

Factors Influencing the Adoption of AI-Powered Chatbots in the Moroccan Banking Sector: An Extended UTAUT Model

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Abstract. This study investigates the factors influencing the adoption of chatbots by Moroccan bank customers using an adapted version of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The model incorporates additional variables such as perceived playfulness and perceived usefulness, which are considered relevant to the context of chatbot adoption in the banking sector. A quantitative survey was conducted among 390 Moroccan bank customers, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that social influence, expected effort, and perceived playfulness have significant positive effects on customers' intention to use chatbots, while perceived usefulness does not. The findings also reveal that intention to use has a significant positive impact on the actual use of chatbots. Moreover, the study highlights the moderating effects of age and gender on the relationship between social influence and intention to use. The study contributes to the growing literature on chatbot adoption in the banking sector and provides valuable insights for Moroccan banks looking to enhance customer engagement through artificial intelligence. However, the study also acknowledges the limitations of the convenience sampling approach and the need for further research incorporating a broader range of variables and customer segments.

Keywords: Extended UTAUT model, Factors, Chatbots, bank customers, adoption, PLS-SEM.

1. Introduction

Companies are closely linked to innovation, which plays an essential role in stimulating growth. Successful companies are often those that continue to innovate, whether by launching new products, improving manufacturing processes, or Exploring new approaches to satisfying customer demands (Jednak et al., 2018). There are many ways in which companies can encourage innovation. Investing in R&D to generate new technologies and products is one. In addition to that due to the corona virus pandemic, digital technologies have been rapidly adopted, with banks moving quickly to remote sales and distribution (Buehler et al., 2020) Artificial Intelligence (AI)-based technologies are at the heart of the change taking place in banking, as banks increasingly use AI-based applications to connect with customers, provide tailored services, detect and deter fraud, strengthen money-laundering detection arrangements and save money (Suhel et al., 2020). Among the growing illustrations of artificial intelligence being adopted by businesses and individuals are chatbots. Conversational agent technology is an AI-based system that performs basic tasks and interacts with users via on-line or voice dialogue interfaces (Nguyen et al., 2022). For example, banking chatbots can be used to check account balances, transfer funds between accounts, provide information on recent transactions, or even help solve common problems such as lost bank cards (Cîmpeanu et al., 2023).

According to Mordor Intelligence¹, the market value of this technology is expected to reach 102.29 billion USD by 2025, while Juniper Research² (2020) predicts that the success rate of queries made without human assistance in the banking sector will exceed 90% by 2025. Chatbots, or interactive agents based on messaging systems, can be of interest to banks, as they simplify the purchasing process into a single channel (Ambawat & Wadera, 2019). There is no need for a platform, as they use existing messaging infrastructure (Pierson, 2021). With the ongoing development of AI and the demand for new methods of human-computer interaction, these agents have become an effective means of communication that can deliver automated services in a personalized way (Sotolongo & Copulsky, 2018).

Chatbots are used for multitude reasons, in particular commercial transactions and support in the banking sector. They have evolved to include voice recognition, animation and the ability to interact over the internet or in integrated applications such as Face book Messenger, Whats'App or Skype (Mogaji et al., 2021).

Despite the rapid expansion of online services in Morocco, the use of banking services by this form of AI remains significantly lower than that of other online services such as M-mobile or even traditional services (Mogaji et al., 2021). Thus, there is a lack of knowledge among consumers about the usefulness of banking chatbots. Customers may not fully understand the benefits of these chatbots in terms of speed, convenience and 24/7 availability to perform banking transactions (Doherty & Curran, 2019). What is more, they may not perceive the fun aspect of interacting with chatbots, seeing them more as functional tools with no added value (Rapp et al., 2021). Furthermore, consumers may invest less effort in adopting banking chatbots compared to other online services such as M-mobile, perhaps due to a perception of complexity or a lack of interest in this new technology (Chukwu et al., 2021). Consequently, the capacity to generate technological value from AI-based Chatbots remains untapped. In this situation, Moroccan banks need to take control of these new technological interfaces and apprehend how customers will react to this overwhelming amount of technology (Pal et al., 2021). For this reason, we have chosen to adopt the UTAUT model as our theoretical basis, as it is more exhaustive than other models, incorporating most of the variables present in various theories dealing with "technology acceptance and adoption".

¹<https://www.mordorintelligence.com/fr/industry-reports/digital-transformation-market>, consulted the 05/12/2023

² <https://www.juniperresearch.com/researchstore/operators-providers/Chatbots-trends-research-report>, consulted the 17/11/2023

The UTAUT model explains technology adoption by integrating four key factors: performance expectation, effort expectation, social influence and enabling conditions (Venkatesh et al., 2003). In the context of banking chatbots, this model is relevant. Customers expect chatbots to improve their banking experience by providing fast access to account information and facilitating transactions (performance). The ease of use of chatbots reduces the effort required to carry out banking operations (effort). Social influence, through positive recommendations, and facilitating conditions, such as transaction security, are also important (Catherine et al., 2017). Two additional variables, perceived usefulness and perceived playfulness, are relevant to understanding the adoption of chatbots in the banking sector. Perceived usefulness concerns their usefulness for banking tasks, while perceived playfulness concerns the pleasure and engagement felt when using them (Eren, 2021). By integrating these elements, the UTAUT model offers a comprehensive perspective on customer adoption of chatbots in the banking sector.

As it is known, only a few studies have analyzed the UTAUT model in relation to artificial intelligence. The majority of which were carried out in Asian nations and, according to our information, no one has been carried out on the use of virtual agents in the Moroccan banking sector. Several studies have used the UTAUT model, and we have adapted it by simplifying it to include only those variables relevant to our research.

Our challenge is to answer the following two questions:

- What factors do influence the adoption of AI-powered chatbots in the Moroccan banking sector?
- How do these factors extend the Unified Theory of Acceptance and Use of Technology (UTAUT) model in the context of chatbot adoption in the Moroccan banking sector?

The aim of this research is to:

Identify and analyze the factors influencing the adoption of AI-powered chatbots in the Moroccan banking sector.

-Extend the UTAUT model by incorporating additional factors “perceived usefulness and perceived playfulness” that are relevant to the adoption of this artificial intelligence.

Thus, this study has both theoretical and practical importance. On the one hand, it aims to enrich technology adoption theory by shedding light on the specific factors influencing chatbot acceptance in a Moroccan banking context. On the other hand, on a practical level, the results of this study seek direct implications for Moroccan banks. By better understanding the factors influencing customer adoption of chatbots, banks can fine-tune their strategy for deploying these technologies.

This research focuses on an in-depth analysis of existing literature concerning the link between chatbots and usability factors, highlighting previous research that has explored this complex interaction. Taking into consideration the principles established in the UTAUT model, this study constructs a conceptual framework aimed at examining the various aspects of usability when interacting with chatbots. Next, the conceptual framework is elaborated in detail through hypotheses, describing the methods and tools used to gather the data required for the analysis. Finally, the examination of the findings highlights the implications of these results and offers practical advice for improving the design and deployment of chatbots with a view to increasing the number of users.

2. Theoretical Framework

2.1. Chatbots

In the specialized literature, there is a significant divergence of perspectives among researchers regarding the concept of chatbots, resulting in the absence of a strong consensus. This plurality of interpretations reflects the complexity and variability of theoretical approaches and practical applications of chatbots in different fields. For example, some researchers focus on the technical and algorithmic aspects of chatbots, while others concentrate on the psychological and interactional aspects of the user experience. This diversity of approaches contributes to a theoretical richness but can also give rise to debate as to the exact definition and scope of chatbots. Studies such as those by Haugeland

et al. (2022), illustrate this diversity of perspectives and the challenges inherent in conceptualizing chatbots. In order to overcome the divergence that exists between researchers in different fields, we propose a detailed reading of the classic and recent functional characteristics of chatbots.

