is conducted in a southern European country, a first of its type, with a focus on a poorly explored field, mobile stock trading. This study also aims to identify the most relevant adoption variables. Lastly, the final goal this study wants to achieve, is to investigate the direct and indirect effects of the AI in Mobile Stock Trading acceptance determinants and post-adoption determinants to recommend the technology.

The research is structured in the manner described as follows. Section 2, review of prior research and definition of the state of art of the subject. Section 3 explains the proposed model and hypotheses to be tested. Section 4 states the methodology used. Section 5, a detailed analysis of the results is conducted. In Section 6 theoretical and practical implications as well as limitations and future research are presented and identified. Lastly in Section 7, conclusions are retrieved.

2. LITERATURE REVIEW

2.1. ARTIFICIAL INTELLIGENCE

Even though Artificial Intelligence is not a recent topic, and vast and thorough research efforts have been put into it, there is still no consensus regarding its definition Collins et al. (2021). In the Darthmouth Conference of 1956, John McCarthy proposes the term "Artificial Intelligence" (McCarthy et al., 1955; McCorduck, 2004). AI within our study is considered as John McCarthy defined, "the science and engineering of making intelligent machines" McCarthy et al. (1955).

AI has the power to transform sectors and industries, by enabling businesses to make more efficient use of their data (Collins et al., 2021; Duan et al., 2019). It has been implemented in an immense variety of domains, from medicine, to supply chain management, to financial markets (Berente et al., 2021; Collins et al., 2021; Noonpakdee, 2020). As stated by Berente et al. (2021) AI can provide incalculable possibilities of enhancement of people's lives, it can be applied in areas such as homes, healthcare, education and transportation. Due to its benefits and the huge amounts of structured and unstructured data, in recent years AI has been widely used across the several domains (Duan et al., 2019; Kruse et al., 2019). According to Dwivedi et al. (2021) AI enabled systems are expanding rapidly within companies, transforming business and manufacturing, extending their reach into areas normally seen as exclusively human domains.

The ever-increasing usage of AI in the several domains leads to an increase of AI amount spending, according to Michael Shirer (2023), a forecast conducted from the International Data Corporation (IDC) Worldwide Artificial Intelligence Spending Guide, shows that the global spending on AI, that is, software, hardware and services, will reach 154 billion dollars in 2023, which represents an increase of 26.9% in comparison to 2022. The usage of AI and its impact on the economy has been previously studied and found to be disruptive (Collins et al., 2021; Ferreira et al., 2021; Furman & Seamans, 2019; Mhlanga, 2020; Michael Shirer, 2023), yet they also demonstrated challenges we need to face while using, implementing, and adopting it Ghallab (2019). One of the challenges is AI anxiety, a term coined by Johnson & Verdicchio (2017), as the fear and trepidation being expressed about out-of-control AI. This fear and trepidation are based on the misunderstanding and confusion about what AI is and what can ever be. Feuerriegel et al. (2020) exposes another challenge in AI implementations, the Fair AI. The term refers to the probabilistic decision support that prevents doing harm to different subgroups; the lack of fairness in AI has already been demonstrated, resulting in the harm to people. The approach taken to develop AI is bound to human biases, consequently resulting in the exposure of people to risks Borenstein & Howard (2021). These type of challenges increases the need for Responsible AI developments Ghallab (2019), with the identification of the relative responsibility of all actors involved in the design and development of it Dignum (2019). The actors should be diversified to comprehend the ethical, social, legal and economic impact of AI, and thus, reducing the probability of bias the development (Dignum, 2019; Duan et al., 2019; Ghallab, 2019).

2.1.1. Artificial Intelligence in Finance

Artificial Intelligence has been increasingly adopted and used in the financial sector over the last years (Buchanan, 2019; Cao, 2020, 2022; Milana & Ashta, 2021). The adoption and utilization increase can be justified by the observed benefits, from the automation of financial investment processes, eliminating the momentary irrationality or emotional decisions (G. Cohen, 2022; Ferreira et al., 2021), to the decision-making support through high quality information systems and processes (Cavalcante et al. 2016). AI provides an unparalleled opportunity for financial services and product providers by making available the means to reduce costs, increase revenue, and improve efficiency (Ashta & Herrmann, 2021; Manrai & Gupta, 2023). The financial services sector has inserted AI as an integral part of their operation automatization, contributing to increase efficiency and effectiveness (Ahmed et al., 2022; Buchanan, 2019; Kruse et al., 2019). AI is radically transforming trading and investment decisions Goodell et al. (2021). Milana & Ashta (2021) demonstrated the results of thirty-six Exchange Traded Funds of AI securities that provided annual returns averaging 43-48%, which are higher than any other market index. The above-average returns generated by successful autonomous trading systems lead to a lack of communication about AI advancements within the scientific community, as investors aim to protect their intellectual property (Cavalcante et al. 2016). AI not only strengthens the financial services' efficiency and security, but it also innovates unprecedented, intelligent, explainable and secure financial products and services Cao et al. (2021) that have been made available to customers.

Milana & Ashta (2021) have provided three perspectives of AI applied to finance, the first being AI techniques, such as expert systems, machine learning, genetic algorithms, neural networks and fuzzy logic. The second is applications of AI, such as forecasting, decision-making, bankruptcy, credit scoring and accounting. Lastly, the final perspective is the sub-sectors of finance and financial markets, such as financial management, financial markets, banks, fintech's, financial advisory and blockchain. Generally, AI is applied to financial markets in three different areas, portfolio optimization, stock price prediction and sentiment analysis of social media data, yet there are works that have combined techniques from different areas (Ferreira et al., 2021; Goodell et al., 2021). Most of the extensive literature on AI in finance focused in trying to forecast the future behaviors of the market (Cavalcante et al. 2016). Nowadays 80% of trades in the stock market are made by high frequency machines, that have a huge advantage over human traders due to their ability to integrate a large number of information sources into a single trading strategy G. Cohen (2022). AI trading systems can incorporate information from several sources, one of those various sources, being social media tweets Ferreira et al. (2021). The findings by Bollen et al. (2011) demonstrated that twitter mood can be incorporated as source of information and used to predict the stock market since emotions play a significant role in decision making.

Technologies such as AI act as catalyst to change, but do not initiate it, hence further research on AI adoption is of utter importance (Atwal & Bryson, 2021; Kruse et al., 2019). Prior research on AI adoption in finance has identified several factors influencing technology adoption. Regarding AI based investments, Manrai & Gupta (2023) have found that trust is a very significant aspect influencing the adoption of AI as well as ease of use of the technology. In banking services AI adoption, Rahman et al. (2022) identified the lack of relevant skills and IT infrastructure in addition to the absence of regulatory requirements, data privacy and security as major challenges of AI adoption. The success of adoption within the banking industry will depend on gaining a critical understanding of the potential barriers to adopt AI, emphasizing the importance of research on AI adoption Atwal & Bryson (2021). Financial literacy affects financial decision making, since in the absence of understanding of economics and finance there is a direct consequence to a significant deterrent to stock ownership van Rooij et al. (2011). As AI tools have proven beneficial in the stock market (G. Cohen, 2022; Ferreira et al., 2021), it's use could contribute to a better understanding of economics and finance, consequently improving financial decision making and people's lives Berente et al. (2021).

2.2. Mobile Stock Trading

Our life, as we knew it, was greatly altered with the introduction of smartphones and mobile technologies (K. M. et al. 2013). The usage of the mobile phone has spread globally, reaching both developing and developed countries, giving rise to a new terms, such as mobile commerce or m-commerce, which is defined by applications of wireless communication networks and devices to the execution of transactions with monetary value (G. Kim et al., 2009; Safeena et al., 2012). Mobile commerce has several advantages and benefits, namely the instantaneity, ubiquity and localization, thus creating added value to the customer (Baptista & Oliveira, 2015; Gupta & Dey, 2023; Zhang et al., 2012). The added value to customers has proven to be extremely important for gaining a competitive edge in the mobile marketplace (M. C. Lee 2009).

