Assessing attitude and behavioral intention toward chatbots in an insurance setting: a mixed method approach

Jorge de Andrés-Sánchez, Social and Business Research Laboratory, University Rovira i Virgili, jorge.deandres@urv.cat 0000-0002-7715-779X

Jaume Gené-Albesa, Business Management Department, University Rovira i Virgili, jaume.gene@urv.cat 0000-0001-7156-8304

FUNDING SOURCE

This research has benefited from the Research Project of the Science and Technology Ministry "Sostenibilidad, digitalizacion e innovacion: nuevos retos en el derecho del seguro" (PID2020-117169GB-I00).

Disclosure statement: None

Assessing attitude and behavioral intention toward chatbots in an insurance setting: a mixed method approach

ABSTRACT

Background: Conversational robots (chatbots) are currently an extended Insurtech that is widely used to enable policyholders' communication with insurance firms. This paper analyses customers' acceptance of chatbots in procedures with regard to in-force policies.

Methods: We analysed a semistructured survey answered by workers of a public Spanish university. Structured questions have been grounded in the well-known technology acceptance model (TAM), which is based on two explanatory variables: perceived usefulness (PU) and perceived ease of use (PEOU). We have also considered two additional explanatory factors: social influence (SI), whose impact on BI is mediated by PU, and trust (TRUST), whose influence on BI is supposed to be made throughout PU and PEOU. Likewise, we asked two open questions about the advantages and disadvantages of chatbot use to make procedures linked with in-force insurance contracts. We performed our analysis by using quantitative and qualitative methods. The quantitative analysis tests the suitability of TAM on our data and has been performed by using structural equation modelling with partial least squares (PLS-SEM). Subsequently, to reach a deeper understanding of the reasons that explain the respondents' behavioral intention, we provide a systematic overview of the answers to open questions with the help of the groundwork provided by TAM.

Results: We have checked that the basic TAM along with social influence and trust provide a satisfactory explanation for behavioral intention (BI) toward bots. Likewise, we have observed a general reluctance toward the use of chatbots. The qualitative analysis showed that arguments explaining resistance come from all explanatory factors considered in the paper. Therefore, mainstream responses have outlined that interaction with chatbots is difficult, and many times, the procedure must be finished with the assistance of a human operator. Likewise, many responses point out as a relevant drawback that they provide a dehumanized service without empathy. Consequently, interactions with chatbots are perceived as cumbersome, ineffective and a loss of time. Although some people perceive that the faster service provided by chatbots in concrete circumstances is an advantage, other theoretical consequences that may add value, such as temporal flexibility and the possibility of proving better services with the same cost and/or reducing insurance prices because of the reduction of firms' administrative costs, are generally not perceived.

Conclusions: Our findings have theoretical and practical implications. We have shown that TAM provides a reliable theoretical model to understand policyhoders' acceptance of chatbot technology in an insurance setting. Perceived usefulness, reliability, social opinion about bot adoption and usability must be improved to avoid generalized policyholders' reluctance. That resistance is because of issues such as conversational skills, the capability to provide an interaction closer to being human and users' perception that chatbots actually add value to policyholders.

KEYWORDS: Insurtech, chatbots, Technology Acceptance Model, Structural Equation Modelling, Qualitative analysis

1. INTRODUCTION

The fourth Industrial Revolution (or Industry 4.0, I4.0) is a disruptive force that is massively impacting the economy, business, and society (Grybrauskas et al., 2022). It is based on the intensive use of digital technologies born in the first and second decades of the 21st century, such as the Internet of Things (IoT), cloud computing, blockchain, big data, and artificial intelligence, in combination with novel and interconnected front-end devices and machines to generate smart industries and services (Marcon et al., 2023). The impact of this technological disruption is also significant on customer experience and encompasses all stages, from pretransaction activities such as providing personalized advice to posttransaction activities, including postsales service (Hoyer et al., 2020).

In that context, we must understand fintech, which, following Arner et al. (2015), can be conceptualized as the application of any new technology to enhancing financial services and processes. Therefore, in the 21st century, fintech is nothing but a consequence of the impact of I4.0 in the financial industry. Insurtech is a branch of fintech placed in the concrete setting of the insurance sector (Stoeckli et al., 2022). This can be defined, by analogy, as the application of I4.0 techs to facing issues with the products, services and processes of the insurance industry (Choon et al., 2018). Although insurtech has grown exponentially since the beginning of the 2010s (Bonhert et al., 2019; Sosa & Montes, 2022), the COVID-19 pandemic has consolidated this tendency, triggering many insurers' initiatives to overcome challenges such as providing policyholders' services despite mobility constraints (Lanfranchi & Grassi, 2022).

Insurtech must be understood comprehensively since I4.0 embraces all the levels of the insurance firms' value chain: risk and data analysis, sales, management, fraud investigation and asset-liability management (Yan et al., 2018). In fact, firms with an integrative vision of the implementation of the digital agenda tend to present better business performance (Bohnert et al., 2019). Njegomir et al. (2021) identify four large areas where digital implementation has different nuances:

- Product development. The use of big data to threat information allows the creation of more personalized products. On the other hand, linked to digitalization comes new insurable damages, such as those by cyber-risks.
- Sales and distribution. Insurtech provides new distribution channels powered by new information communication technologies (ICTs).
- Actuarial. Data analysis instruments such machine learning and deep learning allow improving analytical capability in areas such as pricing or segmentation.
- Claim management. Digitalization improves fraud detection and claim processing costs and claims.

Within the great set of applications of I4.0 technologies areas of the insurance industry (see Greineder et al., 2020; Sosa & Montes, 2022 to have an extended panorama), this paper is focused on the use of conversational robots (chatbots), whose implementation in the insurance sector started in the middle 2010s (Rodríguez-Cardona et al., 2019). They can be defined as virtual assistant software programs that conduct conversations through audio or text and are designed to simulate human conversations (Hoyer et al., 2020).

Although it is expected that conversational robots will have a predominant role in improving financial services, their implementation will be effective when customers are satisfied and engage with them (Hari et al., 2022). Thus, we think it is relevant to understand the factors that impact policyholders' acceptance of chatbots to make procedures linked to in-force policies.

Theoretically, chatbots have emerged as an effective tool to address users' queries in an automated way (Nirala et al., 2022) such that firms have rapidly adopted chatbots to provide assistance to customers (Fotheringham & Wiles, 2022). They have great potential to improve customers' quality attendance in issues such as agility since they avoid queues or accessibility because they are available 24/7 and allow human agents to be focused on nonroutine and more complex issues (DeAndrade & Tumelero, 2022). In an insurance setting, chatbots can develop tasks such as looking for adequate products suited to potential customers by provoking some keywords, providing information to insured about in-force policies and processes, or accelerating and making claiming processes easier (Riikinen et al., 2018). Therefore, it seems that their implementation is welcome by investors since news about the implementation of a chatbot system in companies tends to push the price of their stocks in the markets (Fotheringham & Wiles, 2022).

Although robotic science is having active and fast growth, and theoretically the most advanced chatbots, so-called artificial-intelligence chatbots, are programmed to interact as real human beings and are able to learn continuously from the conversation to provide a better response (Nirala et al., 2022), the technology behind chatbots is still not completely mature and often fails during their interactions with users (Sá-Siqueira et al., 2023). Chatbots are not able to capture the evolution of a conversation by interpreting tones and inflections of users' voices, do not have emotional skills such as empathy or cannot answer complex requirements (Vassilakopoulou et al., 2023). These reasons may explain the existence of several studies displaying a significant reluctance of insurance consumers to interact with bots (Rodríguez-Cardona et al., 2019; PromTep et al., 2021).

This paper assesses the behavioral intention of insurance consumers to use chatbots by using a semistructured survey completed by the workers of a Spanish public university. We ground our analysis on the Technology Acceptance Model (TAM) by Davis (1989) and its refinements (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008) that have been widely used to explain acceptance in fintech and insurtech settings (Andrés-Sánchez et al., 2021). We concretely try to answer the following research questions:

RQ1= *Does TAM provide a reliable framework to analyse chatbot acceptance for managing policies by insurers?*

RQ2= *What is the mainstream behavioral intention to use chatbots in an interaction with the insurer with regard to in-force policies, and what are the arguments supporting that intention?*

To answer these questions, the paper adopts a mixed quantitative–qualitative methodology. To test RQ1, i.e., the adequacy of TAM to our sample, we use partial least squares-structural equation modelling (PLS-SEM). Once we confirm the statistical adequacy of the TAM to our data, we develop a qualitative analysis of open responses that also takes the TAM as a reference. The use of a mixed quantitative–qualitative methodology allows a holistic perspective of the analysed phenomena. Mixed methods provide gains due to complementarity since the qualitative assessment allows additional insights into the findings from a quantitative study and enhances its completeness, providing richer explanations of the findings from the quantitative data and analysis (Venkatesh et al., 2012). Qualitative analysis allows the extraction of concrete practical implications that are hard to find by the unique use of statistical methods (Vogelsang et al., 2013).

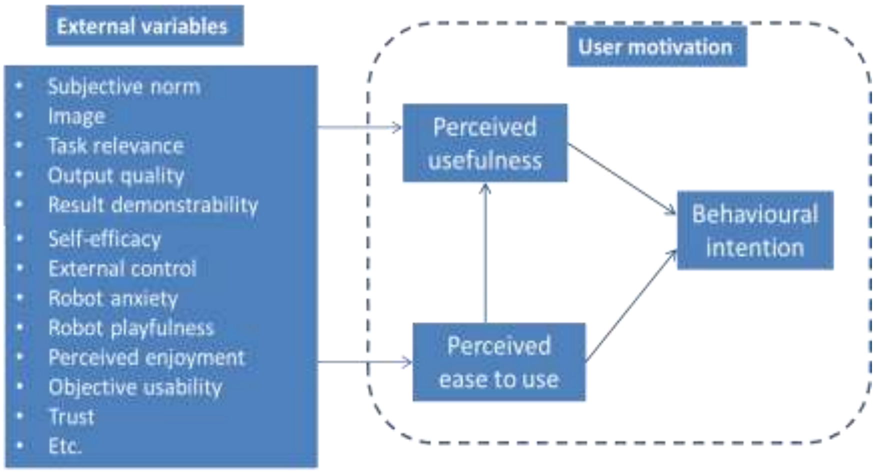
We structure the rest of the paper in the following manner. The second section justifies the use of the basic TAM along with social influence and trust to explain behavioral intention toward chatbot use by revising the literature. Section 3 displays the materials and analytical methodology adopted in the study. We subsequently show the results of data analysis. Finally, we discuss the principal results, outline practical implications and remark limitations and further research.