With the increasing presence of chatbots, we are witnessing a new flexibility in search, as users can easily reduce search time by increasing performance and reducing decision-making time (Chang, 2008). According to the same source, this apparent productivity of artificial intelligence is essentially due to their learning capacity, especially supervised learning, and their functional complexity, which explains the evolution of the system in its current mode. This capacity enables behaviors to be adjusted and revised. For Mahesh (2018), a high-performance learning capability often leads to a better user experience. Functional complexity requires the emergence of data, especially in volume, enabling more complex interactions to be undertaken (Berthier, 2018). In other words, Chatbots need to fulfill six functionalities in order to respond appropriately to users, namely learning capacity, flexibility, autonomy, temporal continuity, purpose and communication (Chang, 2008a). However, this form of artificial intelligence requires continuous improvement, especially in terms of interaction. For Cherif (2016), designers are constantly integrating new functionalities such as ubiquity, availability, animation, conversation, and collaboration. Here is a table detailing the most recent features:

Table 1. The latest features

Labels	Functionality
Ubiquitous Chatbots	Interactivity is guaranteed with several cyber-consumers at the same time.
Chatbots that are available	Their interventions are permanent and in real time. Neither fatigue nor lack of concentration can stop this functional continuity.
Animated Chatbots	These are embodied virtual agents. It is a character present through a face, shape, gestures and attitude. They can be animated with great liveliness.
Conversational agents	This type of Chatbot has both an appearance characteristic, like embodied conversational agents, and a conversational characteristic.
Collaborative Chatbots	These Chatbots can collaborate seamlessly with other Chatbots to carry out a specific mission.

Source: Chang, 2008

Furthermore, in the banking sector, chatbots are widely used to offer customers a convenient and engaging experience. The ubiquity of chatbots enables customers to access their services at any time and from anywhere, whether via websites, mobile apps or social networks (Krishnan et al., 2022). What is more, their 24/7 availability ensures instant assistance even outside physical branch opening hours. To make interactions more lively, chatbots can include animated features such as emojis and GIFs (El Hefny et al., 2021). In addition to that they are able to conduct natural conversations with customers, understanding natural language and answering a variety of questions about products, services and transactions (Olujimi & Ade-Ibijola, 2023). Finally, chatbots can collaborate with other systems, such as CRMs, to personalize interactions according to each user's specific needs (Behera et al., 2021). By combining these features, banking chatbots deliver a seamless, personalized customer experience, contributing to customer engagement and improving service quality in the banking sector.

2.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

2.2.1. Fundamental principles of UTAUT theory

From a longitudinal investigation involving eight models, Venkatesh et al. (2003) constructed and validated the UTAUT model. The authors, who examined four companies during a span of six month, found that the eight models they used can explain a high percentage of the variance (53%) when it comes to the intention to adopt and utilize any technology. In fact, the model includes four essential elements

that constitute the main factors affecting an individual's willingness to utilize technology, namely:

- **Performance expectancy:** This refers to the confidence individuals have when assessing the capacity of an information system at work. It is linked to various theories such as TDI, MAT, UTAUT and the "theory of planned behavior". Age and gender are considered "moderating" variables that can influence this determinant.

- **Expected effort:** It is believed that employing a system can be achieved with little effort from the user. This concept is associated with the adaptability of a technology regarding its utilization. Venkatesh et al. (2003) point out that this factor correlates closely with Rogers (1995) and Davis (1985) in terms of ease of use, as well as with Taylor and Told (1995), who combined (MAT), and (TCP). The model proposes that "age, gender and experience level" are "moderating" variables that impact latent variables;

- **Social influence:** for Mehra et al. (2022), social influence can be described as a phenomenon in which individuals modify their behavior to conform to the expectations of their social environment. Venkatesh et al. (2003) noted that an individual's personal and professional context affects his or her general conduct. Nevertheless, familiarization with anything new has proved tricky in this context, as it is often driven by external pressures such as the desirability or necessity of change, rather than by individual choice;

- **Facilitating conditions** are elements that support the adoption of new technology, thanks to the presence of a technological and organizational infrastructure. This determinant is similar to Rogers' (1995) compatibility, to Fishbein and Ajzen (1975) behavioral control, and to a combination of TAM and TCP. This concept has no effect on a person's intention to utilize it, but it does have a direct effect on behavior when it comes to using an innovative product. Moreover, this element is moderated by two essential factors: age and experience level.

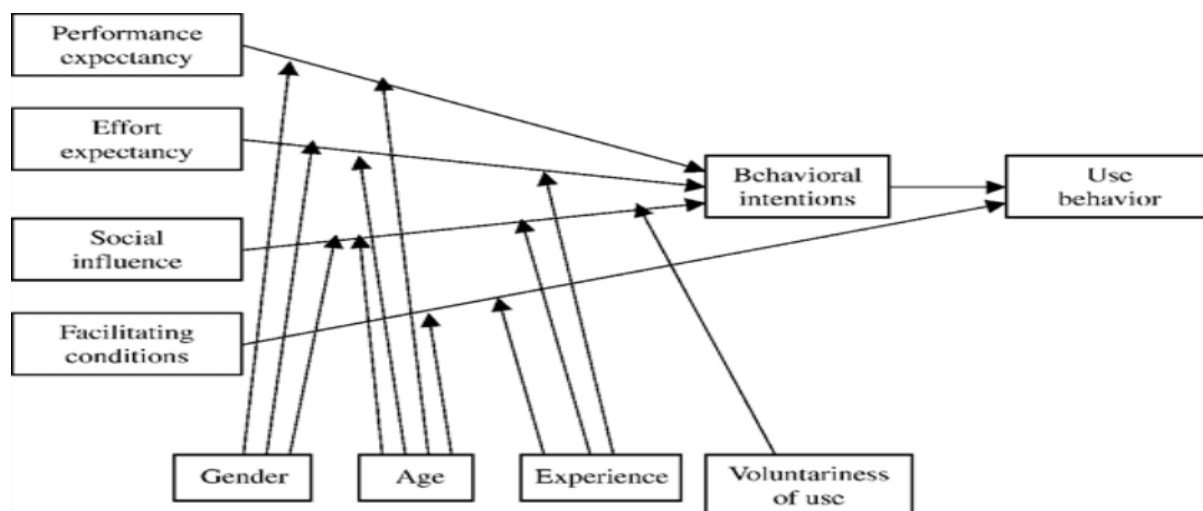


Fig. 1 : UTAUT Model

2.2.2. Experiments on the UTAUT model

Studies on the acceptance of Chatbots are rare. We propose to review the most significant studies in the field. For example, Joshi (2021) presents a mixed-methods study to assess the adoption of chatbots by Millennials in customer service. The aim of this research is to examine the elements that directly and indirectly affect inclination towards this artificial intelligence. Social influence and expected performance were found to have an effect on behavioral intention.

Fernandes and Oliveira (2021) studied the customer service motivation of 238 young customers using mobile applications based on artificial intelligence. To gain insight, they identified three categories of variables that could extend the UTAUT model: social variables (perceived social interactivity, perceived humans and perceived social presence) and trust as a relational variable. As a result, the model explained 88.6% of the variance in the acceptance of artificial intelligence via mobile

applications. This success can be attributed to the positive effect of these three types of variable, while the moderating role was only justified by experience and interaction. For both authors, the results constitute a significant avenue for the under-explored role of social variables and a new perspective for the man-machine relationship.

Song et al. (2022) suggested that virtual agents, as social actors, can disrupt the consumption style of e-consumers. To account for this effect, they added communication quality and privacy risk to the determinants of the initial model, aiming to examine how these two exogenous factors would affect people's willingness. The results indicated that these two factors had a considerable influence on the desire to adopt. The authors emphasize that mastering communication and managing privacy risks in terms of individual risk are remarkable. They believe that this research "offer significant insight into the logical use of human-computer interaction in e-commerce".

Dogra and Kaushal (2021) also conducted research in the same market to understand what might influence an individual's intention to purchase voice-activated virtual agents. The aim was to determine young Indians' level of attraction to AI devices. To do this, the UTAUT model was applied, with two variables which including perceived privacy and perceived risk. After analyzing the results, it was determined that all four UTAUT variables had a positive effect on people's intention to use them. Additionally, perceived risk had a positive effect on expected performance, effort, and intention to act, whereas perceived confidentiality had no influence on social influence and availability of necessary resources. This research may be useful for those in the technology industry who wish to understand why people choose to use smart devices.

