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DRIVERS AND NECESSARY CONDITIONS FOR CHATBOT ACCEPTANCE IN THE INSURANCE INDUSTRY. ANALYSIS OF POLICYHOLDERS' AND PROFESSIONALS' PERSPECTIVES

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ABSTRACT

The adoption of conversational robots (chatbots) for customer service is expanding across many industries. In the insurance sector, where customer interactions are essential to the use of policies, understanding chatbot acceptance is particularly relevant. This study explores the factors and conditions influencing the acceptance of chatbots for insurance policy management via the unified theory of acceptance and use of technology (UTAUT) framework. The analysis is conducted on two groups: ordinary policyholders and policyholders who are also industry professionals. The explanatory factors evaluated are performance expectancy, effort expectancy, social influence, and trust. The findings indicate that effort expectancy, social influence, and trust positively impact the behavioral intention to use chatbots. Additionally, all the variables are found to be necessary for acceptance. The structural equation model assessment reveals that professional status do not moderate the relationships between explanatory variables and behavioral intention; however, professionals demonstrate a greater intention to use chatbots. Among ordinary policyholders, effort expectancy has the largest effect size on acceptance. For professionals, trust and performance expectancy are the most impactful explanatory variables, with very large effect sizes. These results emphasize that while all variables are essential for acceptance, the relative importance of each variable varies between policyholders and professionals, offering insights for implementing chatbot solutions effectively within the insurance sector.

KEYWORDS
Digitalization processes; smart robotization; chatbots for customer assistance; insurance 4.0; insurtech; chatbots for policyholder assistance; unified theory of acceptance and use of technology; partial least squares-structural equation analysis; necessary condition analysis

1. Introduction

1.1. Preliminary considerations

The integration of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, and big data into industrial activities is labeled Industry 4.0 (Leesakul et al. 2022). This integration leads to what is known as smart robotics, which are widely implemented in other economic activities, such as services (Acemoglu and Restrepo 2020). The dynamic and constantly evolving demand for products and services from customers stimulates firms to implement conversational robots (also known as chatbots) powered by AI in service encounters to create a positive consumer experience (Gopinath and Kasilingam 2023).

Chatbots are used across a wide range of business activities, including catering and hospitality, fashion, healthcare services, e-commerce, banking, and financial services (Araujo-Silva, Shojaei, and

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Barbosa 2023). Currently, chatbot systems are widely adopted as part of companies' marketing strategies. Typically, conversational robots are employed to provide customers with personalized support and useful information in an easy and quick manner, 24 hours a day, saving both costs and labor (Gatzioufa and Saprikis 2022). Their use can lead to substantial improvements in customer service by reducing response times to requests, thereby increasing loyalty (Jenneboer, Herrando, and Constantinide 2022).

The successful implementation of any organizational change influences various stakeholders, including employees, customers, suppliers, shareholders, and society in general (Kim et al. 2022). It helps attract and retain talent and builds trust (Harvey and Morris 2012). This explains why empirical evidence suggests that companies undertaking successful digitalization processes tend to increase their market value (Fotheringham and Wiles 2023). Likewise, the use of chatbots in customer service is commonly recognized as a potentially beneficial system from a cost-benefit perspective (Jenneboer, Herrando, and Constantinides 2022).

In contrast, the implementation and development of any information system in which conversational robots are a part can require a great deal of time, effort, and cost (Alsharhan, Al-Emran, and Shaalan 2023). Thus, a perception of conflict due to the digitalization process in an organization can result in the loss of customers (Modliński, Fortuna, and Rożnowski 2023).

The implementation of smart technologies from Industry 4.0 also has a significant effect on the insurance sector. This leads to the term "insurtech" for its applications in this field (Stoeckli, Dremel, and Uebernickel 2018) and the label "Insurance 4.0" for the range of processes and new business areas enabled by these technologies (Nicoletti 2021). A notable example of insurtech is the use of chatbots to assist in providing services to policyholders. This includes offering information about products to potential clients and assisting customers with existing contracts (Ostrowska 2021; Riikkinen et al. 2018). In the latter case, which is our focus, the chatbot acts like a human operator, handling tasks common to active policies: collecting, processing, and expediting claims; providing general information about relevant aspects of the contracted product; or sending reminders about renewals (Koetter et al. 2019).

The analysis of the acceptance of conversational robots in customer service is of particular interest in the insurance industry. In many sectors, such as consumer goods, customer contact with the firm is not a substantial part of the product. In contrast, the use of an insurance policy, which involves reporting claims, always requires communication with the insurer, including both initial contact and subsequent communication of relevant details (Eckert, Neunsinger, and Osterrieder 2022).

There is a positive relationship between the digitalization processes of insurance companies and their performance. They can help add value to firms' stakeholders (Stoeckli, Dremel, and Uebernickel 2018), especially when they take a comprehensive approach by addressing digital technology in both internal activities within their organization and external activities related to customers and business partners (Bohnert, Fritzsche, and Gregor 2019). Two key strategic management areas in insurance companies are the optimization of internal claims processes and the maximization of customer satisfaction (Mahlow and Wagner 2016). Both of them are impacted by the implementation of a robotic system for policyholder service, and embed to the management of insurance claims (Riikkinen et al. 2018; Rodríguez-Cardona et al. 2021). The need to provide customer satisfaction as a condition for business success and a strategic objective also applies to the insurance industry (Mahlow and Wagner 2016). Thus, in this context, greater policyholder satisfaction allows for lower costs not only in maintaining the portfolio of existing contracts but also in the acquisition of new policies (Pooser and Browne 2018).

Among the advantages of robots for clients' service, their ability to provide 24/7 attention without waiting is widely highlighted in financial settings (Mostafa and Tamara Kasamani 2022). Additionally, from the professionals' perspective, conversational robots can perform routine and repetitive tasks, freeing employees from focusing on activities that generate more value (Riikkinen et al. 2018). Approximately 70% of customer interactions with insurance firms involve simple issues such as requesting the status of a claim, which can be automated with virtual assistants (Singh, Karthik, and

Shrey 2019). From an organizational standpoint, automation associated with the use of chatbots can help to reduce costs associated with customer service, data processing, and administrative management and allow for the efficient interconnection of all the processes necessary to manage policy portfolios (Ostrowska 2021; Riikkinen et al. 2018).

However, a survey with more than 20,000 observations report that 42% of customers agree on interactions with chatbots to receive advice on new products, but only approximately 15% of people felt comfortable interacting with chatbots for complex service questions (Euromonitor International Voice of the Consumer 2024). Similar unfavorable perceptions are reported in the insurance field (PromTep et al. 2021; Rodríguez-Cardona et al. 2019).

1.2. Research questions

The preceding paragraphs motivate this study, whose objective is to evaluate the factors influencing policyholders' and professionals in the insurance industry that foster the acceptance of chatbots for conducting procedures such as infill contracts. Specifically, it assesses the influence of performance expectancy (PE), effort expectancy (EE), and social influence (SI), which are commonly employed to explain conversational robot acceptance (Alsharhan, Al-Emran, and Shaalan 2023; Balan 2023; Gatzioufa and Saprikis 2022). These constructs are grounded in explanatory frameworks of attitudes toward technological information systems, such as the technology acceptance model (TAM) by Davis, Bagozzi, and Warshaw (1989) and the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003). To these constructs, we add trust (TR) in cognitive and organizational aspects, which is crucial for both the basic economic activity of the insurance industry (Zarifis and Cheng 2022) and the adoption of conversational robots (Gatzioufa and Saprikis 2022). Therefore, the first research question is formulated as follows:

RQ1: What is the explanatory and predictive validity of the proposed technological acceptance model for explaining chatbot acceptance to make insurance procedures?