2. A TECHNOLOGY ACCEPTANCE MODEL TO ASSESS BEHAVIOAL INTENTION TO USE CHATBOTS IN INSURANCE PROCEDURES

2.1. Analytical framework used in this paper

We have developed our analysis by following the classical technology acceptance model (TAM) proposed by Davis (1989) and extended by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), as displayed in Figure 1. In the original model (Davis, 1989), the antecedent variables of behavioral intention (BI) are perceived usefulness (PU) and perceived ease of use (PEOU). The extensions in Venkatesh and Davis (2000) and Venkatesh and Bala (2008) allow external variables to impact BI by the mediation of PU and/or PEOU.

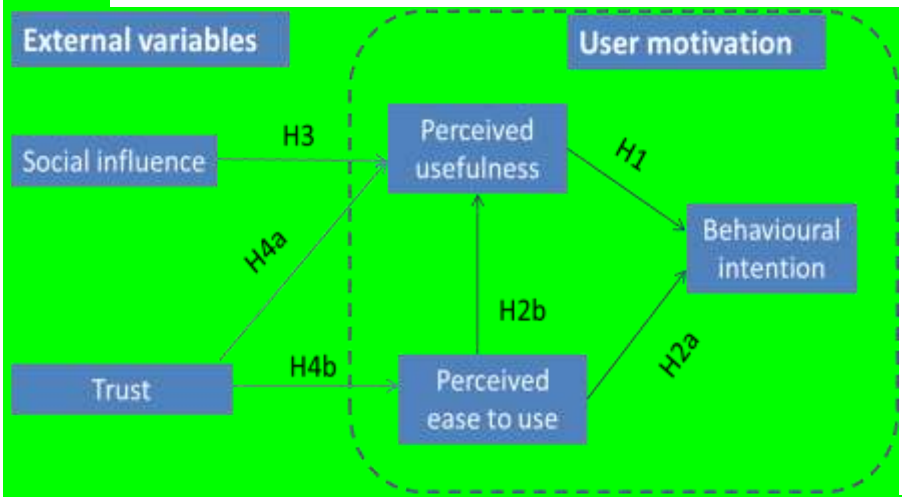
Figure 1. Conceptual framework used in this paper



Source: Own elaboration based on Venkatesh and Bala (2008)

Considering the integration of a mixed quantitative–qualitative approach in our study, we propose to examine a comprehensive TAM-based model that effectively captures the acceptance of chatbots within the context under analysis while maintaining an appropriate level of simplicity to ensure that the qualitative study remains focused on. In light of this, the external variables taken into account will encompass social influence and trust. The model that will be utilized in our analysis is depicted in Figure 2.

Figure 2. A basic technology acceptance model to explain behavioral intention to use chatbots



Source: Own elaboration from Davis (1989) and Venkatesh and Bala (2008)

2.2. TAM original variables: perceived usefulness and perceived ease of use

2.2.1 Perceived usefulness

Perceived usefulness (PU) is defined in Davis (1989) as the intensity of the perception by potential users that the evaluated technology improves their performance. There are several questions that may induce a perception of the usefulness of chatbots for insurance procedures:

(a) Simple queries could be solved faster than if human assistance is used (DeAndrade & Tumelero, 2022).

(b) Chatbot technology does not necessarily substitute other communication channels to interact with the insurer. Therefore, conversational robots may be understood as an available tool that improves service to policyholders (Standaert & Muylle, 2022). The diversification of communication channels is usually appreciated and engages customers (Gene-Albesa, 2007).

(c) The capability of Insutech to add value to customers and enhance production and commercialization efficiency (Stoeckli et al., 2018) must enable it to reach competitive advantages. It is widely known that these advantages could be achieved by being cheaper than competence or by improving the quality of the products and the service (Kaleka, 2002).

On the other hand, chatbots currently present several drawbacks that reduce their usefulness. Thus,

(a) Usually, chatbots are not able to solve complex requirements, and therefore, the query must be finally solved by a human operator (Vassilakopoulou et al., 2023). In those cases, the first interaction with the bot is perceived as a loss of time, and its failure drags perceived utility (Sá-Siqueira et al., 2023).

(b) The use of chatbots in some circumstances may negatively impact the image of the service, which is often an antecedent of PU (Venkatesh & Davis, 2000) because the interaction shows dehumanization. LMI Group (2022) outlines whether policyholders report a great loss; they expect active listening from the interlocutor. A commonly reported drawback is that chatbots are unable to show empathy (Vassilakopoulou et al., 2023).

(c) Rodríguez-Cardona et al. (2019) remark that to obtain a true advantage of bot tech, firms ought to allow coordination between data handling and delivery in the back-end system in such a way that the front-end system is enabled to provide reliable responses and adequate service. Otherwise, the weak quality of the responses from the front-end system results in a poor perception of the interaction utility (Venkatesh & Bala, 2008).

Table 1 shows that the revised literature on technology acceptance usually reports that PU has a positive impact on the perception of the goodness of a tech. That revision embeds blockchain technology acceptance in a financial setting, attitude toward novel services in financial and insurance settings and acceptance of conversational robots. Therefore, the following hypothesis is proposed.

Hypothesis 1 (H1)=*Perceived usefulness of chatbots positively influences behavioral intention.*

2.2.2 *Perceived ease of use*

Davis (1989) defines *perceived ease of use* (PEOU) as "*the degree to which a person believes that using a particular system would be free of effort*". PEOU must be understood in our context as the nonpresence of difficulties when communicating with the company with regard to an in-force policy by means of a chatbot. Conversational robots allegedly provide some advantages with respect to alternative channels.

(a) They are able to give assistance 24/7 and are more flexible than humans in regard to the moment in which they are available.

(b) They have fewer barriers to being used than other digital technologies, such as apps, because they can be used from conventional digital messenger systems or in a phone call (Koetter et al., 2019).

On the other hand, it is widely accepted that conversational robots are not developed enough to be easily used. Failing and confusing answers to customers worsen the perception of utility bots and burden the attitude toward their use (Sa-Siqueira et al., 2023). Some questions that we can outline are as follows:

(a) Creepiness, which is produced by issues such as technology anxiety and the need for human interaction, usually has a significant impact on the usability perception and attitude of customers toward bots (Rajaobelina et al., 2023).

(b) Vassilakopoulou et al. (2023) remark that conversational robots are not able to feel changes in the voice tone or in the direction of the conversation and respond accordingly. Therefore, many times, interaction with the chatbot is difficult, especially if the policyholder has complex queries.

(c) Nuruzzaman and Hussain (2020) outline that the great majority of conversational robots are programmed with conversational trees and trained with basic conversational sets of data. Consequently, their failure in interactions is common (Xing et al., 2022). This issue drags PEOU (Sa-Siqueira et al., 2023) and explains why more than 50% of interactions with bots are not completed (PromTep et al., 2021).

Table 1 shows that the revised literature has widely checked the positive significant impact of PEOU on behavioral intention. Likewise, in TAM modelling, PEOU can also impact attitude with the mediation of PU (Davis, 1989; Venkatesh & Davis, 2000) since the less friendly the use of a system is, the less performance is obtained with its use. Table 1 shows the empirical relevance of this relation. Therefore, the following hypotheses are proposed:

Hypothesis 2a (H2a)= *Perceived ease of use of chatbots positively influences the behavioral intention to use them.*

Hypothesis 2b (H2b)= *Perceived ease of use of chatbots positively influences their perceived utility of making procedures with the insurer.*

Table 1. Reports in the literature of the links between PEOU, PU and BI in technology acceptance models in blockchain, digital banking, insurance products and chatbots

Papers reporting that that PU affects BI	
Albayati et al. (2020), Nuryyev et al. (2020); Sheel and Nath (2020); Palos-Sánchez et al. (2021)	Cryptocurrencies/blockchain
Bashir and Madhavaiah (2015), Farah et al. (2018), Sánchez-Torres et al. (2018), Warsame and Ireri (2018), Hussain et al. (2019).	Digital Banking
Huang et al. (2019), Oktariyana et al. (2019) and Andrés-Sánchez et al. (2021)	Novel insurance products
Eeuwen (2017), Brachten et al. (2021), de Cicco et al. (2022), Pawlik (2022), Joshi (2021), Gansser and Reich (2021), Kasilingam (2020), and Kuberkar and Singhal (2020), Xie et al. (2022); Lee et al. (2022); Silva et al. (2023)	Services by conversational robots
Papers supporting that PEOU affects BI	
Albayati et al. (2020), Nuryyev et al. (2020), Sheel and Nath (2020), Palos-Sánchez et al. (2021)	Cryptocurrencies/blockchain
Bashir and Madhavia (2015) Warsame and Ireri (2018)	Digital Banking
Huang et al. (2019).	Novel insurance products
Brachten et al. (2021), Pawlik (2022), Kasilingam (2020), Gansser and Reich (2021), Kuberkar and Singhal (2020) and Mostafa and Kasamani (2021).	Services by conversational robots
Papers supporting that PEOU affects PU	
Albayati et al. (2020), Nuryyev et al. (2020), Palos-Sánchez et al. (2021)	Cryptocurrencies/blockchain
Bashir and Madhavia (2015)	Digital Banking
Huang et al. (2019), Andrés-Sánchez et al.(2021)	Novel insurance products
de Cicco et al. (2022), Joshi (2021); Silva et al. (2023)	Services by conversational robots

2.3. External variables to the TAM framework: social influence and trust

2.3.1 Social influence

Social influence (SI) is defined by Venkatesh et al. (2003) as "*the extent to which individuals perceive that important others believe they should use a new technology*." Despite the increasing use of AI-based technologies such as chatbots in business practices, particularly since the COVID-19 crisis (Gkinko & Elbanna, 2023), there is widespread awareness that they are prone to failures, which negatively impacts the spread of perceptions about chatbots because of word to mouth (Seeger & Heinzl, 2021). The opinion of peers, such as friends or family, has a significant influence on general technological acceptance, as individuals tend to seek approval from appreciated persons (Venkatesh et al., 2003). This finding applies to areas related to financial communication channels

(Makanyeza & Mutambayashata, 2017) and the acceptance of conversational chatbots (Gansser & Reich, 2021; Melián-González et al., 2021). However, commercial interest in chatbot technology remains high due to its aforementioned benefits, prompting companies to encourage its use among their customers (Xu et al., 2022). Chatbots are commonly used to provide initial assistance to clients and utility service users (Vassilakopoulou et al., 2023).