While the review of studies on chatbot adoption in banking based on the UTAUT model highlights several interesting points, it also raises some questions.

Firstly, the studies presented address various aspects of chatbot adoption, including social influence, expected performance, communication quality, perceived privacy, and perceived risk, demonstrating thorough understanding of the factors influencing consumer adoption of chatbots.

However, it's important to note that most of these studies focus on specific populations, such as millennials or young customers, potentially limiting the generalizability of results to the entire population. Additionally, further research is needed to assess the adoption of chatbots by other demographic groups, such as the elderly or more traditional customers.

3. Assumptions for the Modified UTAUT Model

3.1. The assumptions

In this study, certain variables were found to be irrelevant to the project, so gender and age were chosen as moderators, and education replaced experience. The willingness to use chatbots was discarded as it is not mandatory in this context. However, the model will be enriched with additional variables specific to the banking sector, notably perceived usefulness and perceived playfulness, which replace expected performance and facilitating conditions.

- Social influence: "Social influence" refers to the extent to which the opinions of others can affect the adoption of a particular technology. Venkatesh et al. (2003), this denotes the degree to which an individual perceives that significant individuals in their life, or those who are near to them, believe they should utilize a new system. Theories such as TAM-TPB, TRA and TAM2 all suggest that "social influence" encourages the inclination to utilize a specific technology. Turner et al. (1979) share this same idea of a social vision, as described in their social identity theory. They believe that when a collective has established behavioral norms, its members will be more connected to the group. Gursoy et al. (2019) further assert that if a particular social circle responds positively to artificial intelligence, this will reinforce the individual's feeling of membership within the group.

Several studies Slade et al. (2015) have demonstrated the importance of integrating artificial intelligence into the banking sector. The introduction of Chatbots into mobile banking, websites and

social media has enabled them to become part of the emerging market (Shum et al., 2018). This recognition can create a powerful social impact on banking customers, leading to a positive attitude (Mogaji et al., 2021). Drawing from the preceding conversation, the following hypothesis is proposed:

H1: social influence correlates positively with the "intention to use" Chatbots in banking.

-Expected effort : Patil et al. (2020) consider "expected effort" to be a major factor in creating a strong inclination towards technology. This refers to the degree of personal effort needed of users (Venkatesh et al., 2012). According to Bazi et al. (2020), the information system must reduce the time required to complete a given task. Ease of use is obviously paramount, but the estimated effort that can contribute to fostering a lasting relationship with this system is more important. This concept is similar to many concepts covered by different models (Venkatesh et al., 2003). For example, the "perceived ease of use" proposed by Davis (1989) and the complexity suggested by Thompson (1971) have been taken into account. Balakrishnan et al. (2022) assert that it is essential to reduce the effort involved in interacting with consumers, which is a constant objective for marketing professionals and information systems experts. Chatbots, which are based on artificial intelligence algorithms, have made customer interactions more realistic and human-like, thus decreasing the amount of estimated effort (Zhang et al., 2024). Similarly, Balakrishnan et al. (2022) see Chatbots as a viable substitute for manual labor in the banking sector. The researchers believe that the reduction in user effort could motivate people to use this technology. Thus, we can propose that:

H2: Perceived effort is positively with the "intention to use" Chatbots in banking.

-Perceived usefulness: "Perceived usefulness", as described by Davis et al.(1989), is the user's assessment of how using a particular application system can improve his or her job performance. Rese et al. (2020) corroborates this view, believing that this variable acts as an external motivator that can boost the user's performance, they refer to this effect as utilitarian gratification. To achieve optimal performance, Mulyono and Sfenrianto (2022) assert that this variable must be combined with the caliber of the information supplied by the information system.

Studies consistently demonstrate that "perceived usefulness" is a critical factor in people's adoption and utilization of technology (Venkatesh & Morris 2000; Kulviwat et al. 2007; Zarouali et al., 2018). Garcia et al. (2021) have underscored the significance of this variable for the adoption of virtual agents in artificial intelligence. In banking applications, these agents have proved effective in performing interactive tasks (Lu et al., 2019). For these researchers, customers see these bots as a viable substitute for the human element. They believe that these forms of AI have moved beyond the acceptance stage and are now influencing the services provided by banks. Furthermore, various studies (Safeena et al., 2012 ; Farah et al., 2018; Giovanis et al., 2019) argue that this variable has a beneficial impact on people using banking Chatbots. We therefore propose this hypothesis for Morocco:

H3: The perceived usefulness has a favorable impact on the intention to use Chatbots in banking.

-Perceived playfulness : For Terzis et al. (2012), "perceived playfulness" is made up of three dimensions, namely: concentration, curiosity and pleasure. Indeed, the first dimension measures the level of user focus during interactions with a technology. The second measures the user's cognitive curiosity when searching through an information system. The last, materializes the level of appreciation at the time of this interaction. For our study, it is this last dimension that interests us, given that the sense of fun that a user can build up at the moment of interaction with virtual agents (H. Yang & Lee, 2019).

Researchers in the field of artificial intelligence have found that these virtual agents elicit a positive emotional response, offering users a fun and personal experience (Kasilingam, 2020). Other studies suggest that the "perceived enjoyment" of Chatbots is linked to social skills, which could lead to higher levels of acceptance and use of artificial intelligence. This is the case of Lee & Choi (2017), who consider that the pleasure of using these bots is a social skill that may lead to greater willingness to accept and use AI. Furthermore, they suggest that it should be perceived as a source of pleasure rather

than simply a utilitarian value. Similarly, Chung et al. (2020) believe that when users have a pleasant and fun experience with this form of AI it can produce favorable behavior and overall satisfaction with their use.

Earlier research has illustrated the influence of "perceived playfulness on intention to use" the technology, Yang & Lee (2019) point out that this factor is one of the main drivers of mobile internet adoption. Furthermore, Arcand et al. (2017) observed that the use of these virtual agents in banking services offers a playful human experience. Consequently, several researchers (Rzepka & Berger, 2020; Brandtzaeg & Følstad, 2018) have concluded that these bots are capable of providing enjoyable experiences in banking services. Considering these discoveries, we propose the following hypothesis:

H4: Perceived playfulness positively influences "intention to use" Chatbots in banking.

-The relationship between intention to use and current use of Chatbots in banking

The link between an individual's willingness to utilize mobile banking and their current usage is impacted by intention. The latter is a cognitive factor that lies between belief and behavior (Fishbien & Ajzen, 1975; Song et al., 2022). Put differently, actions are influenced by factors like an individual's intention, which is influenced by their attitude. The latter can be described as a judgement by the individual on the use of something (Kasilingam, 2020a). Research by Nguyen et al. (2021) found that the level of adoption intention has a strong impact on the use and acceptance of Automated chat systems within the banking industry. Specifically, they found that customers with a strong intention to adopt bot technology are more likely to employ it for mundane banking operations such as reviewing their accounts and transferring money. Consequently, the authors suggest that banks should strive to increase their customers' adoption intention in order to encourage greater usage. These findings prompt us to explore this relationship in our study and formulate the subsequent hypothesis:

H5: "intention to use" has a positive impact on the current use of Chatbots in banking.