This first research question involves determining whether explanatory factors are sufficient conditions for inducing behavioral intention. However, strategic decision-making regarding the implementation of information systems requires identifying which variables could act as bottlenecks, i.e., they are necessary conditions. They are needed to produce a result, but their existence is not sufficient for that result (Dul 2016). In fields such as technology and innovation analysis, it is highly useful to establish the variables for which reaching a certain level is a sine qua non condition for acceptance (Cezar 2024; Dul, Hauff, and Bouncken 2023). This is particularly relevant in the context we are analyzing because although chatbots have significantly advanced in terms of functionality and usability, there are still shortcomings and challenges associated with this technology that result in relatively low evaluations within the insurance industry among professionals (Andrés-Sánchez, González-Vila, and Gené-Albesa 2023; Rodríguez-Cardona et al. 2019) and customers (Andrés-Sánchez and Gené-Albesa 2024; PromTep et al. 2021). Therefore, the second research question is as follows:

RQ2: Are there bottleneck factors that hinder behavioral intention such that their absence automatically implies the rejection of chatbots, irrespective of the level of other explanatory factors?

The literature suggests that the successful implementation of robotization processes requires a positive attitude and acceptance from both employees (Çiğdem, Meidute-Kavaliauskiene, and Yıldız 2023) and customers when they have to interact with them (Van Pinxteren, Pluymaekers, and Lemmink 2020). Analyzing both groups can provide a broader perspective that encompasses not only ordinary customers or professionals but also both groups conjointly. Employees, each with unique backgrounds and experience in general and in a specific organization, business unit, and/or job, may have numerous biases (Venkatesh 2022). Notably, at least in Spain, a significant proportion of insurance acquisitions are intermediated by professionals (Latorre Guillem 2022), making it interesting to check whether the perception of professionals toward chatbots aligns with that of users who are potentially advised by them when purchasing policies. Therefore, the third research question addressed in this paper is formulated as follows:

RQ3: Are there significant differences in the presented model depending on whether the responses come from a simple user or a policyholder who is also an insurance professional?

2. Theoretical background

The analysis of the acceptance of a new technology requires the use of a theoretical framework that serves as a baseline, providing a sufficiently comprehensive explanation of the outcome variable. In the case of conversational robots, literature reviews indicate that the main theoretical frameworks are the TAM and UTAUT (Alsharhan, Al-Emran, and Shaalan 2023; Gatzioufa and Saprikis 2022). This statement can also be verified in Table 1.

This study uses UTAUT as the baseline framework. We believe that this theoretical model strikes a good balance between parsimony and the comprehensiveness of factors considered to explain the acceptance of new information systems and, likewise, is a robust conceptual ground (Du and Lv 2024). UTAUT emerges as a synthesis of up to eight explanatory models of technology acceptance, such as the TAM (Venkatesh et al. 2003). Furthermore, UTAUT establishes direct relationships between the explanatory constructs and the variable measuring acceptance without mediation, which makes it easier to use complementary analytical tools. These reasons explain why UTAUT and its extensions have been used to evaluate the acceptance of new technologies in a wide range of settings (Sitar-Taut and Mican 2021).

This study considers three of the four fundamental explanatory constructs of the UTAUT: PE, EE, and SI. These latent variables are widely used in studies examining chatbot acceptance (Balan 2023; Gopinath and Kasilingam 2023) and are relevant in the context of the most specific banking and insurance settings, as shown in Table 1.

The relevance of considering PE and EE is derived from the main advantages attributed to the use of chatbots for assisting policyholders, which are often for convenience (Gebert-Persson et al. 2019). For example, the fact that conversational robots are available 24/7 allows for faster and more efficient management of ongoing policies while also making the insurer easily accessible. In terms of SI, the opinions of close-knit individuals often significantly affect attitudes toward information systems, as people tend to seek approval from their social environment (Venkatesh et al. 2003). This also is applicable to the acceptance of conversational chatbots by customers (Gansser Oliver and Reich 2021), including in financial settings (Hasan et al. 2023).

In addition to the three UTAUT latent variables highlighted in the previous paragraph, we introduce TR as the fourth explanatory latent variable, which is a crucial dimension in the adoption of conversational robots in financial and insurance settings (Zarifis and Cheng 2022). TR is required not only in the organization providing financial or insurance services, as Guiso (2021) outlines but also in the technology mediating the delivery of these services (Chiu et al. 2024; Lappeman et al. 2023; Wang and Lu 2014).

Table 1 presents a compilation of studies on chatbot acceptance centered in insurance and banking settings, underscoring the relevance of the proposed explanatory factors.

To measure the degree of chatbot acceptance, as highlighted in the meta-analysis by Gopinath and Kasilingam (2023), it is common to consider either attitude or intention to use (also referred as behavioral intention). According to Fishbein and Ajzen (1975), attitude is a "*learned predisposition to respond in a consistently favourable or unfavourable manner with respect to a given object*." Additionally, attitude is considered in some versions of the TAM (Davis, Bagozzi, and Warshaw 1989) as the antecedent of the second factor, which is as an individual's willingness to execute a given

Table 1. A review of the literature on chatbot acceptance using technology acceptance models in the insurance and banking industry.

		Significance						
Paper	Setting	PE	EE	SI	TR	Output	Background	R^2
Alt, Vizeli, and Săplăcan (2021)	Banking procedures	Yes	No	Not tested	Not tested	Intention to use	TAM	49%
Andrés-Sánchez and Gené-Albesa (2024)	Insurance procedures, customers' perspective	Yes	Yes	Yes mediated by PE and EE	Yes mediated by PE and EE	Intention to use	TAM	62.7%
Andrés-Sánchez and Gené-Albesa (2023)	Insurance procedures, customers' perspective	No	Yes	Yes	Yes	Intention to use	UTAUT	65.6%
Hasan et al. (2023)	Banking procedures	No	Yes	Not tested	Yes	Intention to use	TAM	47%
Gebert-Persson et al. (2019)	Insurance claiming	Yes, but mediated	Yes, but mediated	Not tested	Yes	Intention to use	TAM	Not reported
PromTep et al. (2021)	Insurance underwriting	Yes	Yes	Not tested	Not tested	Intention to use	TAM	Not reported
Rodríguez-Cardona et al. (2021)	Insurance setting	Yes	No	Not tested	Yes	Intention to use	TAM	48.1%
Toh and Tay (2022)	Banking procedures	Yes	Yes	Yes	Not tested	Intention to use	UTAUT	80.6%
Shaikh, Khan, and Faisal (2023)	Banking	Yes	Not tested	Not tested	Not tested	Intention to use	Ad hoc/other	62%
Huang, Lee, and Lee (2021)	Banking	Yes	Yes	Not tested	Not tested	Continuance intention	Ad hoc/other	54%
Nguyen, Chiu, and Le (2021)	Banking procedures	Yes	Yes to explain user satisfaction	Not tested	Yes	Continuance intention	Ad hoc/other	74.6%
Rajaobelina et al. (2021)	Chatbots for insurance underwriting	Not tested	Yes, but mediated	Not tested	Yes	Loyalty	Ad hoc/other	45.6%

behavior (Ajzen 2002). In this study, the acceptance of using bots in insurance procedures is measured on the basis of the intention to use (IU), which, as shown in Table 1, is the mainstream output quantifying acceptance in the use of chatbots in banking and insurance settings. However, it must be acknowledged that there are exceptions to the general concept, as there are also studies where the variables representing acceptance are continuance intention (Nguyen, Chiu, and Le 2021) or loyalty (Rajaobelina et al. 2021).

The theoretical justification for the model, which is displayed in Figure A1, allows us to propose testable hypotheses about how PE, EE, SI, and TR influence the IU, potentially moderated by the professional status of the survey respondent. This analysis is performed with partial least squares-structural equation analysis (PLS-SEM) and will lead to answers to RQ1 and, in part, RQ3.