As is often the case when implementing disruptive technology, many jobs related to the insurance sector disappear. It is estimated that by 2030, the implementation of Industry 4.0 technologies such as chatbots will have reduced the number of human operators required to serve customers by 70%-80% (Balasubramanian et al., 2018). This consequence is perceived by societies as negative and often occurs with disruptive technological changes (Kovacs, 2018). We must emphasize that the opinion of trusted financial advisors and insurance brokers is often relevant to the decision-making process of policyholders (Andrés-Sánchez et al., 2021), and many of them may face the risk of losing their jobs.

Similarly, although many positive benefits can be derived from AI-driven technology, there is also a widespread social perception that AI entails various dangers beyond generalized job loss, which would diminish its utility. Some examples include multinational companies utilizing AI to amass immense wealth and market power, which can then translate into uncontrolled influence, privacy issues, and, in more extreme cases, dystopias where machines, with superior intelligence to humans, revolt against them (Stahl, 2021).

In the extensions of TAM by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), it is indicated that social influence influences behavioral intention mediated through usefulness. If a person considered to have superior knowledge on the issue, in our case the insurance broker or trusted financial advisor, expresses a judgment about the usefulness of a technology, this opinion impacts perceived usefulness. This relationship has been empirically observed by Albayati et al. (2020) and Nuryyev et al. (2020) in the field of blockchain applications in finance, in the acceptance of m-banking (Kishore & Sequeira, 2016; Farah et al., 2018), and by Brachten et al. (2021) and Silva et al. (2023) in a chatbot acceptance setting. Thus, we formulate the following hypothesis.

Hypothesis 3 (H3): *Social influence has an impact on the perceived usefulness of policyholders in their interactions with the insurance company.*

2.3.2. *Trust*

The relevance of trust in insurance customers is twofold since it involves relational and cognitive trust (Zafiris & Cheng, 2022). Social or organizational trust is because in an insurance agreement, policyholder confidence in the insurance company's ability and willingness to fulfil its commitments is needed (Guiso, 2021), and cognitive trust comes because perceiving reliability in chatbot technology is a keystone to using it (Chen & Park, 2021).

Relational trust is very relevant in phenomena where institutions play a relevant role in the intention to use a technology (Gkinko & Elbanna, 2023). The insurance business, which is the paradigm of the existence of a high degree of moral hazard and adverse selection in the market, is based on mutual trust between the company and the customer (Guiso, 2012). The policyholder must trust that the company will cover claims made in good faith since it is solvent and will not obstruct it. For its part, the insurer must trust that the policyholder provided truthful data in the underwriting moment and, once the insurance has been contracted, will continue to take care to limit the risk covered by the contract (Guiso, 2021).

Giving trust to the counterparty of a contract implies being vulnerable to their actions since the depositors assume that the depositories will perform an action that is relevant to them, but they do not have control that it will effectively be carried out (Glikson & Woolley, 2020). Therefore, granting trust to someone involves a situation of weakness, which explains why society sees trust in insurance companies (by policyholders) as more relevant than in policyholders since insurance companies are much more powerful than individuals (Guiso, 2021).

Along with relational trust, the other aspect that has been analysed in the acceptance of conversational robots is cognitive trust (Gkinko & Elbanna, 2023). It embeds aspects such as reliability and transparency and depends on the tasks that the chatbot must perform (Glikson & Woolley, 2020; Gkinko & Elbanna, 2023). Thus, trust in robots tends to be higher if they perform analytical tasks than jobs that require social skills (Glikson & Woolley, 2020). In the context of remote financial services, cognitive trust in a particular novel mode of interaction can be defined as customers' belief that companies will be able to provide satisfactory service through this channel (Bashir & Madhavaiah, 2015). This approach has been adopted in the context of a technology acceptance model in the evaluation of applications of blockchain to finance (Albayati et al., 2020; Palos-Sánchez et al.; 2021), novel banking and insurance channels (Bashir & Madhavaiah, 2015; Sánchez-Torres et al., 2018; Huang et al., 2019) or in the field of chatbot acceptance (Kasilingam, 2020; Gansser & Reich; 2021).

An aspect of trust that has received less investigation in the use of chatbots is emotional trust (Gkinko & Elbanna, 2023), which is related not only to the user's experience of goal achievement (i.e., perceived usefulness) and the control of outcomes (linked with effort expectancy) but also to the context, social presence, or anthropomorphism (Chen & Park, 2021; Gkinko & Elbanna, 2022). In this paper, the context in which the chatbot must be used is utilitarian, since the interaction with the chatbot is because of a nonhedonic cause but to make an insurance procedure that is not carried out continuously over time but rather sporadically.

In the TAM, the factors that impact behavioral intention are mediated by PU and PEOU. Glikson and Williams (2020) indicate that trust influences the intensity and motivation with which AI-based technology is used, ultimately impacting its usefulness and effort expectancy. Similarly, trust has been found to be a significant antecedent of PU in robot acceptance (Han & Conti, 2020; Brachten et al., 2021; Silva et al., 2023) and of PEOU in a blockchain setting (Albayati et al., 2020; Palos-Sánchez, 2021). Therefore, the following hypotheses are proposed:

Hypothesis 4a (H4a)=*Trust in services provided by chatbots positively influences their perceived utility.*
Hypothesis 4b (H4b)=*Trust in services provided by chatbots positively influences their perceived ease of use.*

3. MATERIALS AND METHODS

3.1. Materials, data collection, sample profile and measurement scales

The survey used in this paper is grounded in a semistructured questionnaire that was redacted in Spanish. To the questions outlined in Table 2, we added two nonmandatory open questions that required exposing freely perceived advantages and drawbacks of making procedures with bots with regard to in-force policies such as declaring a claim. The questionnaire and open questions were previously tested by 10 professionals of the insurance industry, some of them from the Spanish section of the International Association of Insurance Law (SEAIDA). After taking into account their queries, we then distributed it to 12 more volunteers not linked with the financial and insurance industry and considered their comments to state the final questionnaire. These 22 responses allowed us to perform a pretest of the reliability and discriminant validity of the scales. These scales and their theoretical foundation come in Table 2.

We subsequently distributed the questionnaire supported by Google Forms to academic and administrative personnel of the University Rovira i Virgili in Spain through e-mail and, in some cases, contacting them by WhatsApp. The form was completed completely online from 10 January 2023 to 11 February 2023. To ensure that each respondent submitted the questionnaire only once, we have limited the number of IP addresses allowed to submit a response to one. Likewise, to ensure the reliability of the recycling data, the responses were anonymous, and no personal data were provided in the responses. In this process, the authors of this work sought guidance from the ethics committee of the university to which they belong.

Bishop et al. (2019) and Andrés-Sánchez et al. (2022) considered the members of a university community as a target population to analyse social interaction with robots in a noneducational setting. In our opinion, the study within the members of a university allows significant outputs to be obtained for several reasons. The answers must be provided by online methods, and practically all members of a university community use electronic devices to develop their work and are familiar with online surveys, not only in research settings but also to answer surveys linked to daily tasks. Thus, a greater response rate than in other collectives and a lower common variance method are expected because responding that survey is done with the same materials and methods than other actions in a working day. Thus, biases due to context are limited. In any university environment, the members have great heterogeneity in regard to their point of view and sensibility about the implications of technological advances. In the university Rovira i Virgili, there are studies on health sciences, engineering, basic sciences, social sciences and humanities. We feel very suitable the fact that, on the one hand, respondents' perspectives are diverse but, on the other hand, will have a solid intellectual foundation that, of course, could be biased toward technological opinions or ethical concerns. Moreover, in a university community, it is not difficult to achieve parity between men and women.

In survey-based research, the recognition of common method variance (CMV) as a significant issue requires careful attention, as it leads to common method bias (CMB) (Podsakoff et al., 2003). The present study employed a methodology that sought to mitigate this problem, among other objectives. A preliminary test was conducted on the questionnaires, which were meticulously crafted by 22 individuals, to reduce potential item ambiguity. To avoid issues associated with scales comprising only a few points, an extensive eleven-point Likert scale was utilized for response measurement. Moreover, providing the survey in a self-administered manner, without the presence of an interviewer, respondents were provided with anonymity and discretion, effectively limiting certain sources of CMV, such as social desirability and the consistent motif. We think that the complete anonymity and voluntary nature of the responses encouraged careful consideration by the surveyed individuals, thus mitigating potential CMV-related concerns.

We were looking for an opinion based on personal experiences and so, answers come from policyholders. The final number of valid responses was 119 from a population of 1900 members. It supposed a success rate of 6.10%. Given that our population is between

N=1,000 and *N*=2,500, that size allowed an error margin less than ±10%, which we judged to be adequate (Conroy, 2016).

Table 2. Scale measurement

Behavioral intention BI1. I intend to use a chatbot to make procedures of my policies with chatbots. BI2. I predict that I will use chatbots to communicate with the insurer into regard my insurances. BI3. I will opt for insurance procedures by bots.	Based on Farah et al. (2018), which is grounded in Venkatesh et al. (2003) and Davis (1989).
Perceived usefulness PU1. Chatbots allows managing policies smartly PU2. Chatbots enables making easier the procedures with the insurance company PU3. Chatbots allow a faster resolution of issues with my policies. PU4. Chatbots allows making procedures with the insurer with less effort PU5. The use of bots allows providing better service to customers with lower costs.	Based on Venkatesh et al. (2003); Venkatesh et al. (2012); Hussain et al. (2019). and Gansser and Reich (2021) in chatbot setting
Perceived ease to use PEOU1. It will be easy for me to the use of chatbots to communicate with my insurer. PEOU2. How to manage my claims and making other procedures with chatbots will be clear and understandable to me. PEOU3. It will be accessible and low error prone to manage my policies and claims with the help of chatbots. PEOU4. It will be easy for me to fluently use the channels that the insurer makes available to communicate.	Based on Venkatesh et al. (2012) and Makanyeza and Mutambayashata (2018).
Social influence SI1. The people who are important to me think that using bots makes it easier insurance procedures. SI2. The people who have influence over me think that if I have to opt among several channels to interact with the insurer, chatbots are adequate. SI3. The persons whose opinions are relevant to me feel that the use of bots in managing insurance policies is a step forward	Based on Venkatesh et al. (2003) and Gansser and Reich (2021)
Trust TRUST1. Conversational bots are trutsworthy. TRUST2. Using conversational bots to allow policyholder to interact with insurer takes into account customers' interest	Based on Farah et al. (2018) and De Cicco et al. (2022).