Moderating variables

-Age: is considered an significant factor in the acceptance or rejection of a technology (Igbaria & Parasuraman, 1989). It can affect how the technology is used, as people of different ages may have varying levels of knowledge, familiarity and comfort of use. A survey by Mogagi et al. (2021) found that 95% of the use of banking bots is concentrated among people aged between 18 and 50, while people aged 51 or over prefer to use traditional customer relationship services. These findings corroborate previous studies showing that age is related to technology adoption and use (Venkatesh & Morris, 2000; Venkatesh et al., 2003). Consequently, we can posit the following hypotheses:

Age moderates the following variables: **H1, H2, H3, and H4**

-Gender: Recently, the influence of gender on the willingness to use and accept technology has been the focus of much discussion. A substantial amount of research has shown that the two sexes may have different perspectives and activities when it comes to adopting or accepting technology. Kasilingam (2020) revealed that male participants view shopping chatbots as less risky than female respondents. Gender may play a moderating role in the utilization of bots in the banking sector. Yu (2012) has shown that men and women may possess varying attitudes and preferences when it comes to interacting with technology. Drawing from these studies, we aim to examine the following hypotheses:

Gender moderates the following variables: **H1, H2, H3, and H4**

-Education: Education can influence the effectiveness of virtual agents in the banking sector. Studies have indicated that better-educated people may have different opinions and preferences regarding working with technology. For example, Hwang and Chang (2023) reported that better-educated individuals generally possess a greater sense of reliability and usefulness when it comes to using Chatbots, compared with those who are less educated. Consequently, we can posit the following hypotheses:

Level of education moderates: **H1, H2, H3, and H4**

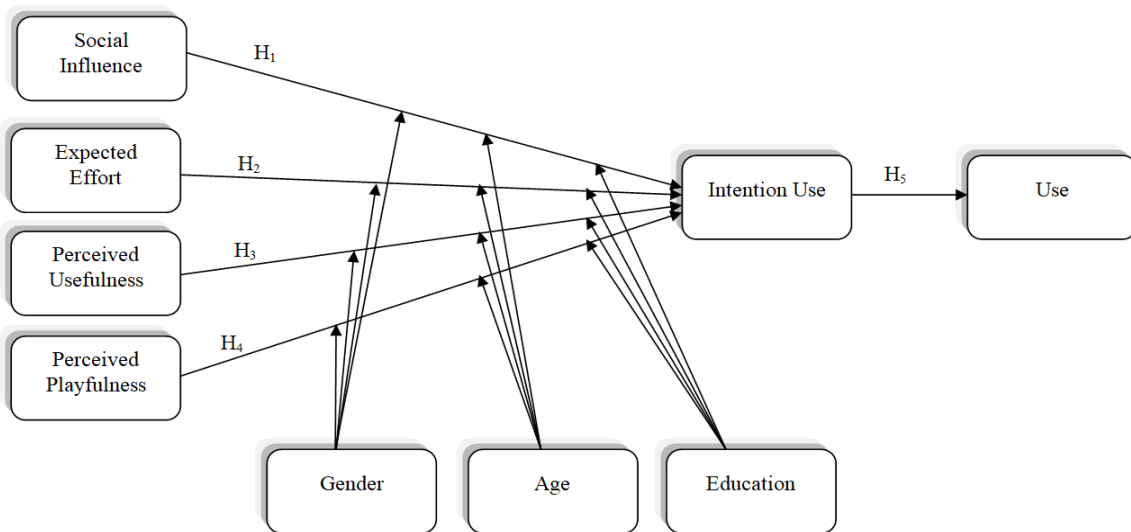


Fig. 2: The conceptual framework of the research

4. Research Methodology

4.1. Measurement tools

Designing a questionnaire requires an organized approach to ensure that the tool actually obtains the data needed to answer the queries. As the ultimate aim of the survey is to accurately portray reality, it is imperative to pay close attention to the engagement, comprehension and reliability of responses (Maisonneuve & Fournier, 2012). All measurements utilized in this study were derived from validated metrics from the work of Venkatesh and colleagues (2003), with the incorporation of two additional variables identified in the literature search. The first variable, perceived usefulness is a key element in the TAM (1989) model of technology adoption. It represents the benefit that users can derive from a technology. Numerous studies have highlighted its importance in technology acceptance. Virtual agents are particularly effective in multitasking environments, and optimizing these systems generally improves performance in banking. We have chosen a measurement scale composed of Three Items initially developed by Ashfaq et al. (2020), Alt and Ibolya (2021), and Huang et al. (2022).

For the second variable, the literature suggests that the level of enjoyment derived from a system is a key factor in user satisfaction, as users may prioritize entertainment value over performance (McLean & Osei-Frimpong, 2019). Thanks to artificial intelligence, perceived playfulness influences user satisfaction. Chatbots and AI can offer a fun and enjoyable experience when communicating with customers, leading to a favorable intention towards this form of AI. In our study, this variable is assessed using four items constructed by different authors. In our study, this variable is assessed using four items constructed by Rietz et al. (2019) as two items and one item for Yang & Lee (2019), and another Terzis et al. (2012).

Validation of the scale items by experts in the field was crucial: two artificial intelligence specialists and two marketing researchers were consulted. The table below shows all the measurement instruments included in our questionnaire.

Table 2. Measurement items and survey questionnaire

Built	Items	Sources
Soc-inf 1	- Individuals significant to me believe I should utilize banking Chatbots	Slade et al. (2015), Venkatesh et al.
Soc-inf 2	- Individuals who impact my actions	(2003,2012),

	believe I should utilize banking Chatbots	Balakrishnan et al. (2022).
Expected-eff 1	-My interactions with the banking Chatbots are clear and comprehensible.	Balakrishnan et al. (2022), Venkatesh et al. (2003,2012), Følstad and Brandtzæg (2017)
Expected-eff 2	- I discover banking Chatbot services simple to utilize.	
Expected-eff 3	- I find it straightforward to become skilled at using banking Chatbots.	
Expected-eff 4	- Using banking Chatbots doesn't require much mental effort from me	
Percieved-usef 1	-I perceive the banking Chatbot as beneficial in my everyday activities.	Ashfaq et al. (2020), Alt et al. (2021), and Huang et al. (2022)
Percieved-usef 2	- Utilizing the banking Chatbot enables me to complete tasks more efficiently	
Percieved-usef 3	- Utilizing the banking Chatbot enhances my efficiency.	
Percieved-play 1	- Using banking Chatbots makes me happy.	Rietz et al. (2019), Yang and Lee (2019), Terzis and al. (2012)
Percieved-play 2	- Using banking Chatbots gives me pleasure.	
Percieved-play 3	- Using banking Chatbots stimulates my curiosity.	
Inten-Use 1	-If I ever get the chance, I'm going to try the Banking Chatbot.	Jin and youn (2022), Venkatesch et al. (2003), Davis (1989)
Inten-Use 2	-I'll probably be using the banking Chatbot soon	
Intent-Use 3	-I intend to request information on the banking platform using the Chatbot.	

Source: The authors

4.2. Data collection

The survey took place in three distinct phases. During the initial stage, 40 individuals were interviewed to validate the content of the questionnaire. Secondly, an online pre-test was carried out with 80 Moroccan bank customers who use chatbots. This stage, carried out between June and July 2023, involved various means of communication with the participants. Participants in the pre-test were randomly selected from customers of different Moroccan banks to represent a variety of user profiles. The feedback received mainly concerned social influence, expected effort, perceived usefulness, playfulness and intention to use chatbots. This feedback was useful in refining the questionnaire, identifying areas for improvement and adjusting the questions accordingly.

The aim was to carry out a preliminary assessment using a principal component analysis (PCA) using SPSS software. Finally, the third phase involved the distribution of the final online questionnaire between September 2023 and January 2024. This last phase targeted customers through the official pages of Moroccan banks on the Face book platform. Sampling was carried out by convenience, due to difficulties in accessing the data. After removing incomplete answers, a sum of 390 usable responses were obtained.

However, convenience sampling has its limitations in terms of generalizability and representativeness of results. This method depends on the availability of participants, which may introduce a bias in sample selection (Mweshi & Sakyi, 2020). The people who take part may not be representative of the target population as a whole. To address these limitations, expanding the sample to include various customer segments could mitigate potential biases and provide more comprehensive information on chatbot adoption in the banking sector.

The overall model was tested using PLS-SEM structural equation methods in Smart PLS 4 software.