Answering RQ1 does not inform whether explanatory factors are bottlenecks for chatbot acceptance. That is, after answering RQ1, it can be established, for example, that PE has a significant positive link with IU. However, we cannot determine whether achieving a threshold in PE is necessary to generate IU or whether its complete absence could be compensated for by high values of other exogenous variables. This information is of special interest in the study of novel technologies (Cezar 2024; Dul, Hauff, and Bouncken 2023). Thus, the RQ2 implies running a subsequent exploratory implementation of necessary condition analysis (NCA), which is performed separately for professional and ordinary customer subsamples to detect changes in patterns.

RQ3 explores whether there are any significant differences among consumers in their perceptions of chatbots for carrying out insurance procedures on the basis of their differences in the level of knowledge of the insurance industry and the implications of digitalization because some of them are also professionals. This is also illustrated in Figure A1, where being a professional of the industry moderates the relationships between PE, EE, SI, and TR and IU.

Modeling two distinct groups as categorical moderating variables is common in the studies about information systems acceptance. A usual case is gender, but there are many other possibilities, including the modeling of a particular educational or knowledge status. To do it, modeling two distinct groups as categorical moderating variables is usual. Having two clearly differentiated groups may provide insights into different expectations and concerns regarding the technology under analysis. For example, Wong (2016), in his study on the determinants of loyalty in B2B relationships, considers whether an organization has an nonprofit objective as a moderating factor. Lee and Hallak (2018), in an analysis of the business performance of restaurant companies, take into account whether the owner has studied entrepreneurship as a differentiating variable. In the field of new communication channels in finance, such as mobile banking, Zhou, Lu, and Wang (2010) observe that student users may be more concerned with usage costs and the variety of functions, whereas working professionals may focus more on reliability and EE.

3. Hypothesis development

3.1. Performance expectancy and effort expectancy

Convenience is a highly relevant reason for accepting chatbot assistance in claiming procedures and includes arguments related to PE and EE (Gebert-Persson et al. 2019). Performance expectancy (PE), is an individual's perception of the extent to which the use of a given technology improves performance (Venkatesh et al. 2003). Effort expectancy (EE) is a user's belief that a particular information system can be used effortlessly (Venkatesh et al. 2003).

From the policyholder's perspective, chatbots offer various advantages, such as continuous time availability and quick response times, leading to faster problem resolution (Mostafa and Tamara Kasamani 2022). Additionally, interactions with chatbots can occur through various platforms and systems (smartphones, webs, and conventional phones), and they do not require the use of new technological elements, such as apps (DeAndrade and Tumelero 2022; Koetter et al. 2019). The contribution of chatbots to customer satisfaction in the insurance field requires not only that the chatbot effectively facilitates contact with the insurance company but also easy communication and that the conversational bot system is part of an omnichannel strategy (Eckert, Neunsinger, and Osterrieder 2022). The possibility of a greater number of channels enhances consumer satisfaction (Gené-Albesa 2007).

Moreover, chatbot systems make the centralized execution of various actions (reporting claims, sending photos, etc.) possible. This results in increased user performance by saving time and effort in management, both for the customer and for the organization (Jenneboer, Herrando, and Constantinides 2022; Ostrowska 2021). The ability of chatbots to handle repetitive, simple, and monotonous tasks allows human operators to perceive greater efficiency in their work and to increase satisfaction (Brachten, Kissmer, and Stieglitz 2021). In a workplace setting, instrumental gratification, such as increasing productivity, is a relevant explanatory factor for the acceptance of chatbots (Kopplin 2023).

However, many conversational robots used on the market are trained with basic databases, so they are not capable of complex interactions with users (Xing et al. 2022). Additionally, they are not able to grasp relevant nuances in human communication, such as voice inflections, slang, idioms, etc., and they lack empathy, making interactions with them challenging (Vassilakopoulou et al. 2023). Failed communication with chatbots is very common (PromTep et al. 2021), which explains the extensive literature on consumer behavior in response to failure in interactions with chatbots (Janssen, Grützner, and Breitner 2021; Xing et al. 2022). Qualitative studies on testimonials of negative experiences are not difficult to find. This includes their use in the business context, "*I would say for the more common issues it would be helpful, but if the issue is very specific or not very common, then you definitely need human help*" (Gkinko and Elbanna 2022), or in banking customer issues, "*I have tried the chatbot with Zenith, but it was not responsive; they were not even seeing my questions. I had to use Twitter to contact them through direct messaging, and they responded faster to that*" (Mogaji et al. 2021). It has also been identified in the specific field of insurance claims, with statements such as, "*No effectiveness when your claim is not standard*" and "*does not understand nuances*" (Andrés-Sánchez and Gené-Albesa 2024). Thus, even if a human agent later resolves a customer's query, the initial interaction with the robot may be perceived as a waste of time (Andrés-Sánchez and Gené-Albesa 2024). Notably, owing to either the technophobia or rejection of robots, it is difficult for some people to interact with this type of technology (Rajaobelina et al. 2021).

Similarly, in Rodríguez-Cardona et al. (2019), various executives from German insurance companies indicate that insurers should increase the development of their own information systems infrastructure to successfully implement a chatbot system for policyholder attention. Only if back-end systems can deliver and transform data and information can the front-end application be fed with the correct content and operate correctly. In addition, in accordance with Andrés-Sánchez, González-Vila, and Gené-Albesa (2023), a professional reports problems arising from the implementation and coordination of new digital systems in the following way, "*In the current generation, chatbots do not work and are a confusing, slow, ineffective application lacking the excellence and immediacy required in proper service to the insured. It is a reality that can be verified in any insurance company (. . .); they do not adequately address claims. The current system in the insurance sector does not work, and insurance intermediaries or insured individuals become frustrated making calls, controlling, and monitoring an operator useless in its functions.*"

As Gatzioufa and Saprikis (2022) note and it is showed in Table 1, both PE and EE are commonly reported to be significant factors in the literature. This is especially true for PE (Gopinath and Kasilingam 2023). Therefore, we propose the following:

H1: Performance expectancy is positively linked with intention to use chatbots to perform insurance procedures.

H2: Effort expectancy is positively linked with intention to use chatbots to perform insurance procedures.

3.2. Social influence

Social influence (SI) can be defined as the perception that a particular behavior should be performed or inhibited on the basis of the opinions of others (Venkatesh and Davis 2000). According to the meta-analyses by Gatzioufa and Saprikis (2022) and Gopinath and Kasilingam (2023), SI is a relevant variable for explaining chatbot acceptance by customers. Additionally, Table 1 shows that although not mainstream, there are various reports in banking and insurance settings demonstrating the relevance of SI in explaining conversational robot acceptance.

The literature indicates that chatbots strongly impact word-of-mouth (Jenneboer, Herrando, and Constantinides 2022), which is one of the ways in which SI develops. Similarly, in financial and insurance decisions, the opinions of trusted financial advisors are often relevant (Andrés-Sánchez and Gené-Albesa 2023). For employees in industries where chatbots are potentially applicable, subjective norms are also influenced by the effects of managers and peer networks (Brachten, Kissmer, and Stieglitz 2021). Moreover, by reviewing the regional distribution of contributions to the literature on the acceptance of conversational robots, Alsharhan, Al-Emran, and Shaalan (2023) note that the culture of the respective country is a crucial factor in their acceptance.

On the one hand, more than 50% of jobs will be lost owing to automation powered with smart technologies (Kovacs 2018), which could reach 80% in certain functions in the insurance industry (Balasubramanian, Libarikian, and McElhaney 2018). In this context, society and affected workers naturally tend to exhibit resistance and rejection due to fear of job loss (Ivanov, Kuyumdzhiev, and Webster 2020). On the other hand, the digital transformation resulting from Insurance 4.0 also creates new opportunities, as it has the potential to enhance the quality of work by creating a more interesting working environment and providing greater autonomy for self-development. In fact, there is a significant perception that managerial job productivity will increase due to enhanced human-AI collaboration since the future of AI in knowledge work should focus not on full automation but on collaborative approaches where humans and AI work closely together (Kopplin 2023). The impact of smart technologies on the insurance industry redefines job roles and the skills necessary to perform them (Nicoletti 2021). Furthermore, Insurance 4.0 creates new business opportunities, such as cyber risk insurance (Jain, Mukhopadhyay, and Jain 2023). Therefore, we postulate the following:

H3: Social influence is positively linked with intention to use chatbots to perform insurance procedures.