Mobile stock trading, a specialized form of m-commerce used in the financial sector, allows investors to perform stock trading activities with the benefits of using a mobile device, such the instantaneity, ubiquity and localization (Chong et al., 2021; K. M. et al., 2013; Sarkar et al., 2020). According to Gupta & Dey (2023), digital innovation in the form of mobile stock trading has already disrupted the traditional financial sector businesses and pose mobile stock trading as the fastest growing field within the financial sector. In the past two decades, the research of mobile technology adoption for personal finances has been increasing Fan (2022). Nowadays, every mobile platform has innumerous mobile applications for the stock market, which permit the users to search and trade stocks rapidly, which leads to lower search, trading and information dissemination costs Johri et al. (2023). Mobile stock trading has allowed investors to become faster while investing, as well as more flexible and transparent. Using mobile applications, investors can check stock performance, execute orders, analyze company information and conduct technical analysis (Chong et al., 2021; M. C. Lee, 2009). Investors have experienced more convenience by using mobile applications for stock trading and other financial operations Nair et al. (2022). Nevertheless, despite being an innovative and promising technology, the adoption M-commerce services has faced challenges such as the fear of losing money Safeena et al. (2012; Wasiq et al., 2022). The above-mentioned benefits and disruptive power emphasize the strong need to understand the use and adoption of mobile stock trading (Gupta & Dey, 2023; Tai & Ku, 2013). More recently, AI related to stock investments has also been integrated in several mobile banking applications, in this more traditional financial channel, providing personalized investment advice, thus becoming a crucial and in demand topic of research (J. C. Lee & Chen, 2022; Manser Payne et al., 2018).

2.3. THEORETICAL MODELS

Both Mobile Stock Trading adoption and AI adoption have been studied in the past supported by several theoretical models in the most varied contexts and localizations, providing different overviews and results to the respective research field. A brief summary of some earlier research on AI and mobile stock trading adoption, their main theories and their respective findings, can be found the Appendix A.

Delone and McLean developed a model to measure information systems within organizations, which consisted of six constructs: information quality, system quality, use, user satisfaction, individual impact, and organizational impact (DeLone & McLean, 2003). However, after ten years of research on the model and after innumerous contributions the authors re-developed the model in 2002 (Alzahrani et al., 2019; DeLone & McLean, 2003). A new variable defined by Service Quality was added in the new model due to the necessity of measuring support in information systems implementation success and intention to use Alzahrani et al. (2019). In the new model, all the impact measures were grouped into a single impact or benefit category called Net Benefits. The new category generated some critics due to the fact that it is too conceptually broad to define and also doubts about what can be qualified as a benefit, for whom and at what level of analysis Wang (2008). Nevertheless, this model is one of the most widely applied models for IS success in a diverse spectrum of study areas, such as online learning, electronic-government and digital libraries (Almaiah & Alismaiel, 2019; Alzahrani et al., 2019; Wang & Liao, 2008).

Another interesting theory is the SOR, developed by Mehrabian & Russell (1974), based on the assumption that the environment contains stimuli that leads to people's cognitive state or organism state to change, which subsequently will result in responses. It comprises some limitations in comparison to other technology adoption theories, namely some of the most used ones in literature – technology acceptance model (TAM) Davis (1989), unified theory of acceptance and use of technology (UTAUT) Venkatesh, Walton, et al. (2012) and diffusion of innovation (DOI) Rogers (1971). Since the classification of the study variables into the 3 categories, stimulus, organism and response is a complex and nonlinear process (Kapoor et al., 2022; Vieira, 2013). However, the SOR theory is widely and successfully used model in different fields, namely the mobile wallet adoption, web development and purchasing behaviors (Kapoor et al., 2022; J. Kim & Lennon, 2013; Xu et al., 2020).

3. RESEARCH MODEL AND HYPOTHESES

As we reach an era of ever-increasing use and adoption of new technologies, Artificial Intelligence plays a major role in our lives. Dependent on the manner of development and use, it can be very beneficial or detrimental to people's day to day lives. As with all other domains, the financial sector is no exception to the effects that such disruptive technology has. For the purpose of this work, we developed an innovative and consolidated theoretical model, as shown in Figure 1. It is based on a combination of SOR theory Mehrabian & Russell (1974) with the Delone & Mclean model (DeLone & McLean, 2003) and an intention to recommend the technology construct. From the SOR theory, we try to understand how perceived intelligence and anthropomorphism, the stimuli, influence the organism, defined as perceived cost and risk, trust and task technology fit, which subsequently influences the intention to adopt, the response. From the Delone and Mclean (2003) model we try to understand the effect that adoption and satisfaction have on each other, as well as the effect adoption intention has on net benefits, which in turn also influences the intention to recommend the AI technology. Lastly control variables such as age, gender, education background, were used, since they have a determinant role in determining the existent of demographic bias (Atwal & Bryson, 2021; J. C. Lee & Chen, 2022).

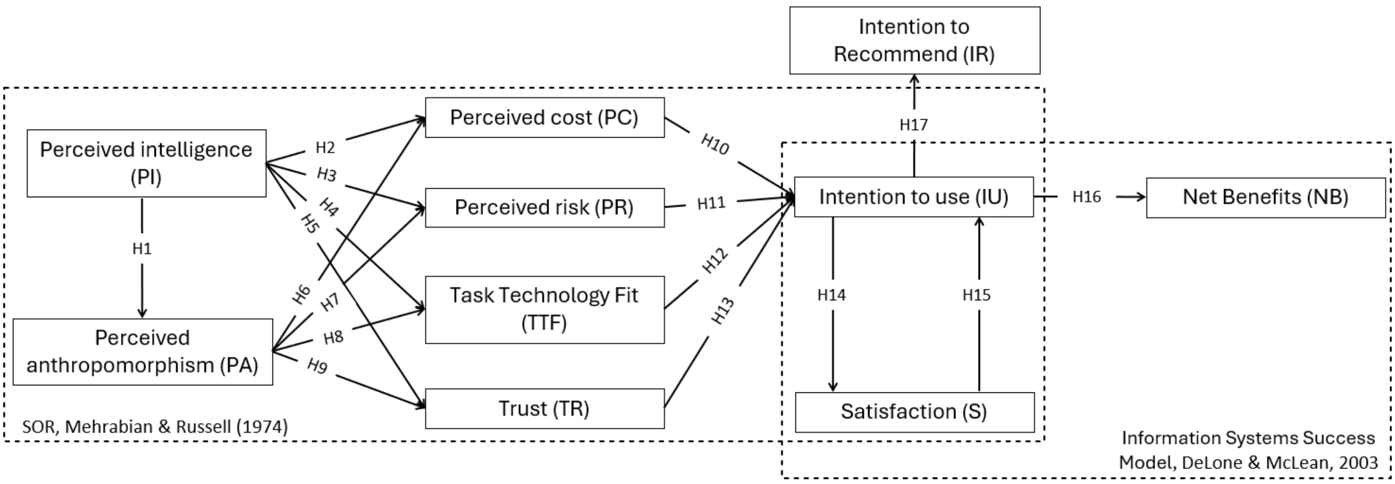

Figure 1 - Research model

3.1. PERCEIVED INTELLIGENCE AND PERCEIVED ANTHROPOMORPHISM

Perceived intelligence has various definitions that vary based on the context. In the computing technology with human-like characteristics context, it can be defined as the perception of users regarding the technology's intelligence, knowledge, and general purpose Moussawi et al. (2020). In the personal intelligent agents' context, perceived intelligence is defined as the user perception of the personal intelligent agent behavior, specifically its efficiency, autonomy, usefulness, and natural language capabilities (Moussawi et al., 2020; Moussawi & Koufaris, 2019). Perceived anthropomorphism is defined as the degree a user perceives the agent to be human-like based and its attribution of human capacities to a non-human agent (R.-R. Lin et al., 2021; Moussawi et al., 2020; Moussawi & Koufaris, 2019). The capacities range from fluency, humor, friendliness and happiness Moussawi et al. (2020). Thus, we can create the following hypothesis:

H1: Perceived intelligence can promote perceived anthropomorphism.