Thus, the PLS-SEM (Partial Least Squares Structural Equation Modeling) approach is a statistical method used to analyze relationships between latent variables in a research model. Unlike the CB-SEM (Covariance-Based Structural Equation Modeling) approach, PLS-SEM is more flexible and suitable for complex models or when data is limited, as it is less restrictive in terms of data distribution and sample size (Hair et al., 2019). In the context of chatbot adoption in banking, PLS-SEM is relevant because it can model complex relationships between interdependent factors such as perceived usefulness, user experience and satisfaction, and is more tolerant of violations of data distribution conditions, being able to be used with smaller samples or non-normally distributed data.

4.3. Population and Sample

We selected several characteristics for interviewing our target audience, including 'gender', age" and "education". Here are the findings:

Table 3. Respondents' individual narratives regarding their use of chatbots in banking

Respondent Characteristics	Frequency (n=370)	Percentages
SEX		
Men	230	59%
Women	160	41%
Total	390	
Age		
25 and under	36	09%
26-35	121	31%
36-45	130	33%
46-55	79	20%
55 and over	24	7%
Total	390	
Level of education		
with or without baccalaureate	36	9%
Bac+2 or Bac+3	91	23%
Bac+5ou plus	263	68%

Source: Research Data

The data provided in the table above offers a summary of chatbot usage in banking, focusing on the personal characteristics of the respondents. It is notable that 59% of participants are male, while 41% are female, meaning that there is a fairly even gender split among users of this technology in the banking sector. In terms of age groups, 36-45-year-olds are the most represented, making up 33% of the sample, followed by 26-35-year-olds with 30% and 46-55-year-olds with 21%. The under-25s account for a further 9%, while respondents aged 56 and over make up 7% of the sample. These results suggest that users of chatbots in the banking sector come from different age groups, with a notable presence of working professionals (26-55 years). The majority of participants, 68%, have a level of education of "BAC+4 and above", followed by those with a level of "BAC+2 or BAC+3" at 23%, and those with or without a Bac represent 9% of the sample. These figures indicate that users typically possess a greater level of education, with most having at least a BAC+2 diplomas.

5. Research Results

The objective of this section is to present the findings of our explanatory analyses to confirm our research hypotheses. We will first check the measurement model using the PLS method. Next, we will examine the structural model by presenting the outcomes of our hypothesis testing.

5.1. Evaluating the measurement model

Smart PLS uses the PLS method to evaluate the measurement model. This means that it uses the PLS algorithm to establish the relationship between latent variables and their observables, as well as to assess the magnitudes of influence exerted by formative constructs on their indicators, as described by (Hulland,

1999). To do this, we examine all the indicators associated with the evaluation of the measurement model, encompassing construct reliability as well as convergent and discriminant validity.

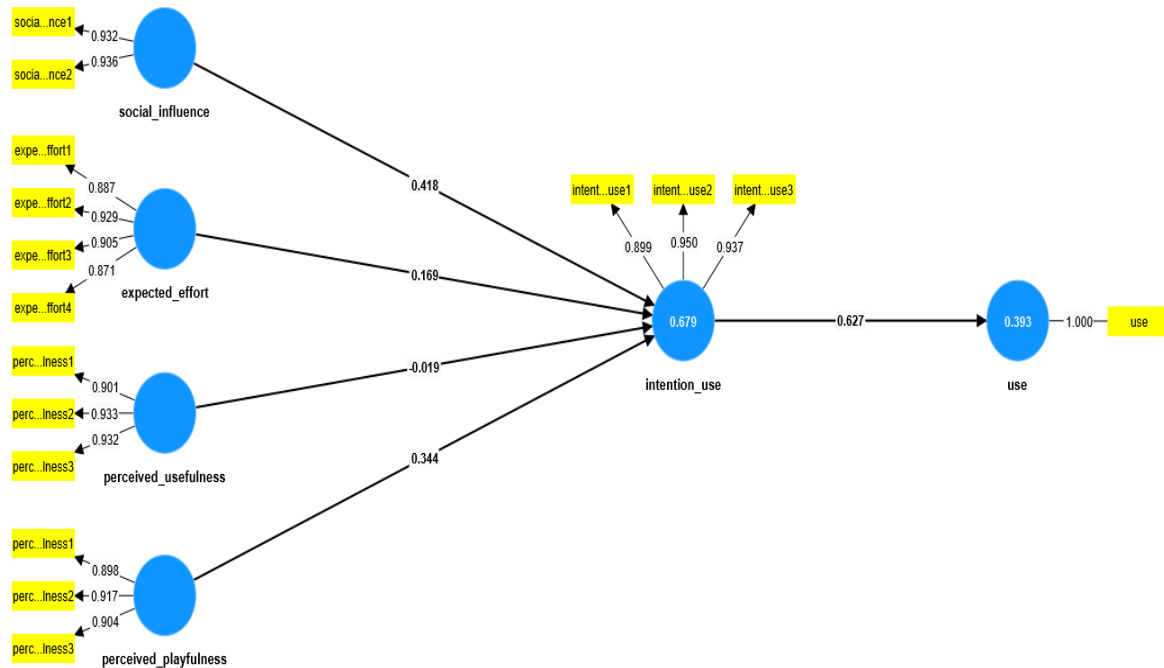


Fig. 3: The 'use' model in Smart PLS software (*SmartPls 4.0*)

5.1.1. Construct reliability

In order to guarantee the accuracy and reliability of our model, it is essential to assess the robustness of its design. Two frequently used tools for this purpose are Cronbach's alpha and composite reliability. If one of these assessments is less than 0.7, we need to reconsider our current indicators or include new ones to strengthen the reliability of our model (Fornell and Larcker, 1981).

Table 4. Reliability of constructs

	Cronbach's alpha	Composite reliability
Social_influence	0,854	0,854
Expected_effort	0,920	0,924
Perceived_usefulness	0,912	0,914
Perceived_playfulness	0,892	0,892
Intention_use	0,920	0,922

Source: *SmartPls 4.0 Software*

Table 4 presents the reliability results for the different dimensions of the model. Cronbach's alpha and composite reliability values are provided for each dimension. Reliability is high for most dimensions, with values above 0.9 for "Expected_effort" and "Intention_use", and values slightly below 0.9 for "Perceived_playfulness" and "Perceived_usefulness". However, the social influence dimension has a slightly lower reliability, with values of 0.854 for both measures. In general, these results indicate good model reliability.

5.1.2. Convergent and loading validity

We will assess the validity of the model components in two stages in order to determine their accuracy. First, we will adjust the parameters by considering only those factors whose correlation exceeds 0.7. Next, we will examine the AVE (Average Variance Extracted), which is normally greater than 0.5 (Fernandes, 2012).

Table 5. "Convergent validity" of measurement scales

The constructs	The Items	Loading	AVE
Social_influence	Soc-inf 1	0,932	0,872
	Soc-inf 2	0,933	
Expected_effort	Expected_eff 1	0,887	0,806
	Expected_eff 2	0,929	
	Expected_eff 3	0,905	
	Expected_eff 4	0,871	
Perceived_usefulness	Perceived_usef 1	0,901	0,850
	Perceived_usef 2	0,932	
	Perceived_usef 3	0,933	
Perceived_playfulness	Perceived_play 1	0,897	0,822
	Perceived_play 2	0,917	
	Perceived_play 3	0,904	
Intention_Use	Intent_Use 1	0,899	0,863
	Intent_Use 2	0,950	
	Intent_Use 3	0,937	
Use	Use	1	1

Source: SmartPls 4.0 Software

Table (5) presents the criteria required to guarantee "Convergent validity", produced by the PLS system. It shows that 'Convergent validity' is well established, since all items exhibit a correlation exceeding 0.7 and an average shared variance (AVE) value surpassing 0.5 (ranging from 0.702 to 0.863).

5.1.3. "Discriminant validity" of constructs done

Careful analysis of the correlation between variables and the "square roots" of their estimated variance (AVE) is essential to establish the discriminant validity of the variables. This ensures the reliability and validity of the variables used, as well as highlighting any problems or biases in the data (Voorhees et al., 2016).