3.3. Trust

Trust (TR) is a dimension particularly relevant in the insurance industry (Guiso 2021; Wang and Lu 2014) and also in the relationship between individuals and conversational robots (Gkinko and Elbanna 2022, 2023). The timely and trouble-free fulfillment of obligations by the insurer is the foundation on which TR in the insurance company is built (Guiso 2021). As shown in Table 1, TR is a variable commonly tested and demonstrated to be particularly relevant to IU conversational bots in the finance industry. Several reviews about chatbot acceptance also outline this significance (Alsharhan, Al-Emran, and Shaalan 2023; Gatzioufa and Saprikis 2022; Gopinath and Kasilingam 2023).

A comprehensive understanding of TR in AI-based chatbots encompasses customers' readiness to disclose confidential information, their approval of the suggested actions they receive, and the probability that they will adhere to the chatbot's recommendations (Sonntag, Mehmann, and Teuteberg 2023). Among the three commonly distinguished types of TR, cognitive, organizational, and emotional (Gkinko and Elbanna 2023), following Zarifis and Cheng (2022), we concentrate on organizational and cognitive TR. Organizational TR, from the policyholder's perspective, is the belief that the insurer will address claim coverage without delays or effort on the part of the policyholder when the time comes (Guiso 2021). Organizational TR concerning the use of technologies powered by artificial intelligence is also influenced by the perception that the firm is concerned with the security and privacy of personal data (Gkinko and Elbanna 2023). It can also be defined as someone's rational expectation that the trustee has attributes, such as competence and integrity, that can be relied upon (Lappeman et al. 2023). Organizational TR from an employee is reflected in statements such as, "*Well, I would say it does not give me any bad feelings if the bot fails. Because I turned to the bot when I was advised to use it, then I rely on what they say use this … I take it as an official tool that we are allowed to use*" (Gkinko and Elbanna 2023).

Cognitive TR is reflected in users' confidence in the technology they are going to use (Zarifis and Cheng 2022). In society and organizations, individuals are predisposed to accept and reject robotization processes because of their different motivations and profiles. Thus, among those who are favorable, supporters and embracers can be distinguished, whereas those with an unfavorable judgment can be distinguished as resisters and saboteurs (Paluch et al. 2022). Moreover, AI-powered techs often lack transparency, which poses a barrier for many users to trust them (Venkatesh 2022). For example, in the qualitative analysis of Andrés-Sánchez and Gené-Albesa (2024), a user state, "*It is not clear to me whether the casualty and its details can be communicated adequately and will meet all the requirements issued by the policyholder*." Insufficient security and transparency, restricted social functionalities, and concerns regarding the communication style and quality of AI-based chatbots pose barriers to customer TR, ultimately impeding chatbot adoption (Sonntag, Mehmann, and Teuteberg 2023). Thus:

H4: Trust is positively linked with intention to use chatbots to perform insurance procedures.

3.4. Professionals versus nonprofessional users

In this study, we consider it relevant to differentiate between policyholders who are also insurance professionals and those who are not. The former group has a more complex perspective, as they may have used chatbots both as policyholders and workers whose jobs are directly impacted by the implementation of AI-based technologies. The influence of new technologies on their specific organization, department, and/or tasks may also introduce some biases into their judgments (Venkatesh 2022).

The literature indicates that there is a statistically positive relationship between the level of financial knowledge and the acceptance of fintech. Thus, Akbar et al. (2021) and Andreou and Anyfantaki (2021) reported that the frequency of internet banking use is positively linked with financial literacy. Similar results have been reported for mobile banking acceptance (Phan et al. 2024; Ullah et al. 2022). It has also been reported that greater financial knowledge leads to greater acceptance of novel payment methods such as mobile and electronic money (Ha, Şensoy, and Phung 2023; Yoshino, Morgan, and Trinh 2020). Therefore, it is logical to suppose that these findings may also apply to the insurance sector, which is part of the financial industry.

Moreover, if we introduce insurance literacy in the analysis of chatbot acceptance, being a professional may provide a more reliable measurement of literacy than a self-reported evaluation in a questionnaire. In the financial domain, self-reported literacy is often biased by so-called blind spots, which can lead respondents to overestimate actual financial knowledge (Balasubramnian and Springer Sargent 2020). Therefore, we postulate the following:

H5: Being professional in the insurance industry moderates and positively influences behavioral intention toward insurance procedures performed with chatbots.

4. Materials and methods

4.1. Study design

This study uses a self-administered questionnaire that inquired about the acceptance of conversational robots when performing insurance procedures. The survey is stratified into two subsamples. The first group consisted of 119 participants, and the second had 58 participants. The first subsample included employees of a Spanish university who have at least two insurance policies, and the target population is policyholders. The second group focused on insurance sector professionals, who are also owners of at least two insurance policies. The overall sample included 177 responses.

Using a subsample of workers from a higher education institution to capture the perceptions of an average consumer has several advantages. It is easier to find respondents who are accustomed to remote work and who have a certain motivation to contribute to research. Therefore, a higher response rate is anticipated compared to other population segments (Andres-Sánchez et al. 2022). Additionally, members of the university community usually have higher educational levels than average citizens do; thus, it is anticipated that they hold well-reasoned opinions. In addition, responses come from diverse perspectives and sensitivities owing to the different fields of study covered by university studies since they include humanities, social sciences, engineering, pure sciences or life sciences (Andres-Sánchez et al. 2022).

With the group of professionals, we seek a perspective different from that of the ordinary user. Unlike users, professionals have close experience with the usability and real advantages of chatbots from the insurer's point of view and how the implementation of conversational bots currently affects the execution of insurance procedures in their professional activities.

4.2. Sampling

Both subsamples were collected in Spain during the spring of 2023. The survey for the first group was distributed via the e-mail distribution lists of the university. With respect to the subsample of professionals, the questionnaire was distributed to professional associations and interest groups on social networks such as LinkedIn. Distributing it to specific groups on a social media platform such as this allowed an easy and rapid dissemination at an affordable cost while also ensured that the audience is appropriate for our purposes, which is highly desirable (Ong et al. 2023).

In both groups, the survey was completed via the same Google Forms hyperlink. The responses were completely anonymous and voluntary. The questionnaire included a binary question inquiring whether the respondent was a professional in the insurance field, similar to other sociodemographic aspects such as sex or age. Additionally, the respondents were not informed that they belonged to any group of special interest. Thus, although the data belonged to two different groups, they exhibited configurational invariance. This means that the survey had exactly the same items (in our case, even the same Google Forms link), the data were treated and curated via the same methods, and identical algorithms and optimization criteria were used to extract information (Henseler, Ringle, and Sarstedt 2016).

Additionally, no compensation was offered in either case for completing the survey. Thus, we believe that we obtained good responses because the participants responded at a time that was preferred to them and in a completely altruistic manner.

We verified that, in both groups, the size allowed us to fit a model by using PLS-SEM, in which IU is explained by PE, EE, SI, and TR, ensuring that the power of the basic tests on the significance of the overall model and individual coefficients was 80%, considering significance levels in two-tailed tests of 5%. We assumed a determination coefficient of at least 25% (i.e., a size effect f^2 greater than 0.35), which is fairly conservative for this type of empirical analysis (see Table 1). Note that in the reviewed papers in Table 1, R^2 is never below 45%. Using the software G*Power 3.1 (Faul et al. 2009), we observed that with the smallest group, professionals ($N = 58$), for a significance level of 5%, the power

Table 2. Profile of the sample and the groups used in the survey.