Table 3. Profile of the survey

Gender Male: 49.58% Women: 47.06% Other/NA: 3.36%	Age <=40 years: 15.97% >40 years: <=55 years 51.26% >55 years 31.09% NA: 1.68%
Number of policies More than 4: 47.90%	Income >=€3000: 52.26%

Between 3 and 4: 46.21% Less than 3: 4.20%	>=1750: <3000: 32.28% <=1750: 11.92% NA: 3.16%

The questionnaire started with the following text: "*We are requiring your judgment about managing your in-force policies when you need to get in touch with the insurer and use automated systems such as voice robots and text robots instead of using a human operator. As an example, take into consideration a common procedure such as declaring a claim*".

Regarding ethical approval, (1) all participants were given detailed written information about the study and the procedure; (2) no data related directly or indirectly to the subjects' health were collected, and thus, the Declaration of Helsinki was not generally mentioned when the subjects were informed; (3) the anonymity of the collected data was ensured at all times; (4) the research received a favorable evaluation of the Ethics Committee of the researchers' institution (CEIPSA-2022-PR-0005); and (5) permission was obtained by all the respondents.

3.2. Data analysis

RQ1= *Does TAM provide a reliable framework to analyse chatbot acceptance for managing policies by insurers?* It has been answered to by fitting the model in Figure 2 using partial least squares structural equation modelling (PLS-SEM). Its use is adequate to fit models when there is not any requirement about data distribution and can be run with few observations (Hair et al., 2019). Note that the maximum links of factors is 3 (PU); in such a way, the 10-times rule requires only (N>30) (Kock & Hadaya, 2018). Likewise, following Kock and Hadaya (2018), under the requirement that minimum R^2 must be 25% for PEOU, PU and BI, N>55 and so, this criterion is also met.

Before fitting the model displayed in Figure 2, we assessed the univariate and multivariate normality of the data by using the Cramer-Von Mises test and examining the skewness and kurtosis of the data (George & Mallery, 2010). Rejecting that normality will reinforce the suitability of the PLS-SEM methodology. We also checked the internal consistency and reliability of the scales and their discriminant validity. We evaluate that internal reliability with usual measures: Cronbach's alpha, the composite reliability measure (CR), Dijkstra and Henseler's ρ_A and average extracted variance (AVE). We have also analysed the factor loadings of all items in Table 2. Subsequently, we assess the discriminant validity of constructs with both the Fornell-Larker criterion (Fornell & Larker, 1981) and heterotrait-monotrait (HTMT) ratios (Henseler et al., 2015). We also considered of interest stating if there were relevant problems with CVM. To do so, we run the Harman one-factor test and method by Kock and Lynn (2012) based on the analysis of the variance inflation factor (VIF) of the evaluated constructs when they are put in a regression model as input variables of an instrumental uncorrelated variable.

We fitted the path coefficients (β) by the bootstrapping method using 5000 subsamples and the studentized bootstrap technique. We also stated the Cohen's effect size (f^2) of each path coefficient (Cohen, 1988). The overall quality of the adjustment has been stated with usual measures such as the determination coefficient R^2. Likewise, we tested the normality of residuals. The rejection of the normality of residuals will reinforce that the use of PLS-SEM was fully justified.

We finally tested the predictive capability of the model with Stone-Geisser's Q^2 and ran the cross-validated predictive ability test (CVPAT) (Liengaard et al., 2021). All calculations in this step were implemented with SmartPLS4.0.

To answer RQ2= *What is the mainstream behavioral intention to use chatbots in an interaction with the insurer with regard to in-force policies, and what are the arguments supporting that intention?* We have followed two steps. To state mainstream behavioral intention, we have examined the mean and median of responses in items linked with BI and compared them with 5. Values significantly under (over) 5 denote that a relevant degree of resistance (acceptance) toward robots exists. Subsequently, we systematically display open answers justifying the perceived benefits and drawbacks of conversational bots. This analysis is built up with the help of theoretical development in section 2, and it classifies those arguments into regard to whether they correspond to perceived usefulness, perceived ease of use, social influence and trust. Thus:

- Reasons related to perceived usefulness (PU) should be formulated using sentences such as “*suited/not suited to my needs*”, “effective/ineffective” or “*Saves/does not save me time*” (Davis, 1989).
- Arguments pertaining to perceived ease of use (PEOU) can be expressed through statements such as "*pleasant interaction/cumbersome*," "*confusing/understandable*," or "*objective usability/nonusability*" (Davis, 1989).
- Reasons associated with social influence may arise from peer influence, advice from insurance advisors, and the respondent's internalization of perceived social pressure regarding the desirability of engaging in or avoiding a specific behavior (Graf-Vlachy et al., 2018).
- To evaluate arguments concerning trust, Gkinko and Elbanna (2023, p.4) offer a useful framework that identifies arguments related to cognitive trust (e.g., "*a human person may forget something*"), organizational trust (e.g., "*I used the bot when I was advised to use it*"), and emotional trust (e.g., "*I have the feeling that the chatbot* listens").

To perform this analysis, no specific software was used. Authors personally examined carefully every response to decide the construct in which it must be understood. The need for personal supervision is reinforced by the fact that a relevant piece of responses was obtained in the Catalan language, which is a local language that is not supported by the majority of software.

4. RESULTS

4.1. Results from PLS-SEM analysis for research question 1

Table 4 shows that the Cramer-Von Mises test rejects the normality assumption of the items. However, the absence of normality is not extreme, as the skewness of the items, in general, ranges between -2 and 2, and the kurtosis ranges between -7 and 7 (George & Mallery, 2010). Table 5 presents very similar patterns when assessing normality from a multivariate perspective, considering latent variables. Although the skewness and kurtosis do not exhibit extreme values, the Cramer-Von Mises test rejects the normality assumption for all constructs.

Harman's single-factor test accounts for 41.69% of the variance. This value is below the commonly considered threshold of 50%, which indicates a consistent signal of possible common method variance (CMV), and well below the 70% threshold associated with the possible existence of common method bias (Fuller et al., 2015). Furthermore, the results of the Kock and Lynn (2012) test also reveal at least no CVM issues of concern. The variance inflation factor (VIF) of the constructs, when considered with input variables from an uncorrelated instrumental variable, remains below 3.3 in three cases. In the case of TRUST and PE, this VIF is slightly greater than 3.3 but clearly under 5, which is a critical value to suspect about the existence of CVB problems.

Table 5 shows that the scales linked to BI, PU, PEOU, SI and TRUST are consistent and reliable because Cronbach's alpha, CR and ρ_A >0.7, AVE >0.5. Likewise, Table 4 shows that the factor loadings for all the items are >0.7. The results in Table 6 suggest that we can accept that the constructs have discriminant capability from the perspective of the Fornell-Larker criterion. The correlations between two constructs are always below the squared root of their AVEs. Likewise, HTMT ratios are practically <0.90 in all pairs of latent variables, so this discriminant validity criterion is often fulfilled. The exception is the relation of TRUST with PU, whose HTMT is slightly greater than 0.9 (0.92).

Table 4. Descriptive statistics about the items used in this paper

Construct	Mean	Median	SD	Skewness	Kurtosis	Cramer-Von Mises	Factor loading
BI1	0.86	0	1.49	1.91	6.40	3.07	0.83
BI2	1.53	0	2.18	1.44	4.42	2.10	0.89
BI3	0.91	0	1.59	2.02	7.06	2.95	0.91
PU1	2.02	1	2.47	1.13	3.48	1.17	0.86
PU2	2.50	2	2.68	0.76	2.49	0.83	0.90
PU3	2.24	1	2.43	0.59	2.08	1.10	0.89
PU4	2.09	1	2.40	1.03	3.34	1.01	0.91
PU5	2.87	2	2.74	0.51	2.47	0.58	0.80
PEOU1	2.55	2	2.74	0.82	2.80	0.80	0.90
PEOU2	2.36	2	2.51	0.84	2.78	0.80	0.93
PEOU3	1.80	1	2.11	1.10	3.94	1.06	0.90
PEOU4	2.27	1	2.54	0.97	3.07	0.94	0.92
SI1	1.64	1	1.85	1.00	3.21	1.06	0.94
SI2	1.35	1	1.74	1.25	3.54	1.58	0.95
SI3	1.74	1	1.87	0.80	2.46	0.97	0.93
TRUST1	1.61	1	2.17	1.45	4.65	1.76	0.94
TRUST2	1.71	1	1.93	0.93	2.83	1.21	0.82

Note: (1) In all cases, we have rejected the hull hypothesis that the mean and/or the median is 5 with p<0.01. (2) The Cramer-Von Mises statistic rejects the normality of items with p<0.01 in all cases.

Table 5. Evaluation of internal consistency of scales and variance common method

Construct	Cronbach alfa	CR	ρ_A	AVE	Cramer-Von Mises	VIF (Kock-Lynn test)
BI	0.850	0.853	0.91	0.771	1.85	2.99
PU	0.922	0.928	0.941	0.762	0.578	3.92
PEOU	0.933	0.936	0.952	0.832	0.577	3.19
SI	0.933	0.945	0.957	0.881	0.865	1.88
TRUST	0.727	0.851	0.874	0.777	0.995	3.55

Note: (1) The Cramer-Von Mises statistic rejects the normality of items with p<0.01 in all cases. (2) The Harman one-factor test shows that the first factor extracts 41.69% of the variance.