Table 6. Correlations between constructs and the square root of the AVE

	Expected- _eff	Intention_ use	Perceived _play	Perceived _usef	Social_Influence	Use
Expected -eff	0.898					
Intention_ use	0.650	0.928				
Perceived _play	0.671	0.821	0.906			
Perceived _usef	0.275	0.376	0.406	0.922		
Social_Inf luence	0.585	0.848	0.797	0.426	0.934	
Use	0.446	0.653	0.616	0.365	0.641	1

Source: SmartPls 4.0 Software

Table 6 reveals that the "square root of AVE " amounts exceed the correlations of the construct with other constructs. This implies that each measure generates results that are distinct from those of the other constructs, thereby guaranteeing its discriminant validity. The results validate that all conditions for testing the hypotheses are satisfied; the consistency of the hypotheses is acceptable, and

the "convergent and discriminant validity" are reasonable.

5.2. Assessment of Structural Model and Hypotheses Testing

5.2.1. R-square

To validate the accuracy of the results, we examine the coefficient of determination (R^2) of each dependent variable.

Table 7. R-square and adjusted R-square

	R-square	R-square adjusted
intention_use	0,679	0,674
use	0,393	0,390

Source: SmartPls 4.0 Software

Regarding the intention to use variable, the coefficient of determination stands at 0.679, implying that 67.9% of the variability in this variable is elucidated by the independent variables in the model. The adjusted coefficient of determination, marginally under 0.674, adjusts for the number of explanatory variables in the model, offering a more conservative assessment of model fit.

For the use variable, the coefficient of determination is 0.393, indicating that 39.3% of the variation in this variable is accounted for by the independent determinants. The adjusted coefficient of determination is slightly less than 0.390.

Our R^2 is high, implying that the independent constructs within the models in the model contribute significantly to explaining the variation in the dependent variable (Wetzels, Odekerken-Schröder and Van Oppen, 2009).

5.2.2. Stone Geisser Q^2

Stone Geisser's Q^2 measure in this analysis is used to assess the fit of each structural equation, typically evaluated using the Blindfolding method. A positive Q^2 result suggests that the model demonstrates validity in its ability to make predictions (F. Hair Jr et al., 2014).

Table 8. Stone-Geisser Q^2 coefficient

	Q^2 predict
Intention_use	0,666
Use	0,386

Source: SmartPls 4.0 Software

For the "Intention_use" variable, the Q^2 coefficient is 0.666. This means that the model used to predict this variable has a relatively high capacity to account for the variability in the observed data, with a Q^2 of 0.666, which is generally considered to be a good fit. For the 'Use' variable, the Q^2 coefficient is 0.386. Although this figure is lower than that for "Intention_use", it still indicates a reasonable ability of the model to predict this variable. These findings suggest that the model has an interesting predictive capacity.

5.2.3. Results Hypotheses

5.2.3.1. Structural model

For a precise evaluation of our hypotheses, two PLS approaches are available, each with its own strategies: Jackknife and Bootstrapping. After examination, Bootstrapping proved to be the method best suited to our needs. The corresponding data are presented in the table provided.

Table 9. Current state of hypothesis validation through the bootstrapping technique

	T statistics (O/STDEV)	P values	VIF	Decision
H1: Social_influence ->intention_use	6,329	0,000	2,059	Validated
H2: Expected_effort ->intention_use	3,411	0,001	1,642	Validated
H3: Perceived_usefulness ->intention_use	0,528	0,598	1,194	Rejected
H4: Perceived_playfulness ->intention_use	4,763	0,000	2,363	Validated
H5: Intention_use -> use	11,747	0,000	1,000	Validated

Source: SmartPls 4.0 Software

This table presents the results of the validation of the hypotheses using the Bootstrap method. The relationship between the variables is as follows:

Social_influence ->intention_use: The high value of ($T=6.329 > 1.96$) suggests a notable correlation between SI and intention to use. The very low p-value of ($P=0.000 < 0.005$) verifies the statistical significance of this correlation, indicating that SI significantly influences intention to use. VIF: With a VIF of 2.059, there is a slight sign of multicollinearity, but this is still acceptable.

Expected_effort ->intention_use: T statistics (|O/STDEV|), the substantial value of ($T=3.411 > 1.96$) signifies a noteworthy correlation between anticipated effort and intention to utilize. P values: The very low p-value of ($P=0.001 < 0.005$) affirms "the statistical significance" of this association, suggesting that expected effort has a notable influence on the intention to use. With a VIF of 1.642, there is little sign of multicollinearity, which reinforces the validity of the relationship.

Perceived_usefulness ->intention_use: The value of ($T=0.528 < 1.96$) indicates a limited correlation between perceived usefulness and intention to use. The high p-value of ($P=0.598 > 0.005$) indicates that this association lacks statistical significance. With a VIF of 1.194, there are no signs of multicollinearity.

Perceived_playfulness ->intention_use: The high value of ($T=4.763 > 1.96$) suggests a notable correlation exists between perceived playfulness and intention to use. The very low p-value of ($P=0.000 < 0.005$) validates the statistical significance of this association, indicating that perceived enjoyment exerts a significant influence on the intention to use. With a VIF of 2.363, there is a slight sign of multicollinearity, but this is still acceptable.

Intention_use ->use: The remarkably high T statistics of ($T=11.747 > 1.96$) underlines a very strong relationship between intention to use and actual use. The p-value of ($P=0.000 < 0.005$) indicates strong statistical significance, supporting the idea that intention to use is a powerful predictor of real-world usage. With a VIF of 1.000, there are no signs of multicollinearity, confirming the robustness of this relationship.

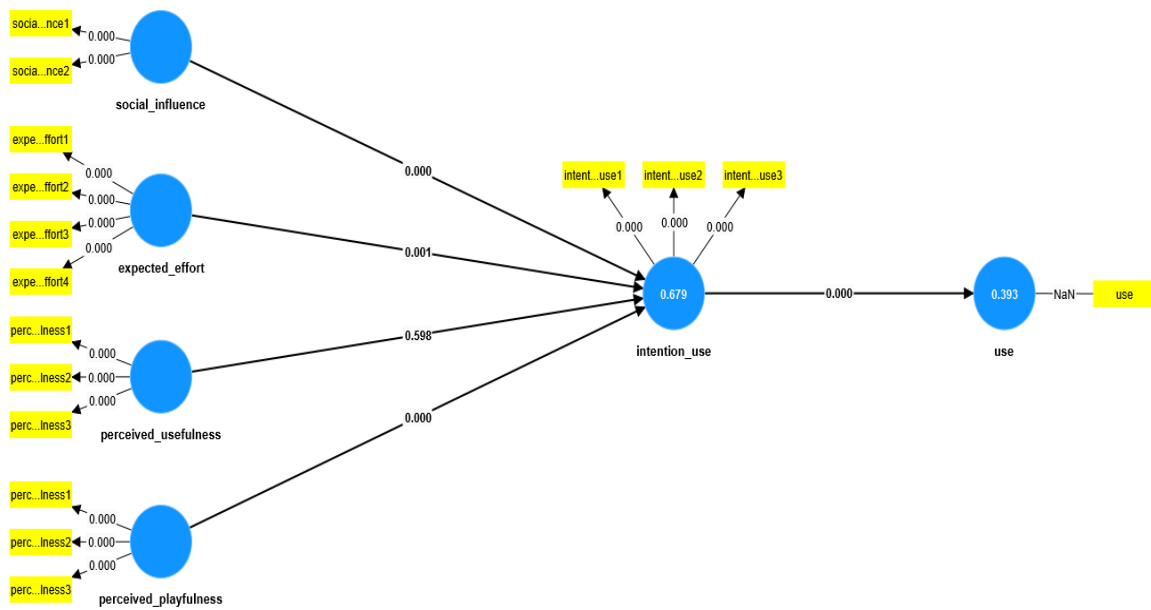


Fig. 4: Bootstrap model (SmartPls 4.0)

5.2.3.2. Mediation test

The bootstrap mediation test allows us to robustly and accurately assess whether the effect of an independent variable on a dependent variable is mediated by an intermediate variable in our model of Chatbot adoption in banking (Sabir et al., 2023).