	Group 1, $N = 119$		Group 2, $N = 58$		Whole sample, $N = 177$	
	Overall	Percentage	Overall	Percentage	Overall	Percentage
Gender						
Male	59	49.58%	41	70.69%	100	56.50%
Female	56	47.06%	15	25.86%	71	40.11%
NA	4	3.36%	2	4.88%	6	3.39%
Age						
≤50 yrs	58	48.74%	9	15.52%	67	37.85%
>50 ≤ 55	22	18.48%	19	32.76%	41	23.16%
>55	37	31.09%	27	46.55%	64	36.16%
NA	2	1.68%	3	5.17%	5	2.82%
	mean = 49.59, SD = 10.88		mean = 53.1, SD = 8.33		mean = 50.74, SD = 10.12	
Number of policies						
>4	64	53.79%	44	75.86%	108	61.02%
≥2 and < 4	55	46.21%	14	24.14%	69	38.98%
Monthly income						
≥3500	62	52.26%	22	37.93%	84	47.56%
<3500	53	44.20%	33	56.90%	86	48.36%
NA	4	3.54%	3	5.17%	7	4.07%

NA stands for not answered.

for Student's t ratios for an individual coefficient is 99%, and for Snedecor's F to test the overall model, it was 95%.

Additionally, we verified that the overall sample provided a power of 80% for a model explaining IU with 9 potential exogenous variables, as shown in Figure A1. These variables correspond to PE, EE, SI, TR, and being a professional, as well as the interaction terms between being a professional and the latent variables explaining acceptance. Again, considering a significance level of 5% and assuming a minimum coefficient of determination of 25%, G*Power 3.1 indicated that the power was indeed 99%.

4.3. Sample profile

Table 2 displays the profiles of the two groups and the overall sample. With respect to the gender distribution, the group of university respondents was balanced (49.58% males and 47.06% females), whereas the group of professionals was biased toward males (70.69%). The average age of the respondents was slightly younger in the customer subsample (49.49 years) than in the second subsample (53.1 years). Insurance professionals tended to have more policies, with 75.86% reporting more than four policies, whereas in the first group, only 53.79% reported more than four policies. Overall, 100 men (56.50%) and 71 women (40.11%) aged 50.74 ± 10.12 years were included in the sample. Similarly, 61.02% (108 people) reported having more than 4 insurance contracts.

4.4. Measurement of the variables

The variables were measured with the questions displayed in Table A1 of the APPENDIX and were redacted and distributed in Spanish. The questionnaire was initially tested by fifteen professionals from the insurance sector, most of whom were from the Spanish Section of the International Association for Insurance Law (SEAIDA). The suggested modifications, although very useful, did not entail any changes to the questionnaire. Additionally, these fifteen responses allowed for an initial test of the reliability of the scales configured by the questions in Table A1.

All the items were responded via an 11-point Likert scale varying from 0 ("complete disagreement") to 10 ("complete agreement"). This scale, which extends beyond typical scales with less granularity, has been used by numerous authors for several reasons. First, most individuals can recognize finer distinctions than five or seven degrees. Second, the 11-point Likert scale provides enhanced perceptiveness and more closely approximates an interval scale with normal distribution properties. Furthermore, a 0–10 range is intuitive and easily interpreted as a percentage (Leung 2011).

Notably, in the introductory text motivating the questionnaire, our objective was to collect evaluations of interactions with chatbots for managing existing policies, such as, for example, communicating material damage covered by a home insurance policy. We were not interested in other applications, such as purchasing a new insurance policy or seeking advice about insurance issues.

The scales employed to measure IU, and PE, EE and SI, were based on those commonly used in similar studies, as it is displayed in Table A1 of the APPENDIX. For TR, the questions were adapted from Morgan and Hunt (1994). While cognitive TR was captured by the item TR1, "*Chatbots provide a secure and trustworthy service to manage policies*," its organizational dimension was reflected in the question TR2, "*The use of chatbots to interact with the insurance company takes into account the interests of policyholders*." All the latent variables were reflective.

4.5. Data analysis

The tools used to evaluate the explanatory and predictive power of the proposed model, as well as the presence of necessary conditions, use sequentially PLS-SEM and NCA. Combining these two instruments enables data analysis from a supplementary standpoint, yielding a deeper perspective than using only PLS-SEM (Richter et al. 2020).

With PLS-SEM, we analyze the statistical significance of the overall model and the impact of explanatory variables on IU, thus answering RQ1. This analysis allows examining the sufficiency of the explanatory variables for producing IU. We also use PLS-SEM to answer RQ3 partially and determine whether the intensity of the impact of PE, EE, SI, and TR on IU depends on whether the respondent is a simple policyholder or professional in the insurance industry.

The sizes of the overall sample (177 observations) and the two groups (119 and 58 observations) are not large. Compared with other methods, PLS-SEM has an advantage, as it does not require a substantial amount of data to achieve adequate statistical power (Hair et al. 2022). Additionally, PLS-SEM does not impose strict assumptions regarding data normality (Hair et al. 2022) and enables the evaluation of the predictive capability of the proposed conceptual model (Panigrahi et al. 2023; Shmueli et al. 2016). These factors may explain why this correlational method is widely used in sociological studies (Sitar-Taut et al. 2023), and in educational assessments (Saihi, Ben-Daya, and Hariga 2024), including the UTAUT approach (Sitar-Taut and Mican 2021). It is also applicable to the field of knowledge management studies and information systems (Hair et al. 2017; Meher et al. 2023) and, consequently, in technology acceptance studies, such as those investigating behavioral intention to use chatbots (Balan 2023; Gatzioufa and Saprikis 2022).

To address RQ2, we apply the NCA (Dul 2016; Dul, van der Laan, and Kuik 2020). With NCA, we measure the extent to which the considered variables are critical for the acceptance of chatbots, as a value below the threshold in such a variable cannot be compensated by very high values in the others, even if they are highly significant in the PLS-SEM implemented to answer RQ1. Like PLS-SEM, NCA does not need specific configuration of data and can be effective for samples of any size (Dul, Hauff, and Bouncken 2023). Additionally, implementing NCA separately in the two subsamples allows us to infer whether the intensity of being a necessary factor depends on insurance literacy, which is embedded in RQ3.

PLS-SEM and NCA are run with SmartPLS 4.0. The combined application of both techniques follows the steps outlined in Richter et al. (2020).

(1) We evaluate the reliability of the scales that are reflective in all the cases, following Hair et al. (2022). The first step in reflective measurement model assessment involves examining the indicator loadings. Loadings above 0.708 are recommended, as they indicate that the construct explains more than 50% of the indicator's variance, thus providing acceptable item reliability. The internal consistency of the scales is evaluated with Cronbach's alpha (C-α) and composite

reliability (CR), and their values are expected to be above 0.7 but below 0.95. Convergent validity is evaluated with the average variance extracted (AVE).

(2) Discriminant validity is assessed via the criterion of Fornell and Larcker (1981) and heterotrait-monotrait (HTMT) ratios (Hair et al. 2022). This last measure is expected to be less than 0.9.

(3) We fit the inner model in both subsamples and run a bootstrap multigroup analysis to identify potential differences in path coefficients, indicating whether being a professional in the insurance industry moderates the influence of the explanatory variables on behavioral intention.

(4) The analysis of the significance of individual coefficients and the overall model in both samples reveals a test power that comfortably exceeds 80%, assuming a significance level of 5% when R^2 is at least 25%. Independently, with the help of G*Power 3.1 software (Faul et al. 2009), we establish the critical significance level (α_{crit}) for a two-tailed test that ensures a power of at least 80% when comparing the equality of path coefficients between groups. This level, rather than the conventional 5%, is compared with the p-values of the differences in the path coefficients.

(5) We estimate the definitive structural model by considering only the significant moderating effects and evaluate the causal hypotheses of latent variables and the path coefficient linked to professional knowledge of insurance. The moderating effects of being a professional of the insurance industry are measured by using a dummy variable, PROF, whose value is 1 if the surveyed individual has such a circumstance and 0 otherwise.

Following Hair et al. (2022), in steps 3 and 5, the PLS percentile bootstrapping method is applied to 10,000 subsamples.