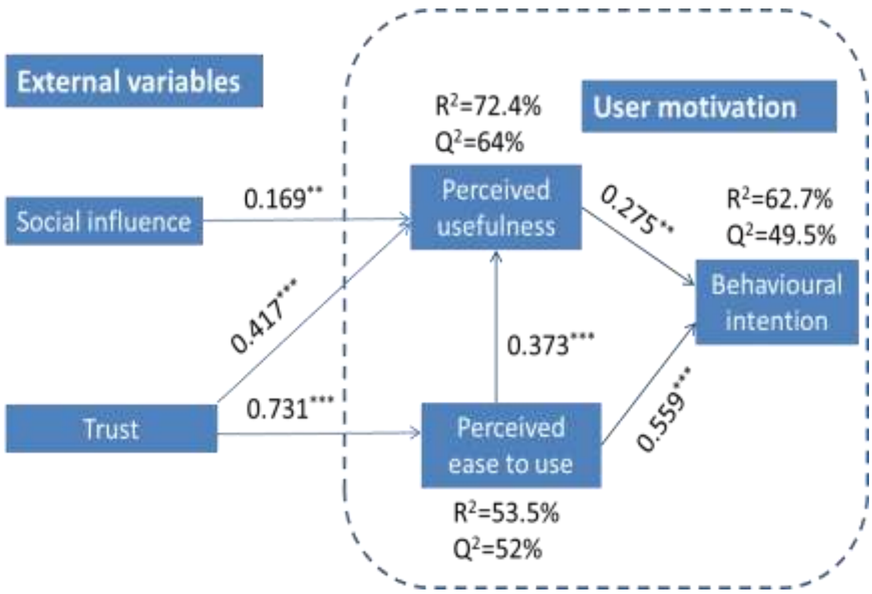
Table 6. Discriminant validity with Fornell-Larker and HTMT criteria

Construct	BI	PU	PEOU	SI	TRUST
Behavioral intention (BI)	**0.88**	*0.792*	*0.828*	*0.69*	*0.87*
Perceived Usefulness (PU)	0.70	**0.873**	*0.865*	*0.67*	*0.92*
Perceived Ease to Use (PEOU)	0.77	0.74	**0.912**	*0.62*	*0.84*
Social influence (SI)	0.62	0.64	0.59	**0.939**	*0.72*
Trust (TRUST)	0.71	0.78	0.74	0.58	**0.881**

Note: The data in the principal diagonal are the square roots of AVEs. Above that diagonal comes the HTMT ratios and above correlations between factors.

The goodness-of-fit measured by R^2 is displayed in Figure 3. BI reaches R^2=62.7%, PU R^2=72.4% and PEOU 53.5%. Following Hair et al. (2019), the accuracy attained can be considered between moderate and substantial. Figure 3 and Table 7 report that the value of β and their statistical significance level lead us to accept hypotheses H1 ($p<0.05$) and H2a and H2b ($p<0.01$). Likewise, hypotheses H3 and H4a are also accepted with $p<0.01$ and H4c with $p<0.05$. With regard to effect size, we can label PU on BI (f^2=0.08) as "small" and SI on PU (f^2=0.06). In the other paths, this impact is commonly labelled "large" since in all cases, f^2=0>0.15 (Cohen, 1988). Likewise, Cramer Von-Misses on residuals reveal that the hypothesis of their normality can be rejected. Note that we have rejected the normality of items, latent variables and residuals in such a way that the use of PLS-SEM is fully justified.

Figure 3. PLS-SEM estimate of the model in Figure 2



Note: "***", "**" and "*" stand for statistical significance with p <0.01 and p <0.05

Table 7. Coefficient paths and results of testing the hypotheses in section 2

Effect	β	Students' t	f^2	Hypothesis acceptance	Output	Cramer-Von Mises (residuals)
PU-> BI	0.275	2.265**	0.08	Accept	BI	0.298***
PEOU -> BI	0.559	4.874***	0.33	Accept		
PEOU -> PU	0.373	4.267***	0.21	Accept	PU	0.271***
SI->PU	0.169	2.134**	0.06	Accept		
TRUST->PU	0.417	5.142***	0.27	Accept		
TRUST->PEOU	0.731	15.349***	1.149	Accept	PEOU	0.503***

Note: *** and ** indicate rejection of the null hypothesis at the 1% and 5% levels, respectively.

Figure 3 and Table 8 show that the proposed PLS-SEM has a good predictive capability. In all output variables, we obtained $Q^2>0$, and thus, our model is able to provide significant predictions (Hair et al., 2019). The use of CVPAT shows that PLS-SEM gives good out-of-sample predictions since it provides more accurate predictions than the IA benchmark (average loss difference=-2.486, p<0.01).

Table 8. Results of PLS predictive analysis and cross-validated predictive ability test

	Predictive measures			*Indicator average*	
	Q^2	**RMSE**	**MAE**	**ALD**	**p value**
BI	0.495	0.733	0.488	-1.295	<0.01
PU	0.64	0.614	0.466	-3.142	<0.01
PEOU	0.52	0.708	0.542	-2.561	<0.01
Overall				-2.486	<0.01

Note: RMSE stands for root-mean-square error, MAE for mean absolute error and ALD for average-loss difference.

4.2. Results of qualitative analysis for research question 2

Table 4 shows that the mean and median of answers BI1, BI2 and BI3 are significantly <5 (p<0.01). Likewise, we obtained responses to open questions from 65 surveyed persons who outlined at least one advantage or disadvantage. All responses were done in Spanish and Catalan. Advantages and disadvantages have been classified by using the criteria exposed in section 3.2. The responses clearly tend to report more disadvantages than advantages. In fact, while 17 responses regarding advantages were "*none*" or "*none for me*", there was no answer explicitly indicating "*none*" in the disadvantage question.

4.2.1. *Favourable arguments for the use of chatbots*

We classify the arguments that sustain the use of chatbots as follows.

(1) Regarding reported reasons that may positively impact the *perceived usefulness* of chatbots, we found the following:

- One extended positive perception of bots is that they save time, at least in some kind of procedures. We have registered nine answers such as "*fast response*", *"It is not needed a long wait for a human operator*", "*for easy procedures are very useful because they are fast, but not to claiming*", "*chatbots accelerate the attention of easiest cases*".
- We have obtained responses indicating that in some circumstances, the use of chatbots improves the claiming procedure. This is the case for "*makes easier the procedures*" and "*in some ease cases the issue may be processed more efficiently*".
- A response indicates that chatbots are useful because they *"reduce costs to the company and so policy prices can be fitted*"

(2) Regarding favorable perceptions of *perceived ease of use*, one response outlines some kind of flexibility: "*24/7 attention and so great flexibility to claim"*.

(3) Four responses outlined *cognitive trust*: "*in chat texts you can check what you are writing and so, errors are less common*", "*not human errors when introducing data*", *"fewer fails due to less human handling", and "lower error probability.*"

4.2.2. *Arguments against the use of chatbots*

On the other hand, the number of responses outlining drawbacks was clearly greater and embedded all the variables of the model developed in section 2 and Figures 2 and 3. Thus:

(1) Regarding *perceived usefulness*, we can outline the following answers:

- Several responses indicated the belief that chatbots increase insurers' productivity but do not report any advantage for the customer; in contrast, they give a worse quality of service. Several responses in this way are "*chatbots may present advantages for the insurer, but not for the customer*", "*The unique advantage is that they save costs to the firm*", "*good for the company, bad for the customer*", "*I feel that the result is less costs for the company, but the service is much worse for the insured. I understand that chatbots are a low-cost model*".

- Several responses indicated that the output provided by the bot is not effective because in the end, the assistance of an agent is often necessary. Responses in this way are "*No effectiveness when your claim is not standard*", "*does not understand nuances*", "*My home insurer already uses bots and there are always problems for me to be understood and we end up contacting a human manager*".

- Twelve responses indicated that being attended by bots often supposed a loss of time. Many answers report that whether the first interaction of the procedure is provided by a bot and it is unsatisfactory, further attention by a human agent is required and it supposes a loss of time. This waste of time could be amplified because *"currently human agents are scarcer because of the implementation of bot services*".

- There is an extended feeling that the quality of the services mediated by bots is low. Responses in this way are as follows:
    - "*Under my experience, chatbots do not improve in any item the assistance by the human operator. Tech cannot solve services that firms do not want to provide*";
    - "*Less quality on customer attention and in users' perception*";
    - "*Worse service at the same or greater price*".

- Many times, bots do not address insurers' needs, such as empathy or human warmth. An extended reason that explains the extended option of the low usefulness provided by chatbots is the impersonality and dehumanization of the interactions (23 responses), which is viewed as a drawback. The main problem reported in this regard is the lack of empathy. While one respondent told us that *"no person on the other side of the electronic device*", one response indicates that "*this impersonal service produces poor results*".

(2) We have also registered several answers reporting a negative opinion about the *perceived ease of use* of chatbots:

- Many people simply tend to reject robots and feel their interaction disgusting and cumbersome. The reasons may be, for example, suffering from robot anxiety or feeling creepiness. In this regard, we found answers such as "*I do not like this tech every time I have to use it", "I cannot stand bots..."* and "*I find it unpleasant and lead to misunderstandings*".

- It is detected in several options that communicating with bots is more difficult than communicating with human agents. One reason is that the conversation with bots is not flexible, and the conversation becomes uncontrollable: "*there is no flexibility in* *the conversation*" and "*Not everything is binary. They provide little flexibility*", "*Recurrent answers*".

- Chatbots cannot understand humans if the level of conversational complexity increases, which spoils their objective of usability. This issue has been outlined in many responses:
  - "*You cannot express nuances. The bot does not understand what are you explaining*",
  - "*it is very difficult to explain to them the casualty to be reported*",
  - "*Using bots delays procedures because they are not yet familiar with the terms that we humans use when speaking by phone. I waste much time making him understand*",
  - "*The communication with a professional is easier than with chatbots. Bots have no intelligence*",
  - "*Not being attended by a person, if you have doubts, need some clarification or want alternatives to be proposed, it is much colder and difficult to find the answer you want to receive."*
- Some responses indicate explicitly low capability of error recovery. Therefore, one answer indicated that "*The advantage is that it eliminates waiting on the phone, but if the system does not understand you or you make a mistake when selecting an option, it is not very well resolved*".
- There are also responses reporting a lack of self-efficacy and confusion about how to use chatbots. Whereas one respondent outlines that "*required skills to deal with bots are not owned by all users (especially the older ones)*", another: "*It is not clear to me whether the casualty and its details can be communicated adequately and will all the requirements issued by the policyholder* "
- Several people emphasize that communicating with bots may lead to frustration because communication with them is difficult. This fact is reported by responses such as "*My experience with bots from different companies is absolutely disastrous (...)rather than solving any problem bots run out of the users' patience*"; "*we pay to insurer to get help, not to get nervous with ineffective bot services…*", "*When bots reach an adequate level of development, they will provide many advantages. Unfortunately, today, they are hell*".