Table 10. Mediation test using the bootstrapping method

	Specific indirect effects
social_influence -> intention_use -> use	0,262
expected_effort -> intention_use -> use	0,106
perceived_usefulness -> intention_use -> use	-0,012
perceived_playfulness -> intention_use -> use	0,216

The specific indirect effects analysis reveals several key insights into the relationship between various factors and the use of Chatbots in banking:

Social Influence: The indirect effect of social influence on Chatbot use through intention to use is 0.262. This implies that when users are influenced by social factors to use Chatbots, it significantly increases their intention to use them, leading to higher Chatbot use.

Expected Effort: The indirect effect of expected effort on Chatbot use through intention to use is 0.106. This suggests that when users perceive less effort in using Chatbots, it positively influences their intention to use them, which in turn leads to increased Chatbot use.

Perceived Usefulness: Surprisingly, the indirect effect of perceived usefulness on Chatbot use through intention to use is -0.012. This suggests that while perceived usefulness may influence users' intention to use Chatbots, it has a negligible or even negative effect on actual Chatbot use, possibly indicating that perceived usefulness alone may not be a strong predictor of Chatbot adoption.

Perceived Playfulness: The indirect effect of perceived playfulness on Chatbot use through intention to use is 0.216. This indicates that when users perceive Chatbots as playful and enjoyable, it significantly increases their intention to use them, consequently leading to higher Chatbot use.

5.2.4. Confirming research hypotheses with moderating variables

The study uses the PLS approach, in particular the Bootstrap method, to test its hypotheses. All hypotheses were validated with a Student's t-score exceeds 1.96 at the 5% significance level. The results are presented in a table.

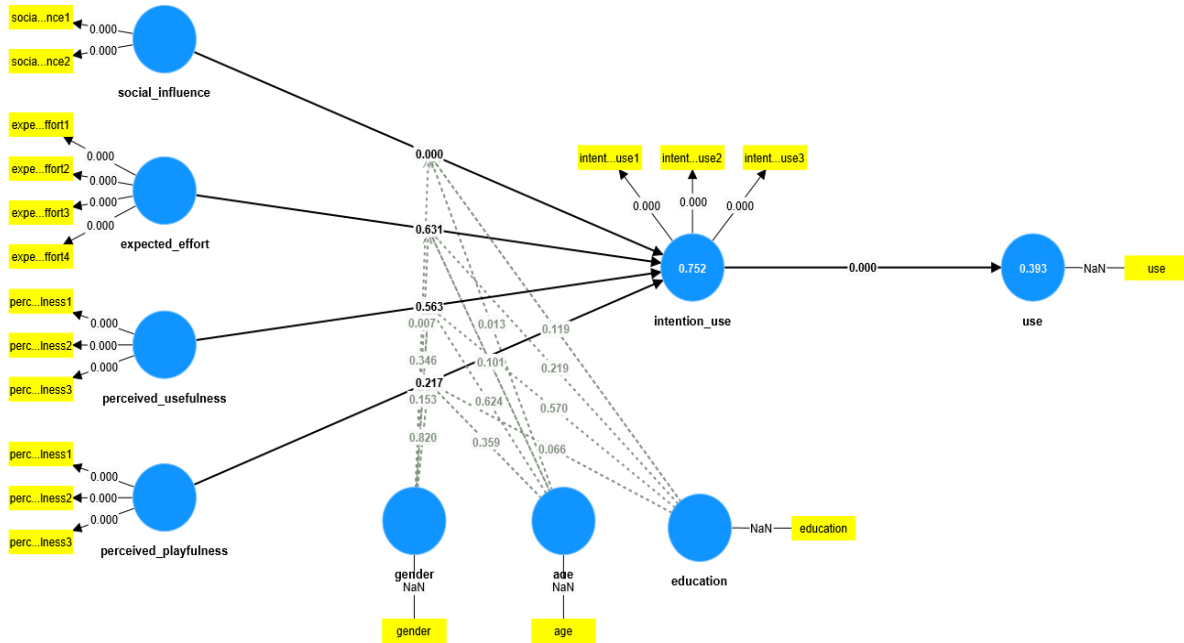


Fig. 5: Moderator variables in the model(SmartPls 4.0)

Table 11. The results of the test of the moderating effect of gender, age, education

	T statistics (O/STDEV)	P values	Decision
gender x social_influence ->intention_use	2,692	0,007	Validated
age x social_influence ->intention_use	2,491	0,013	Validated
age x expected_effort ->intention_use	1,638	0,101	Rejected
gender x expected_effort ->intention_use	0,942	0,346	Rejected
education x social_influence ->intention_use	1,559	0,119	Rejected
education x expected_effort ->intention_use	1,229	0,219	Rejected
gender x perceived_usefulness ->intention_use	1,430	0,153	Rejected
age x perceived_usefulness ->intention_use	0,491	0,624	Rejected
education x perceived_usefulness ->intention_use	0,568	0,570	Rejected
age x perceived_playfulness ->intention_use	0,918	0,359	Rejected
gender x perceived_playfulness ->intention_use	0,228	0,820	Rejected
education x perceived_playfulness ->intention_use	1,840	0,066	Rejected

Source: SmartPLS 4.0 Software

This table appears to show a single moderating effect of gender ($P=0.007$; $T=2.692$) and age ($P=0.013$; $T=2.491$) regarding the link between social influence and intention to use. For the other variables, gender, sex and education had no moderating effect.

6. Discussions

The exposure of our integrative model to the field showed the marked influence of Chatbots in the banking sector, explaining 69.7% of the intention to use them and 39.3% of their actual use.

Hypothesis (1) "social influence (SI) to a positive effect on the intention to use Chatbots in banking" is validated in our research ($T=6.329 > 1.96$; $P=0.000 < 0.005$) This finding aligns with numerous studies (Suoranta & Mattila, 2004 ; Sripalawat et al., 2011 ; Lu et al., 2019) that indicate that IS can have an effect on people's willingness to exploit online services. In this case, we aim to understand how much individuals value the social significance of utilizing an AI (Verma & Sinha, 2018). Thus, the implementation of social Chatbots would notably boost relations with the public, which exerts a powerful social pressure motivating customers to accept the proposed offers (Kaczorowska-Spychalska, 2019). Moroccan banking customers are strongly influenced by the opinions of their family and friends, with 60% of respondents indicating that their relatives think they should use this artificial intelligence.

The validation of Hypothesis 1, which suggests that social influence (SI) positively impacts the intention to use Chatbots in banking, is a significant finding. This aligns with previous studies indicating that social influence can affect individuals' willingness to use online services. However, there are critical points to consider. Firstly, the generalizability of the result may be limited to Moroccan banking customers, and it's unclear if it applies to other populations or banking contexts due to potential cultural and demographic differences. Secondly, while a positive relationship between social influence and Chatbot adoption was found, it's important to note that correlation doesn't imply causation (Cheng et al., 2022). Other factors may also influence both social influence and the intention to use Chatbots, and the relationship may be more complex than suggested. Furthermore, the finding raises questions about whether customers are using Chatbots primarily due to genuine usefulness or social pressure (Mogaji et al., 2021b).

Hypothesis (H2) "Expected effort has a positive influence on intention to use chatbots in banking" is accepted by our results ($T=3.411 > 1.96$; $P=0.001 < 0.005$). This confirms the majority of previous studies, in particular the initial model of our thesis, i.e. UTAUT, not forgetting the TAM model. Thus, a number of studies Meli'an-Gonzalez and et al. (2021), Foon and Fah (2011), Følstad and Brandtzæg (2017) have argued that the accuracy of AI algorithms is a major factor in the application of AI. This has been particularly evident in Chatbots, where high accuracy decreases the necessity for human input (Mogaji and et al., 2021). Balakrishnan et al. (2022) suggest that these bots can take over services provided by humans in the banking sector (Alt et al., 2021). However, while this result aligns with existing research suggesting that the accuracy of AI algorithms is crucial for Chatbot adoption, there are critical points to consider. Firstly, while high accuracy may reduce the need for human input in Chatbots, there may still be concerns about the complexity of interactions and the effort required from users to engage effectively with these systems (Rapp et al., 2021b). Secondly, while Chatbots may indeed take over certain services provided by humans in the banking sector, there are potential drawbacks such as reduced personalization and the inability to handle complex queries (Nguyen et al., 2021b).