(6) For the overall model, we evaluate the existence of collinearity issues by using the variance inflation factor (VIF), the ability to fit data with R^2 and the predictive accuracy with Q^2 (Hair et al. 2022). The model estimated in step 5 allows us to evaluate H1, H2, H3, and H4 and to answer RQ1. It also enables the determination of the extent to which the acceptance of chatbots as consumers depends on being a professional in the industry (H5) and thus partially answers RQ3.

(7) A deeper evaluation of the predictive capacity of models is necessary, as a lack of predictive ability may be attributed to a weakness in the theoretical model or to the quality of the measurement model (Shmueli et al. 2016). This is assessed via Stone and Geisser's Q^2, as well as the cross-validated predictive ability test (CVPAT) (Sharma et al. 2023).

Following these steps, we perform NCA analysis separately for the two groups, and the results will guide us in answering RQ2 and also, in part, RQ3:

(8) We measure the constructs using latent variable scores from PLS-SEM regressions.

(9) Scatter plots of bivariate representations of IU against explanatory factors are analyzed to identify outliers. These methods enable us to adjusting the ceiling envelopment-free disposing hull (CE-FDH) and ceiling regression-free disposing hull (CR-FDH).

(10) We remove the outliers and determine the size of the necessity effect (*d*) and its statistical significance from the CE-FDH and CR-FDH. While the first approach provides an optimistic value of *d*, the second approach provides a pessimistic value.

(11) We fit the bottleneck tables indicating the necessity of the degree of each explanatory construct for attaining IU.

5. Results

5.1. Results of PLS-SEM analysis

We initially checked that the factor loadings are greater than 0.708 for all the items. Table A2 of the APPENDIX shows that the scales exhibit internal consistency, as indicate CA and CR, both between 0.7 and 0.95, and that the scales have convergent validity since the AVE is above 0.5. Additionally, Table A3 of the APPENDIX suggests that the scales and the dummy variable PROF also possess adequate discriminant validity. In all the cases, the squared AVEs of all factors are greater that their Pearson's correlations with other factors. Generally, the HTMT ratios for pairwise variables are smaller than 0.85, except for those of TR with IU (HTMT equal to 0.879) and PE (HTMT equal to 0.893). However, in both cases, they are less than 0.9, making the value suboptimal but not critical.

The results of the multigroup analysis in Table 3 indicate that the impact of PE is not significant in either of the two groups. Furthermore, the factor with the greatest impact is EE in both groups, with a path coefficient (β) of 0.457, a p-value less than 0.001 in group 1, and β equal to 0.370, and a p-value equal to 0.045 in group 2. It should also be noted that, while in the professionals' group, the second most impactful factor is SI (β is 0.366 with a p-value of 0.008), which has almost as much influence as EE does; in the policyholder group, TR is more relevant (β equal to 0.260 with a p-value of 0.01). For both samples, the coefficient of determination of the model clearly exceeds 25%, which ensures a statistical power above 99% in the analysis of the significance of the individual path coefficients.

Table 3 also displays the results of testing the moderation of the effects of PE, EE, SI, and TR by professional status in the insurance industry. In all the cases, the differences between the path coefficients obtained for groups 1 and 2 are not significant, as the p-values of the differences are greater than the critical significance level that ensures 80% power in Student's t test, leading to the rejection of the moderating effect.

We subsequently fit the model shown in Figure A1 to the complete sample. In addition to PE, EE, SI, and TR, being a professional in the insurance industry is included as an explanatory variable. However, there are no cross-moderating effects of PROF because we find that they are not significant.

Regarding the overall fit of the model, Table 4 shows that there are no critical collinearity issues, as the VIFs are below 5. However, for three latent variables, the VIFs are above 3. Figure A2 shows that the R^2 value is 68.8%, which is substantial, as it is closer to 75% than to 50% (Hair et al. 2022). It also shows that the predictive accuracy of the model, measured with Q^2, is large, since it is greater than 50% (Hair et al. 2019). Assuming a significance level of 5%, the power of both the tests on individual coefficients and the overall model achieves a power greater than 99%.

Table 4 shows the estimates of the path coefficients (β). Surprisingly, the path coefficient from PE to IU has a negative and nonsignificant sign, indicating that H1 is not supported. In contrast, in other cases, the hypothesis is sustained by the positive signs of the paths, which are always statistically

Table 3. Results of bootstrap multigroup analysis.

	Sample 1 ($N = 119$) $R^2 = 65.30\%$ ($f^2 = 1.88$)		Sample 2 ($N = 58$) $R^2 = 71.74\%$ ($f^2 = 2.54$)		Mediating effects		
	β(1)	p-value	β(2)	p-value	difference	p-value	α_{crit}
PE -> IU	0.027	.789	−0.100	.445	−0.127	.443	0.167
EE -> IU	0.457	<.001	0.370	.048	−0.087	.688	0.556
SI -> IU	0.173	.047	0.366	.008	0.193	.240	0.107
TR -> IU	0.260	.010	0.298	.058	0.038	.837	0.673

β(1) represents the path coefficient in Sample 1, and β(2) represents the path coefficient in the sample of professionals. The critical α is used to reject the null hypothesis in the case of $p < \alpha$, ensuring a power of 80%.

Table 4. Path coefficients for the inner model.

Relation	β	SD	VIF	p-value	Decision
PE-> IU	−0.019	0.071	4.820	0.788	Rejection
EE->IU	0.390	0.085	3.268	<0.001	Acceptance
SI-> IU	0.243	0.068	2.102	<0.001	Acceptance
TR-> IU	0.284	0.074	4.144	<0.001	Acceptance
PROF -> IU	0.285	0.092	1.139	0.002	Acceptance

significant. The path for the influence of EE on IU is 0.390. The SI has an estimated influence on the IU whose path is 0.243. The influence of TR on IU is quantified with a β of 0.284. Finally, being a professional in the industry has a positive influence on IU, with β equal to 0.285.

Regarding the predictive capability of the model, the CVPAT results, shown in Table 5, indicate that the model has predictive ability. It outperforms the so-called indicator average benchmark model but not the parsimonious linear model benchmark (Sharma et al. 2023).

5.2. Results of the necessary condition analysis

NCA is conducted separately for the two samples. We remove only one outlier from the university sample, specifically concerning the relationship between IU and TR. Thus, in group 1, while the relationship between IU and TR is analyzed with 118 observations, the NCA of PE, EE, and SI on IU is developed from 119 observations. In group 2, NCA is conducted with 58 observations.

The size effects are shown in Table 6. In group 1, all necessity effect sizes are significant since *d* is greater than 0.1 and the p-value is less than 0.1%. When observing the necessity effect sizes calculated through the CE-FDH, EE is strong, according to Dul (2016), since *d* reaches 0.415. In contrast, PE (*d* equal to 0.282), SI (*d* equal to 0.237), and TR (*d* equal to 0.278) are considered moderate. With the CR-FDH approach, we obtain slightly lower necessity effect sizes but with the same interpretation for all explanatory latent variables. The final scatter plots associated with this analysis are shown in Figure 1 of the APPENDIX.

Table 6 shows that the size effects in the group of insurance professionals are at least high (*d* greater than 0.3) and are always significant at levels less than 0.1%. Even for the SI and TR, when the estimation through the CE-FDR approach is considered, the values that can increase substantially *d* are greater than 0.5. The final scatter plots of NCA in the subsample of professionals are displayed in Figure 2 of the APPENDIX.

Table A4 of the APPENDIX shows the bottlenecks observed in group 1. The results from NCA performed with the CE-FDH approach indicate that for a high level of chatbot acceptance (from the 80th percentile onwards), the main bottleneck comes from EE (the 90th percentile is required to achieve the 80th percentile in IU, and the 97th percentile is required for full acceptance). In contrast, the less stringent requirement seems to come from the SI, as obtaining 80% of the IU requires only the 60th percentile of the SI. Similar results are obtained via the CR-FDH approach.