3.2. PERCEIVED COST

Perceived cost is often seen has a barrier of adoption of new technologies, not only the adopters have to determine the real cost of adopting and using a new technology, but they are also sometime faced with hidden costs which much likely affect mobile adoption Hanafizadeh et al. (2014). With AI technology services cost can be reduced, efficiency and productivity can be increased, due to the perceived anthropomorphic and intelligent characteristics (Cao et al., 2021; Kruse et al., 2019; Manrai & Gupta, 2023; Noonpakdee, 2020). The perceived cost is also reduced due to the utilization of mobile technologies, which lead to lower search, trading, and information dissemination costs (Johri et al., 2023; M. C. Lee, 2009). Therefore, we hypothesize that:

H2: Perceived intelligence positively influences the perceived cost of mobile stock market trading.
H6: Perceived anthropomorphism positively influences perceived cost of mobile stock market trading.
H10: Perceived cost reduces the adoption intention of mobile stock trading.

3.3. PERCEIVED RISK

Perceived risk has a negative impact on the adoption of mobile stock trading, thus reducing the adoption intention (Nair et al., 2022; Safeena et al., 2012). Chong et al. (2021) have found that from all factors studied, perceived usefulness, perceived ease of use, perceived benefit, perceived risk, and trust, all positively influence the attitude towards mobile stock trading acceptance, except perceived risk which negatively influences the attitude towards mobile stock trading acceptance. Alongside trust, risk is identified to be an important factor in predicting online trading acceptance M. C. Lee (2009). Risk is a very important factor in mobile services, due to distant connection Hanafizadeh et al. (2014). People are more willing to adopt a new technology when it is considered secure, and the privacy risks are mitigated Manrai & Gupta (2023). An important driver of adoption is the mitigation of the perceived risk is. Technologies such as AI pose benefits that result in the mitigation of perceived risks and the enhancement of the management of such (Atwal & Bryson, 2021; Cao et al., 2021). AI can be employed in several areas related to risks, namely risk management and risk detection (Mhlanga, 2020; Noonpakdee, 2020). The intelligence of mobile banking apps reduces the perception of risk J. C. Lee & Chen (2022). Thus, we hypothesize the following:

H3: Perceived intelligence positively influences perceived risk of mobile stock market trading.
H7: Perceived anthropomorphism positively influences risk of mobile stock market trading.
H11: Perceived risk reduces the adoption intention of mobile stock trading.

3.4. TASK TECHNOLOGY FIT

The use of AI technology and tools in the financial industry has proven to provide multiple benefits such as increased productivity, efficiency, and reduction of costs (Atwal & Bryson, 2021; Borenstein & Howard, 2021; Ghallab, 2019; Manrai & Gupta, 2023). AI tools sometimes also represent issues such as the lack of transparency, errors, and high learning time, which can lead to barriers to adoption, nevertheless, they are able to perform tasks such as real-time processing of data, arriving at inferences that are the starting point of good decisions, therefore increasing available time of strategic employees for other important tasks Venkatesh (2022). Goodhue & Thompson (1995) proposed the task technology fit (TTF) as an information system' user evaluation model at firm level, hence offering a conceptual foundation. This theory denotes the extent to which technology aids an individual in carrying out his or her portfolio of tasks. In this study, the tasks have been previously identified as the tasks AI tools perform, the technology is defined by this AI tools and technologies used in the mobile stock trading context, thereby assuming that TTF leads users to adopt AI in mobile stock trading due to potential benefits, such as increased performance and efficiency, provided by the anthropomorphic and intelligent capabilities (C. C. Lee et al., 2007; Tam & Oliveira, 2016a). Therefore, we hypothesize the following:

H4: Perceived intelligence can improve TTF of mobile stock market trading.
H8: Perceived anthropomorphism can improve TTF of mobile stock market trading.
H12: TTF can increase the adoption intention of mobile stock trading.

3.5. TRUST

Trust has been found to be a significant determinant that positively influence attitudes of acceptance towards mobile stock trading Chong et al. (2021). In the context of AI advisor-based investments, trust is a very significant aspect to be considered, influencing technology adoption (Manrai & Gupta 2023). M. C. Lee (2009) has identified trust as an important factor in predicting online trading acceptance, since it lacks the physical presence and interaction between the broker and the customer, trust becomes of paramount importance. Interactions between users and AI mobile banking apps with anthropomorphic and intelligent components, will lead users to make trust inferences on their perceptions of intelligence and anthropomorphism characteristics (J. C. Lee & Chen, 2022). Users will trust more on mobile stock trading apps when they think the app has both components; anthropomorphic and intelligence. Hence, we can formulate the following hypotheses:

H5: Perceived intelligence can promote trust in mobile stock market trading.
H9: Perceived anthropomorphism can promote trust in mobile stock market trading.
H13: Trust can promote the adoption of mobile stock trading.

3.6. INTENTION TO USE

The intention to adopt artificial intelligence stills poses great demands for financial services firms (Kruse et al. 2019). The successful adoption and use of AI in the banking industry is dependent on gaining critical understanding of accelerators and potential barriers to technology adoption. Without this understanding, the adoption of AI systems that can be unpredictable and, in some cases, dangerous (Atwal & Bryson, 2021; Johnson & Verdicchio, 2017). Park et al. (2011), that studied the factors that influence the adoption of digital object identifiers, have found that its adoption leads to enhanced end-user satisfaction. Satisfaction has also been defined as a key determinant of information systems acceptance (Al-Adwan et al. 2022). Despite posing a hard challenge for researchers by making the clear definition of net benefits an arduous task, the positive result of the intention to use will occur in net benefits for the user (DeLone & McLean, 2003; Miltgen et al., 2013; Oliveira et al., 2016; Wang & Liao, 2008). Thus, we can hypothesize the following:

H14: Intention to use positively affects satisfaction in the mobile stock trading context.
H15: Satisfaction positively affects Intention to use in the mobile stock trading context.
H16: Intention to use positively affects net benefits.
H17: Intention to use positively affects intention to recommend.

4. METHODS

Based on the research model an English-language questionnaire was developed in a well-known survey platform (Qualtrics), after their content have been reviewed for content validity by an information systems academic. The survey consists of two sections, a section with the questions from the research model and another with demographic characteristics of the participants. The items and scales used in the were all adapted from the literature. The items of the perceived anthropomorphism and intelligence constructs used were adapted from the studies of (R.-R. Lin et al., 2021; Moussawi & Koufaris, 2019). The task technology fit items were adapted from T. C. Lin & Huang (2008). The items of the construct perceived cost were adapted from Zolkepli et al. (2021). Regarding the constructs perceived risk and trust, the items of both constructs were adapted from Hassan & Wood (2020). All items from the construct intention to use were adapted from (Bélanger & Carter, 2008; Venkatesh, Thong, et al., 2012). Regarding the construct, satisfaction, the items were adapted from Wu & Wang (2006). Net benefits construct and its respective items were adapted from Rai et al. (2002). Lastly, the items of the intention to recommend construct were adapted from (Oliveira et al. 2016). All items and constructs can be found in appendix B. A seven-point Likert scale was used to measure each item, ranging from “strongly disagree” (1) to “strongly agree” (7). Just an English version of the survey was developed, thus no translations of any type to other languages were conducted.

The study sample size was defined based on the maximum number of arrows pointing at a construct of the research model and a 5% significance level, resulting in a recommended sample size of 147 answers J. Cohen (1992). The populational target was composed of Portuguese individual adults that own at least one mobile device with Internet access, with experience in stock market investments through a mobile device. Before providing the survey to a broader audience it was pilot tested with a small sample size from the target population to assess the survey’s comprehension and engagement rate from the participants, who were not included in the final sample. After a detailed analysis of the pilot test some adaptations were implemented, to improve the survey’s readability and understanding, resulting in the final version of the survey which was shared to a broader audience through social media sharing and posts on stock market trading communities. The survey was actively receiving responses during the period of March 23rd and May 21st. During that period, a total of 205 answers were received. After conducting an initial data treatment, 50 answers were eliminated, due to being incomplete or other miscellaneous reasons, resulting in a final sample of 155 valid answers, according to what is presented in Table 1.