(3) Diverse responses were recorded that can be attributed to *social influence*. We can outline two issues:

- We obtained responses that referred to the impact of chatbot adoption on workers in the insurance sector, such as "*some agents will be fired from the insurance firm*" and "*this kind of technology increases firms' cash flows since they are only used to reduce staff costs*." Other responses have a broader perspective on the influence on the labor market and economic implications, such as "*many workers may lose their jobs*" and "*unemployment will increase*".
- Likewise, languages such as Catalan, which are not widely spoken globally but are commonly used in specific regions, often lack availability. In Catalonia, there is a significant activist movement demanding more social presence of the Catalan language and its availability for communication with intelligent devices. Two

responses indicate that "*they do not provide service in Catalan*" and "*Bots do not understand Catalan*".

(4) There were several negative responses that can be categorized not only as perceived ease of use but also as *trust* in all three dimensions outlined in section 3: cognitive trust, organizational trust and emotional trust.

- With regard to *cognitive trust*, we have detected issues such as lack of transparency and loss of control over the procedure. Some answers express concern about whether the procedure was performed correctly because of a lack of human acknowledgement about this issue. Some responses in this way are "*I feel a lack of confidence about whether the procedure has been done correctly and that it will be processed correctly. They are just machines*", "*It makes me insecure*", "*The lack of human contact makes me feel insecure if the procedure is being carried out properly*."

  Other issues such as reliability also came:

  - "*Currently chatbots are not developed enough and so, you finally need to be attended by a person*".
  - "*each claim has its nuances and bots are not able to understand it. They are not being able to handle rare cases properly*".
  - "*They will fail if there are issues with the information such as it is not very structured or they have not been trained to resolve any specific case*".
  - "*Chatbot tech needs significant improvement. They often fail and usually the interaction becomes a waste of time*".

- Three responses outline issues related to relational distrust because of the insurer's motives to use chatbots. Therefore, one response outlines "*bots are not the issue, the issue is how firms use them*". Another respondent said, "(…) *they may end up giving up, which favors the insurance firm - and it is probably what they intend in the first instance" "chatbots discourage user claims for breaches by insurers*". Finally, a third person outlined, "*The use of bots can easily be oriented toward creating a service system that ends up being an insurmountable barrier for the users when they do not agree with the assessment of their damages*".

- There were several answers linked with a lack of *emotional trust*. In this way, several responses outlined a lack of closeness to policyholder:
  - "*In the face of an accident, people need solutions, help, and telling us what we have to do. A machine will never be able to replace personalized treatment, especially in unpleasant situations such as any accident.*"
  - "*By containing automatic responses, it does not get adapted to your questions and/or needs.*"
  - *"In regard to claims, bots create a lot of insecurity. People look for help and a bot is very impersonal."*
  - "*Nobody wants to be assisted by a robot when they are in trouble*".
  - "*I see a lack of humanity, lack of empathy, lack of singularity detection. I think a bot does not generate the same level of trust. Sometimes it depends on what kind of care a human is needed, human touch is fundamental*".

5. DISCUSSION AND PRACTICAL IMPLICATIONS

This paper has shown the usefulness of the theoretical groundwork provided by the technology acceptance model (TAM) by Davis (1989) along with social influence and trust to explain policyholders' acceptance of services provided by chatbots. It allows not only making a quantitative assessment but also grounding a qualitative evaluation. Although the usefulness of technology acceptance models in fintech has been widely shown, empirical analyses with this focus in the insurtech setting are scarce, especially from a qualitative point of view.

Regarding RQ1, *Does TAM provide a reliable framework to analyse chatbot acceptance for managing policies by insurers?* We have found that the technology acceptance model by Davis (1989) fits more than half of the variability of behavioral intention (BI) to interact with the insurer by means of bots. This aspect is not only relevant to the quantitative analysis conducted using the PLS-SEM methodology but also significant in the context of the qualitative analysis associated with RQ2, given that the framework utilized for this analysis has been validated.

We have checked that both perceived usefulness (PU) and perceived ease of use (PEOU) present a statistically significant level sufficient to explain BI. The significant impact of perceived usefulness on behavioral intention is consistent with studies on the financial applications of blockchain (Albayati et al., 2020; Nuryyev et al., 2020; Sheel & Nath, 2020; Palos-Sánchez et al., 2021), digital banking (Bashir & Madhavaiah, 2015; Farah et al., 2018; Sánchez-Torres et al., 2018; Warsame & Ireri, 2018; Hussain et al., 2019), novelties in the insurance industry (Huang et al., 2019; Andrés-Sánchez et al., 2021) and conversational bots (Eeuwen, 2017; Brachten et al., 2021; de Cicco et al., 2022; Pawlik, 2022; Joshi, 2021; Gansser & Reich, 2021; Kasilingam, 2020; Kuberkar and Singhal, 2020; Lee et al, 2022; and Xie et al., 2022; Silva et al., 2023).

Perceived ease of use has a positive direct impact on behavioral intention. In fact, that influence is greater than that of PU, while for PEOU, β=0.559 PU attains β=0.275. The relevance of PEOU to explain BI has been widely checked in fields such as crypo/blockchain acceptance (Albayati et al., 2020; Nuryyev et al., 2020; Sheel and Nath, 2020; Palos-Sánchez et al., 2021), the usage intention of banking digital channels (Bashir and Madhavia, 2015; Warsame and Ireri, 2018), innovative actions of insurance firms (Huang et al., 2019) and consumers' perception of conversational bots (Brachten et al., 2021; Pawlik, 2022; Kasilingam, 2020; Gansser & Reich, 2021; Kuberkar & Singhal, 2020; and Mostafa & Kasamani, 2021).

We have also checked that PEOU has a relevant influence on PU since it explains 60% of its variability. This relevance, which is supported theoretically (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), was also observed in our empirical works on issues close to ours (Bashir & Madhavia, 2015; Huang et al., 2019; Albayati et al., 2020; Nuryyev et al., 2020; Palos-Sánchez et al., 2021; Andrés-Sánchez et al., 2021; Joshi, 2021; de Cicco et al., 2022; Silva et al., 2023).

In regard to social influence, we have overserved that its impact on perceived usefulness is significant, which is in accordance with the standard extensions of the TAM model by Venkatesh and Davis (2000) and Venkatesh and Bala (2008) and with empirical findings by Albayati et al. (2020) and Nuryyev et al. (2020) on blockchain applications in finance settings, in the intention to use m-banking (Kishore & Sequeira, 2016; Farah et al., 2018), and with Brachten et al. (2021) and Silva et al. (2023) in a chatbot acceptance setting.

We have observed that the influence of trust on PU and PEOU is highly significant. This finding aligns with the propositions of Zafiris and Cheng (2022) regarding the significance of trust in comprehending users' attitudes towards AI-based fintechs and insurtechs. Thus, our findings are in accordance with the relevance of trust as an antecedent of PU (Han & Conti, 2020; Brachten et al., 2021; Silva et al., 2023) and as an antecedent of PEOU (Albayati et al., 2020; Palos-Sánchez, 2021).

In RQ2, we inquired about *the mainstream behavioral intention to use chatbots in an interaction with the insurer with regard to in-force policies and the arguments supporting that intention.* We have found a generalized reluctance since items of behavioral intention were evaluated (on a scale between 0 and 10) between 0.9 (the first item) and 1.5 (the second). Thus, our findings are in line with those of Brachten et al. (2021), who reported generalized extended customer resistance, and with the findings of Rodríguez-Cardona et al. (2019) in Germany and PromTep et al. (2021) in Canada, who also reported a negative attitude toward chatbots in an insurance setting. This finding could be understood within the acceptance curve proposed by Glikson and Woolley (2020) for AI-based technologies, which suggests that high resistance is expected in the initial stages, with increasing acceptance as consumers become familiar and accustomed to using the new technology.

The systematic overview of responses to open questions reveals that people perceive more negative aspects than positive outcomes in chatbot interactions. There are many responses to that answer simply "*none*" to perceived positive aspects but give detailed arguments for the negative feedback. On the other hand, we have not received any response outlining the response "*none*" to disadvantages. These answers have great managerial usefulness because, in contrast to results from statistical analysis, they give concrete arguments to firms about how and when to use bots and what issues in this regard have to be solved (Vogelsang et al., 2013).

Regarding *perceived usefulness*, the principal advantage reported in the responses is that simple issues may be solved faster than with human assistance, which is in accordance with DeAndrade and Tumelero (2022). However, conversational robots are viewed as a barrier to getting in touch with the insurer and methods to control insurers' costs but not a source of value for the policyholder. This issue contradicts statements by Standaert and Muylle (2022) and Stoeckli et al. (2018). On the other hand, responses to open questions remark on several common failures: the fact that chatbots are not capable of maintaining complex conversations (Rodríguez-Cardona et al., 2019) has limited their effectiveness because the queries need to be finally attended by a human agent (Vassilakopoulou et al., 2023), and thus, the interaction with the bot is perceived as a loss of time.

Responses to free questions also show that chatbot tech needs to improve *usability* and *perceived ease of use*. An extended perception is that they often fail. Therefore, this fact leads to a negative perception about their use. An extended response against bots is that simply "*they are not human*" and "*I dislike bots*", which reveals that issues such as crepiness or robot anxiety are relevant phenomena that impact the mainstream perception of services by bots (Rajaobelina et al., 2023). Additionally, several responses outline that conversations with chatbots are difficult because of issues such as inflexibility and low intelligence that make it difficult to report nuances or complex questions. These indications are in accordance with the fact that chatbots are not able to capture issues such as changes in voice tone (Vassilakopoulou et al., 2023) and that chatbots are often trained with basic conversational sets of data; consequently, their failure in interactions is common (Xing et al., 2022).

Although *social influence* has not been the construct that garnered the highest number of responses, several responses have been identified that are likely to influence behavioral intention, as they can be contextualized within issues associated with subjective norms. In this regard, concerns regarding the displacement of workers in the insurance industry by bots and the inability to interact with chatbots in the Catalan language have been repeatedly highlighted. This result is in accordance with studies that outline the relevance of social norms to understand acceptance in related areas such as financial communication channels (Makanyeza & Mutambayashata, 2017) and conversational chatbots (Gansser & Reich, 2021; Melián-González et al., 2021).

Trust was not only found to be statistically significant, but we were also able to categorize a wide range of responses to the open-ended questions. Consistent with the findings of Zafiris and Cheng (2022), we have verified that both relational trust and cognitive trust are relevant factors in shaping users' perceptions of fintechs and insurtechs powered by AI. However, despite the purported utilitarian and infrequent use of chatbots reported by respondents (limited to specific management tasks of existing insurance policies), we have observed that various responses highlight the absence of closeness, as outlined in Vassilakopoulou et al. (2023). This finding aligns with previous research emphasizing the significance of emotional trust in chatbot acceptance settings (Chen & Park, 2021; Gkinko & Elbanna, 2022; Gkinko & Elbanna, 2023).