Table 5. Results of the cross-validated predictive ability test.

	Indicator average benchmark				Linear model benchmark			
	PLS loss	IA loss	ALD	p-value	PLS loss	LM loss	ALD	p-value
IU	2.394	4.716	−2.322	0	2.394	2.109	0.285	0.029
Overall	2.394	4.716	−2.322	0	2.394	2.109	0.285	0.029

ALD represents the average loss difference between the proposed model and the benchmark model.

Table 6. Necessity size effects of performance expectancy, effort expectancy, social influence and trust on the intention to use chatbots.

	Group 1, *N* = 119			Group 2, *N* = 58		
	CE-FDR	CR-FDR	Size effect	CE-FDR	CR-FDR	Size effect
PE	0.282	0.241	Medium	0.464	0.404	High
EE	0.415	0.392	High	0.414	0.352	High
SI	0.237	0.185	Medium	0.532	0.489	Very high/high
TR	0.278	0.226	Medium	0.540	0.449	Very high/high

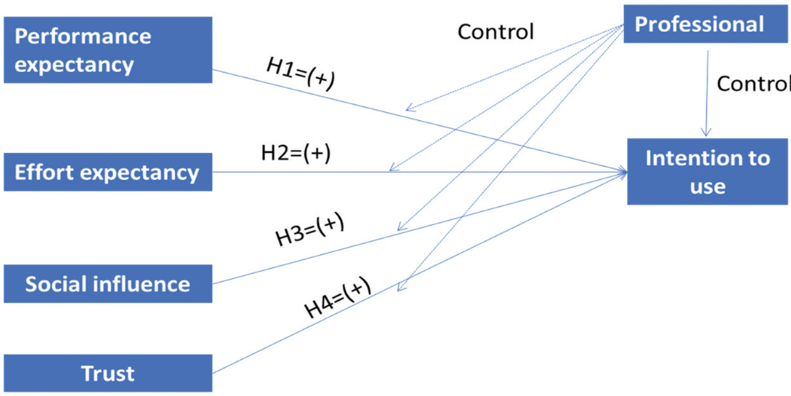

Figure 1. Theoretical background tested in this paper.

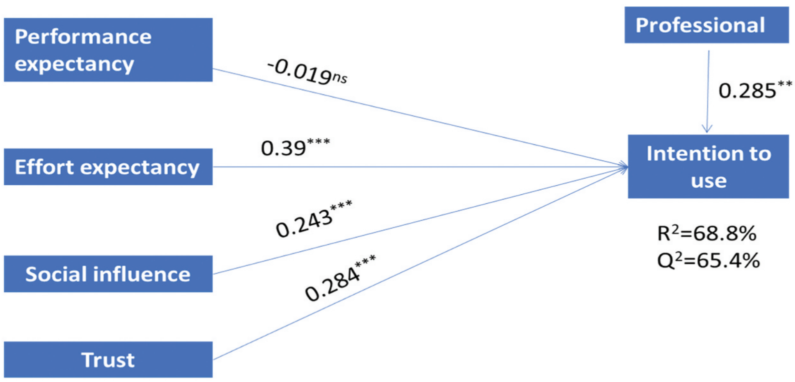

Figure 2. Results of fitting the model in figure 1. Note: With "***," "**" and "ns," we denote significance at 0.01%, at the 1% level and nonsignificance, respectively.

Table A5 of the APPENDIX summarizes the bottlenecks observed in the professionals' group. By analyzing the results of the CE-FDH approach, it can be observed that PE is already a bottleneck in achieving the 10th percentile of IU, and the rest of the latent variables become bottlenecks in reaching the 20th percentile. To achieve the greater levels of acceptance, starting from the 80th percentile of the IU, the 90th percentile is required for all input variables. The use of CR-FDH approach displays allows obtaining similar but not equal conclusions.

6. Discussion

6.1. General considerations

This study addresses three research questions (RQs). RQ1 evaluates the suitability of a modified UTAUT to explain the intention to use (IU) conversational bots for insurance procedures. IU is explained through performance expectancy (PE), effort expectancy (EE), social influence (SI), and trust (TR). In the second RQ, RQ2, we investigate which evaluated variables could be considered necessary conditions for chatbot acceptance. Finally, RQ3 inquiries about the existence of significant differences in acceptance depending on whether the perception comes from a regular customer or from a professional of the insurance industry.

The results from structural equation modeling analysis suggest that hypotheses H2, H3, and H4 are fully supported, whereas H5 is partially supported. However, NCA shows that all explanatory variables need to reach a certain level for acceptance to occur, with slight differences in the degree of necessity depending on whether the perception comes from professionals.

6.1.1. Discussion of research question 1

We can confirm that the fit of the proposed model is good, with an R^2 value close to 70%. The model demonstrates good predictive ability, as Q^2 is greater than 50%, and in the CVPAT, our model outperformed the benchmark, "indicator average" (Sharma et al. 2023).

PE does not significantly influence IU. Although this finding contradicts the mainstream reports in Table 1 and the systematic reviews by Gatzioufa and Saprikis (2022) and Gopinath and Kasilingam (2023), it is not exceptional. Similar result concerning the use of chatbots for customer support is reported by de Cicco et al. (2022), Kasilingam (2020), and Mostafa and Tamara Kasamani (2022). Zhu et al. (2023) outlines no significant link with the purchase intentions of online agencies for tourism activities, and Andrés-Sánchez and Gené-Albesa (2023) reports no significant influence in insurance settings.

We observe a significantly positive relationship between EE and acceptance. As Table 1 shows, this finding aligns with a considerable portion of the reviewed literature on chatbot acceptance and is also consistent with reports in banking and insurance settings (Alt, Vizeli, and Săplăcan 2021; Andrés-Sánchez, González-Vila, and Gené-Albesa 2023; Gebert-Persson et al. 2019; Hasan et al. 2023; Nguyen, Chiu, and Le 2021; PromTep et al. 2021; Rajaobelina et al. 2021). However, in the PLS-SEM estimation, EE has the greatest impact on IU, whereas a review by Gopinath and Kasilingam (2023) suggests that the significance of EE in IU chatbots is often secondary to PE, SI, or TR.

We check a significantly positive relationship between SI and IU. This is again consistent with the reviews conducted by Gatzioufa and Saprikis (2022) and Gopinath and Kasilingam (2023). The relevance of SI is demonstrated in the acceptance of robots for customer assistance (Araujo-Silva, Shojaei, and Barbosa 2023; Mostafa and Tamara Kasamani 2022) and in insurance and banking settings (Andrés-Sánchez, González-Vila, and Gené-Albesa 2023; Toh and Tay 2022).

We observe that the impact of TR on IU is significantly positive. This finding is consistent with mainstream findings about chatbot adoption reported in Table 1 and systematic reviews by Gatzioufa and Saprikis (2022) and Gopinath and Kasilingam (2023). This result aligns with studies on the management of existing insurance contracts by policyholders (Andrés-Sánchez and Gené-Albesa 2023; Gebert-Persson et al. 2019; Rodríguez-Cardona et al. 2021). Additionally, this result confirms the importance of TR in understanding customers' adoption and acceptance of insurance and fintech (Lappeman et al. 2023; Zarifis and Cheng 2022). Notably, we observe that this impact is lower than that of EE, reinforcing the findings of Gebert-Persson et al. (2019) that convenience-related variables have more influence on the acceptance of chatbots in claiming procedures than does TR.

6.1.2. Discussion of research question 2

For RQ2, we find that all the exogenous variables have significant necessity effect sizes in both subsamples. This conclusion applies even to PE, which, on the other hand, does not show statistical significance in the PLS-SEM analysis.

The estimated impact of the explanatory factors on IU in RQ1 should be interpreted from the perspective of sufficiency logic. However, at this stage, we do not determine whether input factors are bottlenecks (Dul 2016). This motivates us to inquire about RQ2 and conduct the NCA proposed in Dul (2016). We check that all the evaluated constructs have a significant necessity size effect.