Table 1 - Demographic data of respondents

Measure	Value	Frequency	Percentage
Gender	Male	84	54,19
	Female	64	41,29
	Other	2	1,29
	Prefer not to say	5	3,23
Education	Elementary school	0	0,00
	Middle school	1	0,65
	High school	18	11,61
	Bachelor degree	89	57,42
	Master degree	42	27,10
	Doctoral degree	4	2,58
	Prefer not to say	1	0,65
Age	18-25	91	58,71
	26-35	22	14,19
	36-45	20	12,90
	46-55	16	10,32
	Above 55	5	3,23
	Prefer not to say	1	0,65

From the demographic table above, we can conclude that in regard to gender, the majority of respondents were men, 54 percent, followed by 41 percent of woman. Regarding education, there were no respondents with the lowest level of education, Elementary school. More than half of the participants have a bachelor's degree, 57 percent, and almost a third of the participants have a master's degree 27 percent. Lastly, analyzing age, we can deduce that most of the respondents, 58 percent, are from the youngest age group, 18-25. The common method bias (CMB) was examined using the Harman's test Podsakoff et al. (2003). Since the variance extracted was lower than 50%, no significant common method bias was found in the data.

5. DATA ANALYSIS AND RESULTS

The Structural equation modelling (SEM) is a common term used to describe several statistical models and evaluate the validity of substantive theories with empirical data Ringle et al. (2022). The are two main techniques, covariance-based and variance-based, the research model of this study was tested using a variance-based technique, the partial least square (PLS). The analysis was conducted in two steps, starting with the measurement model to assess the reliability and validity of the measures and followed by the structural model to assess the structural relationships of the model Kellogg (1988). To conduct the analysis the SmartPLS 4 software was used to test the hypotheses, the structural and measurement model analysis Ringle et al. (2022). Both structural and measurement models were tested using the PLS, partial least squares, while the data analysis was performed using the structural equation modelling. The PLS was found to be a better fit for the research (Dash & Paul, 2021; Hai Jr. et al., 2021) since our research model it's complex and has a large number of constructs Chin (1998), it has not been tested in the literature (Hair et al. 2011) and the sample size is ten times larger than maximum number of paths directed to a single construct Gefen & Straub (2005).

5.1. Measurement Model

The first step of the statistical analysis, the measurement model, included an evaluation of its adequacy, namely the items' reliability, the internal consistency, the convergent validity.

The items' reliability was evaluated based on the criteria that they should be greater than 0.7, as we can see in Table 2, all items are greater than the established criteria, thus confirming the item's reliability (Hair et al. 2017). The item PC5 failed this criterion, therefore it was excluded. The internal consistency was evaluated through the analysis of composite reliability and Cronbach's Alpha. The criterion used was that all constructs should have a value greater than 0.7, which we can confirm in Table 2. For the convergent validity, the criteria used was the average variance extracted (AVE) should be greater than 0.5 Fornell & Larcker (1981), which we can also confirm in Table 2.

Table 2 - Quality Criteria and Loadings

Constructs	AVE	Composite Reliability	Cronbach's α	Item	Loadings
Intention to Recommend (IR)	0.903	0.908	0.893	IR 1	0.958
				IR 2	0.942
Intention to Use (IU)	0.736	0.930	0.928	IU 1	0.895
				IU 2	0.862
				IU 3	0.906
				IU 4	0.852
				IU 5	0.824

Constructs	AVE	Composite Reliability	Cronbach's α	Item	Loadings
				IU 6	0.806
Net Benefit (NB)	0.776	0.967	0.930	NB 1	0.820
				NB 2	0.928
				NB 3	0.902
				NB 4	0.902
				NB 5	0.906
				NB 6	0.868
Perceived Anthropomorphism (PA)	0.696	0.892	0.890	PA 1	0.856
				PA 2	0.785
				PA 3	0.804
				PA 4	0.868
				PA 5	0.855
Perceived Cost (PC)	0.783	0.911	0.907	PC 1	0.866
				PC 2	0.926
				PC 3	0.890
				PC 4	0.855
Perceived Intelligence (PI)	0.660	0.874	0.871	PI 1	0.819
				PI 2	0.878
				PI 3	0.790
				PI 4	0.773
				PI 5	0.798
Perceived Risk (PR)	0.810	0.946	0.941	PR 1	0.869
				PR 2	0.901
				PR 3	0.917
				PR 4	0.907
				PR 5	0.904
Satisfaction (S)	0.815	0.926	0.924	S 1	0.893
				S 2	0.918
				S 3	0.894
				S 4	0.905
Task Technology Fit (TTF)	0.684	0.885	0.884	TTF 1	0.787
				TTF 2	0.852
				TTF 3	0.822
				TTF 4	0.839
				TTF 5	0.835
Trust (T)	0.759	0.901	0.893	T 1	0.889
				T 2	0.793
				T 3	0.911
				T 4	0.885

Regarding the discriminant validity, three different measures were used. Starting with the cross-loadings, the loading of each indicator should be greater than all cross-loadings (Gentle et al. 2009). We can deduct from Appendix C, that the criteria are met for all constructs. Second, the Fornell-Larcker criterion indicates that the square root of AVE should be greater than the correlations between the constructs (Fornell & Larcker, 1981), from Table 3 we can confirm that. Lastly, the heterotrait-monotrait ratio of correlations (HTMT) should be less than 0.9 Henseler et al. (2015), and after analyzing Table 4 we can also confirm it. Overall, the results indicate that the measurement model passed the tests of items reliability, internal consistency, convergent validity, and the three discriminant validity measures: cross-loadings, Fornell-Larcker, and HTMT. Thus, proving that the constructs can be used to test the structural model.

Table 3 - Fornell-Larcker

	IR	IU	NB	PA	PC	PI	PR	S	TTF	T
Intention to Recommend (IR)	**0.950**									
Intention to Use (IU)	0.649	**0.858**								
Net Benefit (NB)	0.582	0.490	**0.881**							
Perceived Anthropomorphism (PA)	0.575	0.445	0.686	**0.834**						
Perceived Cost (PC)	0.462	0.437	0.269	0.201	**0.885**					
Perceived Intelligence (PI)	0.573	0.436	0.598	0.648	0.296	**0.812**				
Perceived Risk (PR)	-0.363	-0.230	-0.307	-0.311	-0.226	-0.320	**0.900**			
Satisfaction (S)	0.774	0.688	0.684	0.605	0.490	0.660	-0.382	**0.903**		
Task Technology Fit (TTF)	0.561	0.478	0.685	0.743	0.259	0.744	-0.283	0.691	**0.827**	
Trust (T)	0.650	0.569	0.641	0.692	0.369	0.573	-0.411	0.740	0.649	**0.871**

Table 4 - Heterotrait-monotrait ratio (HTMT)

	IR	IU	NB	PA	PC	PI	PR	S	TTF	T
Intention to Recommend (IR)										
Intention to Use (IU)	0.707									
Net Benefit (NB)	0.613	0.493								
Perceived Anthropomorphism (PA)	0.644	0.482	0.753							
Perceived Cost (PC)	0.514	0.476	0.267	0.219						
Perceived Intelligence (PI)	0.653	0.482	0.652	0.731	0.333					
Perceived Risk (PR)	0.394	0.244	0.318	0.333	0.242	0.347				
Satisfaction (S)	0.852	0.740	0.716	0.664	0.535	0.736	0.410			
Task Technology Fit (TTF)	0.633	0.526	0.749	0.830	0.290	0.845	0.311	0.760		
Trust (T)	0.722	0.616	0.689	0.770	0.405	0.648	0.443	0.810	0.731	

5.2. STRUCTURAL MODEL

With the objective of performing an assessment of the structural relationships of the model, the structural model, the second step of the statistical analysis, was conducted. The research model's hypotheses and construct's relationships analysis were based on the assessment of the standardized paths. The path's significance levels were estimated using a bootstrapping resampling method with 5,000 iterations. To verify the inexistence of collinearity in the sample data, the variance inflation factor (VIF) was tested. A criterion of VIF lower than 5 was established (Hair et al. 2017), according to best practices. After analyzing the VIF on all items, which can be found on Appendix D, NB2 was excluded due to non-compliance with the established criteria. Given the reciprocal relationship between the constructs intention to use and satisfaction, H14 and H15, two distinct models' process calculation were used. Model 1 uses H14, intention to use to satisfaction, and model 2 uses H15, satisfaction to intention to use.