The results show that the development of chatbots to manage existing policies in issues such as claim reporting is not mature enough, and consequently, insurance consumers are reluctant to use chatbots. Mainstream responses display that a low perception of utility, small levels of usability and limited trust of this technology cause that rejection. It is in accordance with Xing et al. (2022), which outlines that in many contexts, robotic technology may create more problems than solves, and chatbots are neither appreciated by professionals nor by customers in the German insurance market (Rodríguez-Cardona et al., 2019). Therefore, currently, they must be used by the company as a complementary communication tool of the insurance ecosystem that may provide value to the policyholder in singular situations but not as the principal communication channel.

6. CONCLUSIONS AND FUTURE RESEARCH

This paper has developed an empirical application of the well-known technology acceptance model by Davis (1989) to explain the behavioral intention to use chatbots to make insurance procedures such as informing about casualties. This theoretical framework has been used in a twofold analysis: a statistical test of the TAM by Davis (1989) on our data taking into consideration two external variables, social influence and trust, and a qualitative assessment of responses to open questions requiring advantages and drawbacks of bots in communication with the insurer. We can conclude that, from a statistical point of view, the TAM-based model we tested is well suited to our sample. The qualitative analysis shows that respondents perceive many more drawbacks than advantages in perceived usefulness, perceived ease of social influence and trust in the use of conversational bots.

We acknowledge that this empirical assessment is subject to several limitations. Although our model explains over 60% of the variance in behavioural intention and provides a reliable qualitative framework, the quantitative analysis has simplified certain aspects (e.g., the trust scale omits the emotional dimension) and has not accounted for factors such as perceived anthropomorphism in the chatbot or personal innovativeness. Therefore, it is necessary to conduct a more comprehensive quantitative analysis that expands upon the proposed model.

Our analysis has been developed within a specific country, Spain**,** and within a concrete collective, the workers of a public university, that may exercise either academic tasks or administrative works. Therefore, the population of study comprises essentially public workers, most of whom are at least graduates (usually those with a Ph.D.) and have an income level that is at least €1,750 and usually above €3,000. We are aware that educational degree and economic situation may be significant in explaining intention to use chatbots. Thus, issues outlined in this report can be extended to customers from countries whose culture is close to that in our sample and people with similar educational and professional status (public workers with a high educational degree). More accurate conclusions on other personal profiles need to be obtained by expanding the survey to other collectives/other countries.

The analysis in this paper is based on a cross-sectional survey. Therefore, we cannot extend our conclusions to the long term. As far as I4.0 technology is concerned, this issue is very relevant because it is a mutable field in continuous evolution. Of course, a comprehensive view of how insurance customers perceive the use of chatbots for in-force policy management requires assessments of the different milestones reached by the development of chatbot technology.

Acknowledgements

The authors acknowledge two anonymous referees for their helpful comments on a previous draft of this paper.

REFERENCES

Albayati, H.; Kim, S.K.; & Rho, J.J. (2020). Accepting financial transactions using blockchain technology and cryptocurrency: A customer perspective approach. *Technology in Society*, 62, 101320. https://doi.org/10.1016/j.techsoc.2020.101320.

Andres-Sánchez, J., Almahameed, A. A., Arias-Oliva, M., & Pelegrin-Borondo, J. (2022). Correlational and Configurational Analysis of Factors Influencing Potential Patients' Attitudes toward Surgical Robots: A Study in the Jordan University Community. *Mathematics*, 10(22), 4319. https://doi.org/10.3390/math10224319.

Andrés-Sánchez, J., González-Vila Puchades, L. & Arias-Oliva, M. (2021). Factors influencing policyholders' acceptance of life settlements: a technology acceptance model. Geneva Pap Risk Insur Issues Pract. https://doi.org/10.1057/s41288-021-00261-3.

Arner, D. W., Barberis, J., & Buckley, R. P. (2015). The evolution of Fintech: A new postcrisis paradigm. *Geo. J. Int'l L*., 47, 1271.

Balasubramanian, R., Libarikian, A., & McElhaney, D. (2018). *Insurance 2030—The impact of AI on the future of insurance.* McKinsey & Company.

Bashir, I., & Madhavaiah, C. (2015). Consumer attitude and behavioral intention toward Internet banking adoption in India. Journal of Indian Business Research, 7(1), 67-102. https://doi.org/10.1108/JIBR-02-2014-0013.

Bishop, L.; van Maris, A.; Dogramadzi, S.; & Zook, N. (2019). Social robots: The influence of human and robot characteristics on acceptance. *Paladyn J. Behav. Robot. 10*, 346–358. https://doi.org/10.1515/pjbr-2019-0028.

Bohnert, A., Fritzsche, A. & Gregor, S. (2019). Digital agendas in the insurance industry: the importance of comprehensive approaches†. *Geneva Pap Risk Insur Issues Pract*, 44, 1–19 https://doi.org/10.1057/s41288-018-0109-0.

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The acceptance of chatbots in an enterprise context–A survey study. *International Journal of Information Management*, 60, 102375. https://doi.org/10.1016/j.ijinfomgt.2021.102375.

Chen, Q.Q. & Park, H.J. (2021), "How anthropomorphism affects trust in intelligent personal assistants", *Industrial Management & Data Systems*, 121(12), 2722-2737. https://doi.org/10.1108/IMDS-12-2020-0761.

Cohen J. E. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc

Conroy, R. M. (2016). *The RCSI Sample size handbook. A rough guide*, Technical Report, 59-61.

De Cicco, R., Iacobucci, S., Aquino, A., Romana Alparone, F., & Palumbo, R. (2022). Understanding Users' Acceptance of Chatbots: An Extended TAM Approach. In: , et al. Chatbot Research and Design. CONVERSATIONS 2021. Lecture Notes in Computer Science(), vol 13171. Springer, Cham. https://doi.org/10.1007/978-3-030-94890-0_1

DeAndrade, I. M., & Tumelero, C. (2022). Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão*, 29(3), 238-251, https://doi.org/10.1108/REGE-07-2021-0120.

Eeuwen, M. V. (2017). *Mobile conversational commerce: messenger chatbots as the next interface between businesses and consumers.* Master's thesis, University of Twente.

Farah, M.F.; Hasni, M.J.S.; & Abbas, A.K. (2018). Mobile-banking adoption: empirical evidence from the banking sector in Pakistan. *International Journal of Bank Marketing*, 36(7), 1386–1413, https://doi.org/10.1108/REGE-07-2021-0120.

Fornell, C.G., & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50, https://doi.org/10.2307/3151312.

Fotheringham, D., & Wiles, M. A. (2022). The effect of implementing chatbot customer service on stock returns: An event study analysis. *Journal of the Academy of Marketing Science*, 1-21. https://doi.org/10.1007/s11747-022-00841-2.

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research*, 69(8), 3192-3198. https://doi.org/10.1016/j.jbusres.2015.12.008.

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, 65, 101535. https://doi.org/10.1016/j.techsoc.2021.101535.

Gené-Albesa, J. (2007). Interaction channel choice in a multichannel environment, an empirical study. *International Journal of Bank Marketing*, 25(7), 490-506. https://doi.org/10.1108/02652320710832630.

George, D. & Mallery, M. (2010). *SPSS for Windows Step by Step: A Simple Guide and Reference*, 17.0 update (10a ed.) Boston: Pearson.

Gkinko, L., & Elbanna, A. (2022). Hope, tolerance and empathy: employees' emotions when using an AI-enabled chatbot in a digitalised workplace. *Information Technology & People*, 35(6), 1714-1743. https://doi.org/10.1108/ITP-04-2021-0328.

Gkinko, L., & Elbanna, A. (2023). Designing trust: The formation of employees' trust in conversational AI in the digital workplace. *Journal of Business Research*, 158, 113707. https://doi.org/10.1016/j.jbusres.2023.113707.

Glikson, E., & Woolley, A.W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627-660. https://doi.org/10.5465/annals.2018.0057.

Graf-Vlachy, L., Buhtz, K., & König, A. (2018). Social influence in technology adoption: taking stock and moving forward. *Management Review Quarterly*, 68, 37-76. https://doi.org/10.1007/s11301-017-0133-3.

Greineder, M., Riasanow, T., Böhm, M., & Krcmar, H. (2020). The generic InsurTech ecosystem and its strategic implications for the digital transformation of the insurance industry. 40 Years EMISA 2019. Bonn: Gesellschaft für Informatik e.V.. (S. 119-132).

Grybauskas, A., Stefanini, A., & Ghobakhloo, M. (2022). Social sustainability in the age of digitalization: A systematic literature review on the social implications of industry 4.0. *Technology in Society*, 70, 101997. https://doi.org/10.1016/j.techsoc.2022.101997

Guiso, L. (2012). Trust and insurance markets. *Economic Notes*, 41(1-2), 1-26. https://doi.org/10.1111/j.1468-0300.2012.00239.x

Guiso, L. (2021). Trust and insurance. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 46, 509-512. https://doi.org/10.1057/s41288-021-00241-7

Hair, J.F.; Risher, J.J.; Sarstedt, M.; & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

Hari, H., Iyer, R. & Sampat, B. (2022) Customer Brand Engagement through Chatbots on Bank Websites– Examining the Antecedents and Consequences, *International Journal of Human–Computer Interaction*, 38, 13, 1212- 1227, https://doi.org/10.1080/10447318.2021.1988487.

Henseler, J., Ringle, C.M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115-135. https://doi.org/10.1007/s11747-014-0403-8.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing*, 51(1), 57-71. https://doi.org/10.1016/j.intmar.2020.04.0.

Huang, W. S., Chang, C. T., & Sia, W. Y. (2019). An empirical study on the consumers' willingness to insure online. *Polish Journal of Management Studies*, 20(1), 202-212. https://doi.org/10.17512/pjms.2019.20.1.18

Hussain, M., Mollik, A.T., Johns, R., & Rahman, M.S. (2019). M-payment adoption for bottom of pyramid segment: an empirical investigation. *International Journal of Bank Marketing*, 37(1), 362–381. https://doi.org/10.1108/IJBM-01-2018-0013.