The hypothesis (H3) that "perceived usefulness has a positive impact on the intention to use chatbots in banking" is rejected ($T=0.528 < 1.96$; $P=0.598 > 0.005$). Contrary to several researches that have shown that "perceived usefulness" a significant factor of "intention to use technology" (Luo et al., 2022 ; Tahar et al., 2020). This concept is a crucial component of the 1989 (TAM) model and indicates the extent to which users can be successful when utilizing a technology (Davis, 1985).

The rejection of Hypothesis 3, which posits that perceived usefulness has a positive impact on the

intention to use Chatbots in banking, is a significant result that challenges conventional wisdom. While perceived usefulness is typically considered a crucial factor in technology adoption, supported by research such as that of Luo et al. (2022) and Tahar et al. (2020), the findings suggest a different dynamic in the banking sector. This deviation from the norm prompts critical scrutiny. Perceived usefulness, a cornerstone of the TAM model, typically indicates users' belief in the technology's ability to facilitate success. However, Lemley et al. (2017) provide insight into why Moroccan customers may not prioritize perceived usefulness in Chatbot adoption. They argue that Chatbots' simplicity and effectiveness, particularly in multitasking scenarios, may redirect customers' attention to more pertinent concerns such as trust and confidentiality, crucial factors in the sensitive banking sector (Zhou et al., 2022). This departure from expected behavior underscores the complexity of technology adoption and highlights the need for deeper exploration of contextual influences on user attitudes and behaviors.

Hypothesis (H4) "Perceived playfulness positively influences the intention to use Chatbots in banking" is accepted ($T=4.763 > 1.96$; $P=0.000 < 0.005$), a confirmation to some works (Venkatesh et al., 2012; Yang & Lee, 2019), which consider that the perceived playfulness felt when interacting with a computer is an essential hedonic motivation in this context. The pleasurable nature of interacting with a computer was noted by Yang and Lee (2018), with other studies indicating that user satisfaction is often related to the pleasure derived from operating artificial intelligence (Oghuma et al., 2016). Chung et al. (2020b) further revealed that Chatbots and AI can provide an entertaining experience for people when chatting. Nicolescu and Tudorache (2022) observed that people have a preference for self-service when it is enjoyable. The researchers indicated that the pleasure derived from using self-service encourages customers to spend more time engaging with it. Yang and Lee (2019b) also found that this factor exerts a notable impact on the acceptance and usage of M-banking services. In addition, Arcand et al. (2017) noted that virtual banking agents provide an entertaining experience when customers request banking services. For our research, playfulness seems to be a determining element affecting the intention to use this artificial intelligence in banking. According to our survey of Moroccan customers, 77% of responses ranged from "somewhat agree" to "strongly agree". While these findings align with the notion that enjoyment from using technology can drive acceptance, there are critical considerations to be made. Firstly, while perceived playfulness may encourage initial usage, it remains unclear whether it sustains long-term engagement or leads to tangible benefits for banking customers (Rasanjalee & Galdolage, 2021). Secondly, while studies indicate the pleasurable nature of interacting with AI, the specific context of banking introduces unique considerations such as trust, security, and the seriousness of financial transactions (Dwivedi et al., 2021). Moreover, the reliance on self-reported survey data from Moroccan customers may introduce bias, and the generalizability of these findings to other cultural contexts or banking environments warrants further investigation.

For hypothesis (H5), a significant correlation is observed between intention and chatbot use ($T=11.747 > 1.96$; $P=0.000 < 0.005$). This discovery aligns with the conclusions of Venkatesh et al. (2003) in their UTAUT model, as well as those of Sitthipon et al. (2022); Ragheb et al. (2022) in their research on the adoption of this artificial intelligence technology. These results are of paramount importance, as they establish a robust basis for the development and use of chatbots in banking. While this alignment with previous research underscores the validity of the relationship between intention and actual usage, there are critical aspects to consider. Firstly, while intention is a crucial predictor of behavior, it doesn't guarantee actual adoption or sustained use, as factors such as system performance, ease of use, and external influences can also play significant roles (Gathongo, 2019). Secondly, while the significant correlation between intention and Chatbot use provides a strong foundation for the development and utilization of Chatbots in banking, further research is needed to explore the intricacies of user behavior and the factors influencing actual adoption and usage in real-world settings.

We introduced three moderating variables to ascertain the level of influence between independent variables and intention to use chatbots. In contrast to our expectations, only demographic variables had a significant moderating impact on the correlation between social influence and intention to use. This

outcome is in accordance with findings presented in numerous studies (Venkatesh et al., 2003; Mogaji et al., 2021). Age plays a role as a moderating variable regarding the usage of a novel technology such as chatbots. In our situation, age impacts social interactions between Moroccans in a sensitive area such as banking. As we age, questions and concerns become essential aspects of the acceptance process. In turn, gender has a notable effect on this same relationship, confirming the findings of previous research (Venkatesh et al. 2003; Shannon, 2019). Women generally show a heightened awareness of social influence when using a new technology. On the other hand, the moderation is rather surprising by the results concerning education level compared to previous research (Venkatesh et al. 2003; Coeurderoy et al., 2014), which put forward the moderating effect of education regarding technology adoption. The intrinsic nature of AI may explain these results. The simplicity and intuitiveness of chatbots make them accessible to all users, whatever their level of education.

For the mediation test, the specific indirect effects highlight the importance of perceived playfulness and social influence in users' intention to use Chatbots, which ultimately results in increased Chatbot usage. This joins several studies Tsai et al. (2021) and Rese et al. (2020b) which conclude that the intention of use can play a mediating role, especially when it comes to human-machine interaction in the financial field . However, the unexpected negative indirect effect of perceived usefulness suggests that other factors beyond perceived usefulness may play a more important role in actual Chatbot adoption. Contrary to several previous studies Kasilingam (2020b) , Park and Kim (2023) which consider that the intention of use has a notable role between the perceived usefulness and the use of a technology. Moroccans may not be concerned about the perceived usefulness of Chatbots in banking due to a lack of familiarity, preferences for other service channels, concerns about security and privacy, barriers cultural or linguistic issues, as well as accessibility or reliability issues (Mouhcine, 2021).

7. Conclusion

In conclusion, this study provides empirical evidence on the factors influencing the adoption of chatbots by Moroccan bank customers. The adapted UTAUT model, incorporating perceived playfulness and perceived usefulness, proves to be a useful framework for understanding customers' intentions and actual use of chatbots in the banking sector. The findings highlight the significant roles of social influence, expected effort, and perceived playfulness in driving chatbot adoption, while perceived usefulness appears to be less relevant in this context. These results are confirmed by the mediator effect, since the analysis of indirect effects in the use of banking chatbots reveals that social influence and perceived playfulness positively affect users' intention to use chatbots, leading to an increase in use. Expected effort positively influences intention to use, indicating that perceived ease of use encourages adoption of chatbots. Surprisingly, perceived usefulness has a negligible or negative effect on actual use of chatbots, suggesting that it may not be a strong predictor of adoption on its own.

The study also reveals the moderating effects of age and gender on the relationship between social influence and intention to use, suggesting that banks should consider these demographic factors when designing and promoting their chatbot services. The findings have important implications for Moroccan banks seeking to leverage artificial intelligence to enhance customer engagement and service quality. Banks should focus on creating user-friendly and enjoyable chatbot experiences, while also leveraging social influence to encourage adoption. However, the study also acknowledges the limitations of the convenience sampling approach and the need for further research incorporating a broader range of variables, such as chatbot design features and customer personality traits. Future studies could also explore the post-adoption behaviors and loyalty of chatbot users in the banking sector. Despite these limitations, this study makes a valuable contribution to the growing literature on chatbot adoption and provides practical insights for banks in Morocco and other developing countries.

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