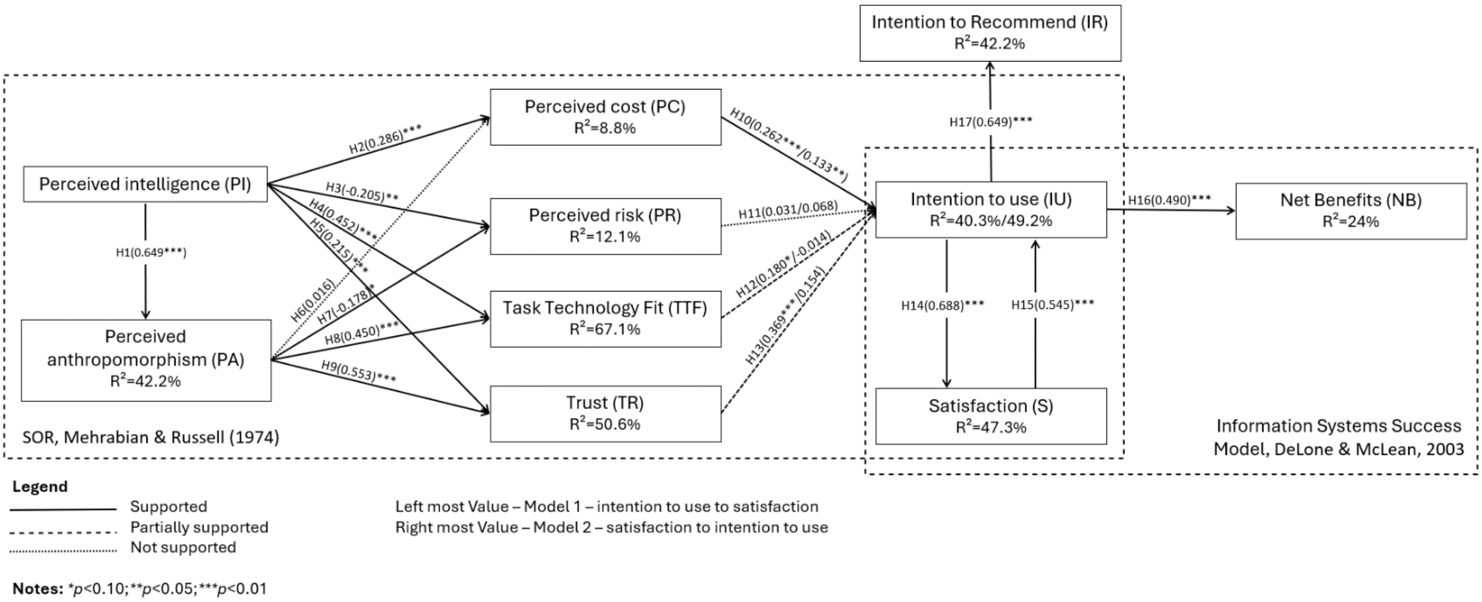

Figure 2 - Structural model results

In Figure 2 we can see how model 1 accounts for 40.3% and model 2 for 49.2% of the variance of the Intention to use. Both models explain 24% of the variance of net benefits, 42.2% of the variance of the intention to recommend, 8.8% of the variance of perceived cost, 12.1% of the variance of perceived risk, 67.1% of the variance of task technology fit, 50.6% of the variance of trust, and 42.2% of the variance of perceived anthropomorphism. Model 2 explains 47.3% of the variance of satisfaction. In more detail, Perceived Intelligence ($\hat{\beta}$ =0.469; $\rho<0.01$) was found to be statistically significant in explaining perceived anthropomorphism, thus supporting H1. While explaining perceived cost, perceived intelligence ($\hat{\beta}$ =0.286; $\rho<0.01$) was found to be statistically significant in contrast to perceived anthropomorphism which was not. Explaining perceived risk, perceived intelligence ($\hat{\beta}$ =0.205; $\rho<0.05$) and perceived anthropomorphism ($\hat{\beta}$ =0.178; $\rho<0.05$) were both found to be statistically significant. Perceived intelligence ($\hat{\beta}$ =0.452; $\rho<0.01$) and perceived anthropomorphism ($\hat{\beta}$ =0.450; $\rho<0.01$) were found to be statistically significant while explaining task technology fit. Regarding trust, perceived intelligence ($\hat{\beta}$ =0.215; $\rho<0.01$) and perceived anthropomorphism (β=0.553; $\rho<0.01$) are both statistically significant. Analyzing the intention to use we can see that for model 1 perceived cost ($\hat{\beta}$ =0.262; $\rho<0.01$) and model 2 ($\hat{\beta}$ =0.133; $\rho<0.05$) hence it was found to be statistically significant. The perceived risk was not statistically significant explaining intention to use. Task technology fit in model 1 (β̂ =0.180; ρ<0.10) was found to be statistically significant and in model 2 it was not, while explaining intention to use. The same occurs in trust whereas in model 1 (β̂ =0.369; ρ<0.01) is found to be statistically significant and model 2 was not while explaining intention to use. In model 1, intention to use (β̂ =0.688; ρ<0.01) was found to be statistically significant explaining satisfaction and the opposite occurs in model 2, satisfaction (β̂ =0.545; ρ<0.01) was found to be statistically significant explaining intention to use. Intention to use (β̂ =0.649; ρ<0.01) was found to be statistically significant explaining intention to recommend. Lastly, intention to use (β̂ =0.490; ρ<0.01) is also found to be statistically significant explaining net benefits. In summary the supported, partially supported and unsupported hypothesis can be found in the table 5, as follow.

Table 5 - Hypotheses summary

Hypotheses		**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Hypotheses statistically supported**
H1	PI -> PA	0.649	0.647	0.046	12.231	0.000	Supported
H2	PI -> PC	0.286	0.287	0.088	3.233	0.001	Supported
H3	PI -> PR	-0.2051	-0.210	0.106	1.935	0.053	Supported
H4	PI -> TTF	0.452	0.451	0.077	5.843	0.000	Supported
H5	PI -> T	0.215	0.216	0.077	2.780	0.005	Supported
H6	PA -> PC	0.016	0.021	0.094	0.168	0.866	Not Supported
H7	PA -> PR	-0.178	-0.186	0.105	1.687	0.092	Supported
H8	PA -> TTF	0.450	0.451	0.076	5.907	0.000	Supported
H9	PA -> T	0.553	0.553	0.082	6.701	0.000	Supported
H10	PC -> IU	0.262/0.133	0.134/0.263	0.061	4.240/2.162	0.000/0.031	Supported
H11	PR -> IU	0.031/0.068	0.033/0.07	0.061	0.489/1.105	0.625/0.269	Not Supported
H12	TTF -> IU	0.180/-0.014	0.180/-0.015	0.095	1.844/0.150	0.065/0.881	Partially Supported
H13	T -> IU	0.369/0.154	0.367/0.148	0.118	1.296	0.001/0.195	Partially Supported
H14	IU -> S	0.688	0.688	0.045	15.222	0.000	Supported
H15	S -> IU	0.545	0.548	0.104	5.238	0.000	Supported
H16	IU -> NB	0.490	0.496	0.060	8.141	0.000	Supported
H17	IU -> IR	0.649	0.647	0.051	12.637	0.000	Supported

6. DISCUSSION

This research intends to study the main determinants of adoption and the intention to recommend artificial intelligence in mobile stock trading. To the best of our knowledge, it is one of the first works to try do it, since previous studies have fallen short in fully exploring this topic. To fill this research gap, we developed an unique research model to support our study, combining the stimulus-organism-response (SOR) theory with the Information System model (DeLone & McLean, 2003; Mehrabian & Russell, 1974), and an intention to recommend construct, benefiting from both models' strengths and benefits. The results obtained show that only H6 and H11 are not supported, all other hypotheses are fully or partially supported.