Joshi, H. (2021). Perception and Adoption of Customer Service Chatbots among Millennials: An Empirical Validation in the Indian Context. WEBIST, 197-208, https://doi.org/10.5220/0010718400003058.

Kaleka, A. (2002). Resources and capabilities driving competitive advantage in export markets: guidelines for industrial exporters. *Industrial Marketing Management*, 31(3), 273-283. https://doi.org/10.1016/S0019-8501(00)00148-6.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, 62, 101280. https://doi.org/10.1016/j.techsoc.2020.101280.

Kishore, S.V.K.; & Sequeira, A.H. (2016). An empirical investigation on mobile banking service adoption in rural Karnataka. *SAGE Open*, January-March, 1-21. https://doi.org/10.1177/2158244016633731

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227-261. https://doi.org/10.1111/isj.12131.

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for information Systems*, 13(7). https://doi.org/10.17705/1jais.00302.

Koetter, F., Blohm, M., Drawehn, J., Kochanowski, M., Goetzer, J., Graziotin, D., & Wagner, S. (2019). Conversational agents for insurance companies: from theory to practice. In Agents and Artificial Intelligence: 11th International Conference, ICAART 2019, Prague, Czech Republic, February 19–21, 2019, Revised Selected Papers 11 (pp. 338-362). Springer International Publishing.

Kovacs, O. (2018). The dark corners of industry 4.0–Grounding economic governance 2.0. *Technology in Society*, 55, 140-145. https://doi.org/10.1016/j.techsoc.2018.07.009.

Kuberkar, S., & Singhal, T. K. (2020). Factors influencing adoption intention of AI powered chatbot for public transport services within a smart city. *International Journal of Emerging Technologies in Learning*, 11(3), 948-958.

Lanfranchi, D., & Grassi, L. (2022). Examining insurance companies' use of technology for innovation. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 47(3), 520-537. https://doi.org/10.1057/s41288-021-00258-y.

Lee, S., Oh, J. & Moon, W.-K. (2022) Adopting Voice Assistants in Online Shopping: Examining the Role of Social Presence, Performance Risk, and Machine Heuristic, *International Journal of Human–Computer Interaction*, https://doi.org/10.1080/10447318.2022.2089813.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. Decision Sciences, 52(2), 362-392. https://doi.org/10.1111/deci.12445.

LMI Group (2022). The psychology of claims. https://lmigroup.io/the-psychology-of-claims/.

Makanyeza, C.; Mutambayashata, S. (2018). Consumers' acceptance and use of plastic money in Harare, Zimbabwe: application of the unified theory of acceptance and use of technology 2. *International Journal of Bank Marketing*, 36(2), 379–392. https://doi.org/10.1108/IJBM-03-2017-0044.

Marcon, É., Le Dain, M. A., & Frank, A. G. (2022). Designing business models for Industry 4.0 technologies provision: Changes in business dimensions through digital transformation. *Technological Forecasting and Social Change*, 185, 122078. https://doi.org/10.1016/j.techfore.2022.122078.

Nirala, K. K., Singh, N. K., & Purani, V. S. (2022). A survey on providing customer and public administration based services using AI: chatbot. *Multimedia Tools and Applications*, 81(16), 22215-22246. https://doi.org/10.1007/s11042-021-11458-y.

Njegomir, V., & Bojanić, T. (2021). Disruptive technologies in the operation of insurance industry. *Tehnički Vjesnik*, 28(5), 1797-1805. https://doi.org/10.17559/TV-20200922132555.

Nuruzzaman, M., & Hussain, O. K. (2020). IntelliBot: A Dialog-based chatbot for the insurance industry. *Knowledge-Based Systems*, 196, 105810. https://doi.org/10.1016/j.knosys.2020.105810.

Nuryyev, G.; Wang, Y.-P.; Achyldurdyyeva, J.; Jaw, B.-S.; Yeh, Y.-S.; Lin, H.-T.; & Wu, L.-F. (2020). Blockchain Technology Adoption Behavior and Sustainability of the Business in Tourism and Hospitality SMEs: An Empirical Study. *Sustainability*, 12(3), 1256, https://doi.org/10.3390/su12031256

Oktariyana, M.D., Ariyanto, D., & Ratnadi, N.M.D (2019). Implementation of UTAUT and D&M Models for Success Assessment of Cashless System. *Research Journal of Finance and Accounting*, 10(12), 127-137. https://doi.org/10.7176/RJFA/10-12-16

Palos-Sánchez, P.; Saura, J.R.; & Ayestaran, R. (2021). An Exploratory Approach to the Adoption Process of Bitcoin by Business Executives. *Mathematics*, 9(4), 355. https://doi.org/10.3390/math9040355.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879. https://doi.org/10.1037/0021-9010.88.5.879.

PromTep, S. P., Arcand, M., Rajaobelina, L., & Ricard, L. (2021). From What Is Promised to What Is Experienced with Intelligent Bots. In Advances in Information and Communication: Proceedings of the 2021 Future of Information and Communication Conference (FICC), Volume 1 (pp. 560-565). Springer International Publishing.

Rajaobelina, L., PromTep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing*, 38(12), 2339-2356. https://doi.org/10.1002/mar.21548.

Rodríguez Cardona, D., Werth, O., Schönborn, S., & Breitner, M. H. (2019). A mixed methods analysis of the adoption and diffusion of Chatbot Technology in the German insurance sector. AMCIS 2019 Proceedings. 18. https://aisel.aisnet.org/amcis2019/adoption_diffusion_IT/adoption_diffusion_IT/18

Sá Siqueira, M. A.; Müller, B.C.N. & Bosse, T. (2023). When Do We Accept Mistakes from Chatbots? The Impact of Human-Like Communication on User Experience in Chatbots That Make Mistakes, *International Journal of Human–Computer Interaction*, https://doi.org/10.1080/10447318.2023.2175158.

Sánchez-Torres, J.A.; Canada, F.-J.A.; Sandoval, A.V.; Alzate, J.-A.S. (2018). E-banking in Colombia: factors favoring its acceptance, online trust and government support. *International Journal of Bank Marketing*, 36(1), 170–183. https://doi.org/10.1108/IJBM-10-2016-0145.

Seeger, A-M. &, Heinzl, A., (2021). Chatbots often Fail! Can Anthropomorphic Design Mitigate Trust Loss in Conversational Agents for Customer Service? *ECIS 2021 Research Papers*, 12. https://aisel.aisnet.o.rg/ecis2021_rp/12.

Sheel, A., & Nath, V. (2020). Blockchain technology adoption in the supply chain (UTAUT2 with risk)–evidence from Indian supply chains. *International Journal of Applied Management Science*, 12(4): 324–346. https://doi.org/10.1504/IJAMS.2020.110344.

Silva, F.A., Shojaei, A.S., & Barbosa, B. (2023). Chatbot-Based Services: A Study on Customers' Reuse Intention. *J. Theor. Appl. Electron. Commer. Res.* 18, 457-474. https://doi.org/10.3390/jtaer18010024.

Sosa, I., & Montes, Ó. (2022). Understanding the InsurTech dynamics in the transformation of the insurance sector. *Risk Management and Insurance Review*, 25(1), 35-68. https://doi.org/10.1111/rmir.12203.

Standaert, W., & Muylle, S. (2022). Framework for open insurance strategy: insights from a European study. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 47(3), 643-668. https://doi.org/10.1057/s41288-022-00264-8.

Vassilakopoulou, P., Haug, A., Salvesen, L. M., & O. Pappas, I. (2023). Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government, *European Journal of Information Systems*, 32:1, 10-22, https://doi.org/10.1080/0960085X.2022.2096490.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926.

Venkatesh, V.; Morris, M.G.; Davis, G.B.; & Davis, F.D (2003). User acceptance of information technology: toward a unified view. MIS Quarterly, 27(3): 425-478. https://doi.org/10.1016/10.2307/30036540.

Venkatesh, V.; Thong, J.Y.L.; & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1): 157-178. https://doi.org/10.1016/10.2307/41410412.

Vogelsang, K., Steinhüser, M., & Hoppe, U. (2013). A qualitative approach to examine technology acceptance. Thirty Fourth International Conference on Information Systems, Milan 2013. https://core.ac.uk/download/pdf/301361231.pdf.

Warsame, M.H.; & Ireri, E.M. (2018). Moderation effect on mobile microfinance services in Kenya: an extended UTAUT model. *Journal of Behavioral and Experimental Finance*, 18: 67–75. https://doi.org/10.1016/10.1016/j.jbef.2018.01.008

Xie, C.; Wang, Y. & Cheng, Y. (2022) Does Artificial Intelligence Satisfy You? A Meta-Analysis of User Gratification and User Satisfaction with AI-Powered Chatbots, *International Journal of Human–Computer Interaction*, https://doi.org/10.1016/10.1080/10447318.2022.2121458

Xing, X., Song, M., Duan, Y., & Mou, J. (2022). Effects of different service failure types and recovery strategies on the consumer response mechanism of chatbots. Technology in Society, 70, 102049. https://doi.org/10.1016/j.techsoc.2022.102049.

Yan, T. C., Schulte, P., & Chuen, D. L. K. (2018). InsurTech and FinTech: banking and insurance enablement. Handbook of Blockchain, Digital Finance, and Inclusion, Volume 1, 249-281. https://doi.org/10.1016/B978-0-12-810441-5.00011-7.

Zarifis, A., & Cheng, X. (2022). A model of trust in Fintech and trust in Insurtech: How Artificial Intelligence and the context influence it. Journal of Behavioral and Experimental Finance, 36, 100739. https://doi.org/10.1016/j.jbef.2022.100739.

Authors' biographies

Jorge de Andrés-Sánchez holds a Ph.D. from Rovira i Virgili University (Spain) and is a lecturer at the same university and member of the research group Social and Business Research Lab. He is expert in applications on technology acceptance and ethical issues of emerging technologies in society. Dr. Jorge de Andrés-Sánchez has published in different high standing international journals about social ald health issues such as Acta Oeconomica, Poverty and Public Policy, Technology in Society or The Geneva Papers on Risk and Insurance.

Jaume Gené-Albesa holds a Ph.D. from Rovira i Virgili University (Spain) and is a professor at the same university, at its Department of Business Administration. He is an expert in marketing and has served as an independent consultant for many firms. Dr. Jaume Gené-Albesa has published in different high-standing international journals about marketing, such as the International Journal of Bank Marketing, Research and Marketing and Top Management.