6.1. PERCEIVED INTELLIGENCE AND ANTHROPOMORPHISM

Perceived intelligence is significant for the perceived anthropomorphism (H1), similar to the findings of (J. C. Lee & Chen 2022; Moussawi & Koufaris, 2019). Perceived intelligence is a significant predictor of perceived cost (H2), perceived risk (H3), task technology fit (H4) and trust (H5). These findings are in line with (J. Kim & Lennon, 2013; J. C. Lee & Chen, 2022). Perceived anthropomorphism was also found to be a significant predictor of perceived risk (H7), task technology fit (H8) and trust (H9), but not a significant predictor of perceived cost (H6). These findings converge with the ones of (J. Kim & Lennon, 2013; J. C. Lee & Chen, 2022). However, (J. C. Lee & Chen, 2022) results demonstrated that perceived intelligence was not a significant predictor of perceived risk, contrary to our results. This may suggest that the location of the study might have a direct impact on the significance of perceived intelligence on perceived risk (J. C. Lee & Chen, 2022) and the demographic characteristics of the respondents and its level of knowledge regarding the topic may affect their decision, whereas found by (J. C. Lee & Chen, 2022; Rahman et al., 2022) younger people are more risk prone and those with less knowledge regarding the topic would found it more risky. Also, our results diverge from (J. C. Lee & Chen, 2022) results, regarding the significance of perceived anthropomorphism to perceived cost. The model explains 42.2% of the variance of perceived anthropomorphism like (J. C. Lee & Chen, 2022), but different from the results of (Moussawi & Koufaris, 2019). Overall, Perceived intelligence and anthropomorphism were found to be catalysts to the increase of user's trust in AI enabled stock trading.

6.2. PERCEIVED COST AND PERCEIVED RISK

The results indicate that perceived cost is a significant predictor of intention to use (H10). However, the results also demonstrate that perceived risk is not a significant predictor of intention to use (H11). Like in previous findings, perceived cost and risk do not have an impact on the adoption of mobile stock trading (Chong et al., 2021; Hanafizadeh et al., 2014; Safeena et al., 2012), thus diverging and converging with our results respectively. These results suggest that perceived risk is still dependent on the user perception of the technology and its demographic characteristics (Hanafizadeh et al., 2014; J. C. Lee & Chen, 2022). Nevertheless, in contrast to previous studies the findings of (Gupta & Dey, 2023; M. C. Lee, 2009; Tai & Ku, 2013; Zolkepli et al., 2021) demonstrated that perceived cost and risk were found to be significant predictors of the intention to use, thus converging and diverging with our results respectively. The model explained 12.1% of the variance of perceived risk and 8.8% of the variance of perceived cost. These findings are similar to the ones of J. C. Lee & Chen (2022).

6.3. TASK TECHNOLOGY FIT AND TRUST

The results indicate that task technology fit (H12) and trust (H13) predict intention to use, however the hypothesis were partially supported, due to, in the model 1 being supported and in the model 2 not being supported. These results are in line with the findings of (C. C. Lee et al., 2007; J. C. Lee & Chen, 2022; Tam & Oliveira, 2016a, 2016b). In addition, the results indicate that trust in model 1 is a driving factor to the increase of intention to use, however in model 2 it is not supported. The partial support of trust diverges from the findings of (Chong et al., 2021; Hanafizadeh et al., 2014; M. C. Lee, 2009; Manrai & Gupta, 2023; Noonpakdee, 2020) where trust is one of the main determinants of and drivers of mobile stock trading adoption. The model explains 67.1% of the variance of task technology fit, thus validating its significance while predicting intention to use (H12). The models also explain 50.6% of the variance of trust.

6.4. INTENTION TO USE

Moreover, the analysis of the results revealed that the intention to use is a strong predictor of the intention to recommend positively (H17), relating to the findings of Oliveira et al. (2016). The model explains 42.2% of the variance of the intention to recommend. This is an important contribution of our work on an area that has not been widely explored, being this study the first to explore it in the mobile stock trading field. The value that the model explains confirms the user’s tendency to recommend the technology and the relevancy to include this construct, intention to recommend in future research. Intention to use also was found to be a string predictor of satisfaction (H14) and net benefits (H16) as identified by (Al-Adwan et al., 2022; DeLone & McLean, 2003) where satisfaction was identified as a key determinant of for intention to use, similar to our results. The model explains 47.3% of the variance of satisfaction and 24% of the variance of net benefits. Indicating a need to further refine and research the construct net benefits DeLone & McLean (2003). In the model 2, satisfaction is a strong predictor of the intention to use (H15). Finally, the model explains in model 1, 40.3% of the variance of intention to use, and in model 2, 49.2% of the variance of intention to use. These values are similar to the findings of other studies (Baptista & Oliveira, 2015; J. C. Lee & Chen, 2022; Oliveira et al., 2016).

6.5. THEORETICAL IMPLICATIONS

This study advances the theoretical and practical understanding of technology adoption of artificial intelligence in mobile stock trading. From the theoretical perspective, this study combines the SOR theory and Information Systems Success model to explain the adoption of AI in the mobile stock trading sector, providing a solid basis for further refinement of the individual models of adoption and net benefits, for future researchers. The integration of both models provides a holistic view and understanding of the main determinants of adoption and information systems success. This study is the first to incorporate AI characteristics such as perceived intelligence and anthropomorphism with the Information Systems Success Model, not yet done in earlier literature. This study extends both theoretical models, providing an analysis of the direct link between intention to use and intention to recommend, thus illustrating the predictive power of adoption intentions for recommended intentions in this specific subject. Nevertheless, when possible, this model should be tested in different countries with different cultures, different age groups and education levels, hence identifying any relevant factors that may be used to further refine and enhance this model.

6.6. PRACTICAL IMPLICATIONS

From a practical point of view, this study provides important practical implications for decision makers that are developing or considering developing AI enabled mobile stock trading applications. While developing mobile stock trading applications, the firms research and development teams should consider embedding AI technology to further enhance the application and tailor it to every user's needs and goals. The integration of AI technology into the applications provides a more customized user experience, resulting in a more pleasurable, efficient and effective user experience. Apart from enhancing the user experience it is also able to reduce costs, increase efficiency and revenue. Overall, our results indicate that mobile stock trading applications should try increase the perceived intelligence and anthropomorphism, aligned with the task technology fit and trust factors to increase user's intention to use and recommend its satisfaction as well as increase the net benefits as a result of the use of the AI technology in mobile stock trading. Also, the intention to recommend is a significant factor regarding the adoption of mobile stock trading. Recommendations by friends and relatives are a powerful way to promote recognition and successful adoption of mobile stock trading. Thus, it is crucial to understand the intention to recommend, to be able to enhance adoption and its net benefits (Oliveira et al. 2016).

6.7. LIMITATIONS AND FUTURE RESEARCH

As with other studies, this one is no exception to the existence of limitations. The first limitation to acknowledge is the assumption that this study does by assuming that the number of applications with AI technology increase with time, thus a longitudinal study should be conducted to assess how the determinants of adoption and the perceived net benefits change over time. A limitation that needs to be addressed is the low variance value, such in the constructs perceived cost, perceived risk and net benefits, with the values 8.8%, 12.1% and 24% respectively. We suggest the addition of more variables in order to increase the predictive capacity of the model. Another limitation is the demographic characteristics of the respondents. The survey respondents are solely located in Portugal, almost 59% are between 18 and 25 years old and more than 80% have at least a bachelor's degree. This may suggest further care when generalizing this study' results, requesting future studies to be conducted in other countries with more diverse age groups and education levels to obtain more generalizable results.

Furthermore, still related to the respondents, the number of answers to the study should be larger. Even though the findings provide valuable insights, the number of participants may restrict the generalizability of the results. Hence a larger sample size would improve the robustness and reliability of the conclusions, offering a more comprehensive and complete understanding of the research topic. Future research should aim to include a larger number of respondents considering their demographic characteristics. Another limitation to consider is the cultural context in which the research was conducted. This research was performed in a southern European country, where cultural values, norms and traditions may have influenced the responses of the participants. Thus, future research should consider performing similar studies in diverse cultural backgrounds and compare the results. Moreover, the construct net benefits as evidenced by (DeLone & McLean, 2003; Wang & Liao, 2008) is too broad to define, generating questions such as what qualifies as a benefit and for whom. Future studies should clearly define the net benefit construct, enhancing the definition provided in this study. Also, the channel of communication should also be considered in further studies. This study focuses on the mobile channel of communication providing detailed insights into the adoption of stock trading via this channel. However, focusing on a single channel of communication can overlook how the interplay between different communication channels can affect user adoption. Future research should perform similar studies in other channels of communication such as internet-based platforms, physical brokerage counters and multi-channel approaches.

7. CONCLUSION

The use and benefits of AI technologies in the financial sector is receiving growing attention globally. The determinants influencing adoption, the benefits perception, and intention to recommend the artificial intelligence technology in mobile stock market trading have not been fully studied and comprehended. Thus, to deal with this gap in the literature, we have created an innovative research model, integrating the Delone and McLean Information Systems Success Model from DeLone & McLean (2003), the SOR theory from Mehrabian & Russell (1974), with an intention to recommend construct. The research model was tested with data from a survey conducted in a south European country, complementing knowledge on this subject. Our results converge and diverge from previous research, supporting the uniqueness of the characteristics which this study focused on. Perceived intelligence and perceived anthropomorphism were found to be the most significant antecedents of perceived risk, task technology fit and trust. To explain the intention to adopt perceived cost, task technology fit and trust were the most important drivers. Intention to use was found to be a strong predictor of intention to recommend, net benefits and satisfaction. Overall, our results demonstrate the main determinants of the intention to adopt and its relation to the intention to recommend. This study provides important theoretical and practical implications for decision makers that are developing or considering developing AI enabled mobile stock trading applications resulting in cost reduction, more efficiency and increased revenue. From a theoretical standpoint, this study combines, the Information Systems Success model DeLone & McLean (2003) and the SOR theory Mehrabian & Russell (1974), this study improves our theoretical understanding of the adoption of AI technology in mobile stock trading. This all-encompassing method offers a solid basis for improving adoption and net benefit models. From a practical standpoint, this study provides valuable data for those creating mobile stock trading applications with AI capabilities. In addition to lowering costs and increasing efficiency and income, integrating AI technology to meet the specific demands of each user can result in a more efficient, effective, and personalized user experience. The study emphasizes that in order to boost users' intention to use and suggest the application, it is crucial to improve task technology fit, trust, and perceived intelligence.

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APPENDIX A: PREVIOUS RESEARCH ON AI AND MOBILE STOCK TRADING ADOPTION

Table 6 - Previous Research

Model	Findings	Author
TAM + TRUST + Subjective Norms	This study has highlighted trust as an aspect of high significance that influences the adoption of AI based investments, moreover, trust also leads to an increase in the perceived usefulness. Lastly, perceived ease of use is identified as a significant predictor of investment attitude.	(Manrai & Gupta, 2023)
TAM	This study has identified perceived risk, perceived usefulness, perceived trust and subjective norms to significantly influence the intention to adopt Artificial Intelligence in banking services, on the opposite side, awareness and perceived ease of use do not.	(Rahman et al., 2022)
DOI	This study found that perceived usefulness, trialability and observability actively contribute to the determination of customer attitudes in adopting mobile stock trading.	(K. M. et al., 2013)
TAM + TPB	Has been found that all factors positively influence attitudes except for perceived risk.	(Chong et al., 2021)
UTAUT + Risk perceptions	The results of this study show that several factors influence the intention to use mobile stock trading, including performance expectancy, effort expectancy, social influence, security risk, economic risk, and functional risk. Additionally, the impact of these factors can be moderated by the gender and age of stock investors.	(Tai & Ku, 2013)

SOR	It is shown in this study that intelligence and anthropomorphism have been shown to increase users TTF when utilizing AI mobile banking. Furthermore, trust plays a significant role in enhancing users' willingness to adopt mobile banking services.	(J. C. Lee & Chen, 2022)
TAM + Perceived Risk + Cognitive risk mitigating factors + Perceived Financial Cost	The research conducted indicates a significant positive relationship between PU and PEOU with behavioral intention in the context of mobile-based online stock trading.	(Gupta & Dey, 2023)
UTAUT	This study shows that the adoption of mobile-based online stock trading is influenced by several factors including performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk and return, habit, and behavioral intention. Notably, perceived return is considered more important than perceived risk for retail investors in this context.	(Nair et al., 2022)
DOI	It was found that subjective investment literacy, risk tolerance, familiarity with mobile financial services, portfolio value, and specific types of investment vehicles were all significantly associated with mobile investment trading.	(Fan, 2022)

APPENDIX B: SURVEY ITEMS

Table 7 - Survey items

Constructs	Items	Source
Perceived Intelligence (PI)	**PI1.** AI enabled mobile stock trading apps can help me complete trading business quickly **PI2.** AI enabled mobile stock trading apps can understand my instructions **PI3.** AI enabled mobile stock trading apps can communicate with me in a way that I understand **PI4.** AI enabled mobile stock trading apps are able to set and pursue tasks autonomously in anticipation of future user needs **PI5.** AI enabled mobile stock trading apps can adapt their behavior based on prior events	Lin et al. (2021), Moussawi and Koufaris (2019)
Perceived anthropomorphism (PA)	**PA1.** Using a AI enabled mobile stock trading app to complete a task feels similar to interacting with a real person **PA2.** The AI enabled mobile stock trading app feels friendly **PA3.** I feel that the AI enabled mobile stock trading app respects me **PA4.** The AI enabled mobile stock trading app makes me feel interesting **PA5.** The AI enabled mobile stock trading app makes me feel considerate	Lin et al. (2021), Moussawi and Koufaris (2019)
Task technology fit (TTF)	**TTF1.** The trading functions provided by the AI enabled mobile stock trading apps are comprehensive **TTF2.** The services provided by the AI enabled mobile stock trading apps meet my business needs **TTF3.** The various trading service functions provided by the AI enabled mobile stock trading app are useful **TTF4.** The functions provided by the AI enabled mobile stock trading apps are consistent with the trading tasks I need to complete **TTF5.** The functions provided by the AI enabled mobile stock trading apps simplify the trading tasks I need to complete	Lin and Huang (2008)

Perceived cost (PC)	**PC1.** The price of AI enabled mobile stock trading apps is economical **PC2.** The AI enabled mobile stock trading apps are good for the current price level **PC3.** The AI enabled mobile stock trading apps are reasonably priced **PC4.** The price of AI enabled mobile stock trading apps gives value for money **PC5.** Because the AI enabled mobile stock trading apps fulfil my needs, I do not mind to purchase the apps	(Zolkepli et al., 2021)
Perceived risk (PR)	**PR1.** I feel that using AI enabled mobile stock trading apps may expose my trading information to potential fraud **PR2.** I think the use of AI enabled mobile stock trading apps may threaten the privacy of my personal information **PR3.** I feel that using AI enabled mobile stock trading apps may expose my trading account to financial risks **PR4.** I think that my private information might be hacked when using AI enabled mobile stock trading apps **PR5.** I think that choosing to conduct stock trading activities through AI enabled mobile stock trading apps is a risky choice	Hassan and Wood (2020)
Trust (TR)	**TR1.** I believe that AI enabled mobile stock trading apps are trustworthy **TR2.** I believe that AI enabled mobile stock trading apps have users' interests at heart **TR3.** I believe that AI enabled mobile stock trading apps provide safe services **TR4.** I trust AI enabled mobile stock trading apps to protect my personal information	Hassan and Wood (2020)
Intention to Use (IU)	**IU1.** I intend to use AI enabled mobile stock trading apps in the next months. **IU2.** I predict I would use AI enabled mobile stock trading apps in the next months. **IU3.** I plan to use AI enabled mobile stock trading apps in the next months. **IU4.** I will try to use AI enabled mobile stock trading apps in my daily life. **IU5.** Interacting with my financial account over AI enabled mobile stock trading apps is something that I would do. **IU6.** I would not hesitate to provide personal information to AI enabled mobile stock trading apps service.	(Bélanger & Carter, 2008; Venkatesh et al., 2012)

Satisfaction (S)	**US1.** I am satisfied that AI enabled mobile stock trading apps meets my knowledge or information processing needs **US2.** I am satisfied with AI enabled mobile stock trading apps efficiency **US3.** I am satisfied with AI enabled mobile stock trading apps effectiveness **US4.** Overall, I am satisfied with AI enabled mobile stock trading apps	(Wu & Wang, 2006)
Net benefits (NB)	**NB1.** Using AI enabled mobile stock trading apps enables me to accomplish student-related tasks more quickly. **NB2.** Using AI enabled mobile stock trading apps improves my job performance. **NB3.** Using AI enabled mobile stock trading apps in my job increases my productivity. **NB4.** Using AI enabled mobile stock trading apps enhances my effectiveness on the job. **NB5.** Using AI enabled mobile stock trading apps makes it easier to do my job. **NB6.** I find AI enabled mobile stock trading useful on my job.	(Rai et al., 2002)
Intention to Recommend (IR)	**IR1.** I will recommend to my friends to subscribe to the AI enabled mobile stock trading service, if it is available **IR2.** If I have a good experience with AI enabled mobile stock trading I will recommend friends to subscribe to the service	(Oliveira et al., 2016)

APPENDIX C: CROSS-LOADINGS

Table 8 - Cross-Loadings

Constructs		IR	IU	NB	PA	PC	PI	PR	S	TTF	T
Intention to Recommend (IR)	IR1	**0.958**	0.66	0.57	0.532	0.426	0.521	-0.354	0.732	0.527	0.625
	IR2	**0.942**	0.567	0.513	0.563	0.454	0.572	-0.334	0.74	0.541	0.61
Intention to Use (IU)	IU1	0.643	**0.895**	0.452	0.424	0.427	0.41	-0.181	0.611	0.439	0.536
	IU2	0.549	**0.862**	0.323	0.292	0.455	0.335	-0.158	0.572	0.378	0.438
	IU3	0.563	**0.906**	0.386	0.328	0.355	0.36	-0.189	0.58	0.393	0.436
	IU4	0.504	**0.852**	0.376	0.336	0.333	0.321	-0.149	0.552	0.371	0.416
	IU5	0.526	**0.824**	0.402	0.413	0.339	0.399	-0.2	0.587	0.476	0.488
	IU6	0.541	**0.806**	0.499	0.477	0.336	0.406	-0.295	0.628	0.393	0.589
Net Benefit (NB)	NB1	0.608	0.587	**0.82**	0.577	0.378	0.557	-0.286	0.686	0.579	0.615
	NB2	0.474	0.374	**0.928**	0.613	0.22	0.502	-0.219	0.573	0.581	0.548
	NB3	0.522	0.418	**0.902**	0.599	0.214	0.514	-0.303	0.616	0.629	0.569
	NB4	0.458	0.35	**0.902**	0.661	0.169	0.549	-0.272	0.572	0.615	0.55
	NB5	0.466	0.359	**0.906**	0.611	0.189	0.546	-0.23	0.536	0.631	0.534
	NB6	0.423	0.326	**0.868**	0.576	0.133	0.424	-0.235	0.522	0.554	0.496
Perceived Anthropomorphism (PA)	PA1	0.498	0.42	0.666	**0.856**	0.2	0.577	-0.21	0.561	0.651	0.668
	PA2	0.421	0.316	0.462	**0.785**	0.225	0.505	-0.297	0.414	0.647	0.507
	PA3	0.51	0.399	0.484	**0.804**	0.214	0.6	-0.362	0.539	0.652	0.58
	PA4	0.448	0.335	0.598	**0.868**	0.08	0.492	-0.208	0.515	0.569	0.557
	PA5	0.511	0.372	0.643	**0.855**	0.099	0.51	-0.203	0.48	0.558	0.556
Perceived Cost (PC)	PC1	0.384	0.374	0.189	0.174	**0.866**	0.243	-0.173	0.398	0.226	0.345
	PC2	0.435	0.408	0.247	0.181	**0.926**	0.304	-0.221	0.466	0.255	0.345
	PC3	0.382	0.366	0.246	0.18	**0.89**	0.298	-0.219	0.423	0.194	0.297
	PC4	0.433	0.4	0.254	0.177	**0.855**	0.197	-0.185	0.445	0.242	0.32
Perceived Intelligence (PI)	PI1	0.477	0.354	0.438	0.47	0.226	**0.819**	-0.195	0.54	0.569	0.478
	PI2	0.504	0.402	0.52	0.544	0.227	**0.878**	-0.35	0.576	0.673	0.498
	PI3	0.432	0.325	0.439	0.574	0.231	**0.79**	-0.283	0.497	0.619	0.481
	PI4	0.452	0.341	0.482	0.499	0.23	**0.773**	-0.219	0.524	0.546	0.471
	PI5	0.462	0.347	0.517	0.542	0.292	**0.798**	-0.238	0.542	0.606	0.397
Perceived Risk (PR)	PR1	-0.291	-0.226	-0.194	-0.225	-0.111	-0.224	**0.869**	-0.312	-0.23	-0.323
	PR2	-0.32	-0.213	-0.264	-0.296	-0.218	-0.34	**0.901**	-0.363	-0.268	-0.414
	PR3	-0.359	-0.221	-0.312	-0.323	-0.214	-0.294	**0.917**	-0.344	-0.259	-0.391
	PR4	-0.325	-0.187	-0.279	-0.295	-0.204	-0.266	**0.907**	-0.353	-0.239	-0.386
	PR5	-0.334	-0.188	-0.274	-0.248	-0.262	-0.305	**0.904**	-0.344	-0.272	-0.324

Constructs		IR	IU	NB	PA	PC	PI	PR	S	TTF	T
Satisfaction (S)	S1	0.669	0.623	0.525	0.522	0.397	0.556	-0.319	**0.893**	0.615	0.668
	S2	0.686	0.632	0.641	0.549	0.489	0.587	-0.349	**0.918**	0.652	0.645
	S3	0.691	0.579	0.645	0.55	0.458	0.614	-0.378	**0.894**	0.597	0.65
	S4	0.745	0.645	0.627	0.565	0.426	0.625	-0.337	**0.905**	0.63	0.705
Task Technology Fit (TTF)	TTF1	0.549	0.414	0.517	0.628	0.299	0.591	-0.263	0.606	**0.787**	0.539
	TTF2	0.37	0.38	0.64	0.691	0.155	0.645	-0.297	0.511	**0.852**	0.566
	TTF3	0.455	0.391	0.504	0.551	0.224	0.582	-0.347	0.54	**0.822**	0.536
	TTF4	0.444	0.365	0.561	0.592	0.155	0.622	-0.221	0.597	**0.839**	0.493
	TTF5	0.503	0.425	0.572	0.603	0.24	0.633	-0.049	0.607	**0.835**	0.546
Trust (T)	T1	0.629	0.561	0.489	0.544	0.419	0.477	-0.278	0.643	0.513	**0.889**
	T2	0.43	0.376	0.576	0.575	0.168	0.467	-0.321	0.582	0.566	**0.793**
	T3	0.546	0.5	0.565	0.592	0.344	0.485	-0.393	0.648	0.609	**0.911**
	T4	0.64	0.529	0.582	0.691	0.338	0.56	-0.43	0.695	0.576	**0.885**

APPENDIX D: VIF

Table 9 - VIF

Item	VIF
IR_1	2,863
IR_2	2,863
IU_1	3,741
IU_2	3,836
IU_3	4,771
IU_4	2,801
IU_5	2,401
IU_6	2,168
NB_1	1,957
NB_3	3,830
NB_4	4,631
NB_5	4,908
NB_6	3,778
PA_1	2,494
PA_2	1,932
PA_3	1,889
PA_4	3,622
PA_5	3,736
PC_1	2,433
PC_2	3,725
PC_3	2,924
PC_4	2,340
PI_1	2,116
PI_2	2,639
PI_3	1,848
PI_4	1,822
PI_5	1,919
PR_1	2,923
PR_2	3,336
PR_3	3,973
PR_4	3,909
PR_5	3,979
S_1	2,968
S_2	3,620
S_3	3,130
S_4	3,145
TTF_1	1,825
TTF_2	2,357
TTF_3	2,135
TTF_4	2,432
TTF_5	2,285
T_1	2,989

T_2	1,808
T_3	3,461
T_4	2,519

ANNEXES

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