Complementing PLS-SEM estimates with NCA allows for a deeper examination of the impact of exogenous variables on the IU. Thus, we find that EE, SI, and TR significantly influence IU from a statistical standpoint and that they also require a certain threshold for acceptance to occur. On the other hand, although PE is not significant in the PLS-SEM analysis of the IU, it is undoubtedly a latent variable that also influences acceptance, as it is a bottleneck for IU. Its absence inhibits the acceptance of chatbots even if the other latent variables are at their maximum. Additionally, there is a certain threshold in the perception of PE beyond which further improvement does not generate greater satisfaction with the service provided by the conversational chatbot.

6.1.3. Discussion on research question 3

We do not observe a significant impact of insurance professional status on the intensity of the influence of the explanatory variables on IU. On the other hand, we detect a direct significant influence. Thus, to some extent, the results align with those of Akbar et al. (2021), Andreou and Anyfantaki (2021), Ha, Şensoy, and Phung (2023), and Yoshino, Morgan, and Trinh (2020), who report a positive direct influence of financial literacy and the use of fintech, such as m-banking.

In contrast, our results align only partially with those of Ullah et al. (2022) in the field of m-banking and Zhu et al. (2023) in the field of chatbots for customer assistance, who suggest that the acceptance of a new information system may be affected by a user's competence in the field of use. However, while in these studies, such influence is via a mediation or moderation effect, this paper reports evidence of a direct influence on IU.

The differentiation of the whole sample into two groups allows us to observe clear nuances in how regular customers and professionals perceive the variables as necessary. On the one hand, professionals, with the exception of EE, tend to perceive greater necessity effect sizes than customers do. While the customers perceive effects fluctuating from moderate (PE, SI, and TR) to high (EE), the experts perceive effects ranging from high (PE and EE) to very high (SI and TR). Additionally, while in the university workers sample, the largest necessity effect sizes come from EE, in the professional sample, the largest effects come from TR and SI.

6.2. Theoretical and practical implications

The proposed chatbot acceptance model, provides a good fit and has adequate predictive ability to explain the drivers of chatbot technology acceptance in an insurance setting. The developed model explains nearly 70% of the variance in the intention to interact with chatbots, and also a good predictive ability.

An insightful explanation of the acceptance of a new technology requires not only the sign of the relationship between explanatory factors and the IU but also whether these explanatory factors are necessary conditions and whether the failure to reach a threshold may become a bottleneck in the implementation of a technology (Dul, Hauff, and Bouncken 2023; Kopplin 2023; Richter et al. 2020). We verify that for a certain degree of chatbot acceptance, simultaneous attainment of a specific level of PE, EE, SI, and TR is necessary. Thus, the statement that, "a more intense perception that chatbots are easy to use for making insurance claims increases intention to use them" should be nuanced by the fact that, "it is only true if certain levels of PE, SI, and TR are achieved."

The implementation of robotization systems in companies requires a positive attitude and willingness to adopt both by employees and customers. However, in most of the analyzed works, the acceptance of conversational robots is carried out from a specific point of view, either from the consumer's or the professionals' perspective. This work presents a comparative analysis of broad points of view that allows for a more complete overview. We observe the common aspects and differentiate nuances regarding how the tested exogenous factors are configured in sufficient and necessary conditions of IU.

The results obtained in this study also have implications for the insurance industry and can be useful for managers in decision-making regarding the implementation of chatbot systems. In general, there is reluctance to use chatbots to assist consumers (Camilleri and Troise 2023; Van Pinxteren, Pluymaekers, and Lemmink 2020), as observed in the insurance domain (Andrés-Sánchez and Gené-

Albesa 2024; Andrés-Sánchez, González-Vila, and Gené-Albesa 2023; PromTep et al. 2021; Rodríguez-Cardona et al. 2019).

The widespread adoption of chatbots necessitates a reduction in conversational failures and effective management during the error resolution process (Xing et al. 2022). When a user is redirected to a human operator following a bot error, it is crucial for the operator to be informed of the nature of the contact and seamlessly continue conversations with the bot (Vassilakopoulou et al. 2023). This ensures that the initial interaction is not perceived as a waste of time. This issue negatively impacts the convenience of interacting with bots to conduct procedures (Gebert-Persson et al. 2019). Given the significant influence of EE and its large necessity size effect on the IU, addressing this issue is particularly relevant.

All the proposed explanatory factors are necessary conditions; therefore, without a minimum level of PE, EE, SI, and TR, widespread acceptance of chatbot use in the insurer-insured relationship will not be perceived as desirable. The fact that the four analyzed factors can act as bottlenecks means that isolated improvements in certain factors will not increase the acceptance of chatbots in the insurance field. For example, a reduction in conversational failures and an improvement in usability, which enhance PE and EE, do not necessarily improve the acceptance of conversational bots if they are not accompanied by simultaneous improvements in social acceptance (e.g., reducing the perception that robots take jobs from human professionals without any compensation) and the perception that chatbots effectively allow insurers to better meet the needs of policyholders.

Even though the regression analysis does not indicate the significance of PE, it does not mean that it should not be an area for improvement by insurance firms. Like the other factors, it is a necessary variable to produce behavioral intention to make insurance procedures mediated with chatbots. The combined use of correlational and necessary condition analysis suggests that once a level of PE is deemed adequate, further increases in this construct do not enhance acceptance. This finding may suggest that respondents expect the development of chatbots to allow them to be reliable in resolving simple issues or those with little emotional component. However, improvements to conversational robots that enable them to handle more complex requirements or those with a high affective part may not be appreciated by consumers, who would likely prefer to be served by a human operator, in whom they would probably place more emotional TR.

Furthermore, the remaining variables (EE, SI and TR) also prove to be necessary conditions. Moreover, the results of the structural equation modeling indicate that they have a significantly positive statistical relationship with the IU. This finding suggests that a perception of the intensity of these variables above the threshold values does indeed generates greater behavioral intention. For example, with respect to EE, improvements in the bots' ability to understand human conversations above the acceptance threshold have an impact on their acceptance. Thus, even though the acceptability threshold for EE may not include recognizing voice inflections or the use of jargon, if a chatbot is able to understand these aspects of human communication and take them into account when responding, it would increase the EE and, therefore, its acceptance. Notably, in the PLS-SEM analysis, EE is revealed as the variable with the greatest impact on behavioral intention.

We can make similar considerations regarding the SI and TR. For example, in the case of organizational TR, suppose that the required threshold involves the perception that the insurer has considered, even if only secondarily, not worsening the service to the consumer. However, the perception that the motivation for implementing a chatbot system is more relevant to improving user service than optimizing a company's financial results could increase organizational TR, which would have positive repercussions on the IU.

6.3. Limitations of the study

The present research is distinctive in that it incorporates two different perspectives on the perception of chatbots in insurance consumer services: an ordinary policyholder and a policyholder who is also a professional in the industry. However, this study also must to recognize limitations. The first group of policyholders is drawn from the university environment. Using this group as representative of policyholders has several advantages but also some limitations. The collected opinions may be representative of specific social strata, such as the middle or upper-middle classes with university education, but not necessarily other segments.

We must also note that this study is conducted in Spain. These results may be extrapolated to countries with similar cultural backgrounds, such as Italy, but not necessarily to culturally distinct regions. Certainly, cultural, social, and economic differences between regions can influence chatbot adoption and user behavior (Alsharhan, Al-Emran, and Shaalan 2023).

The acceptance of the use of automated systems in consumer-related actions is context dependent. Attitudes toward the use of chatbots vary depending on whether consumer advice is needed or whether the interaction pertains to service questions (Euromonitor International Voice of the Consumer 2024). Different perceptions are also observed on the basis of whether consumption serves a utilitarian or hedonic purpose (Belanche, Casaló, and Flavián 2024).

7. Conclusions

One of the consequences of the digital transformation underway in the insurance industry since the mid-2010s is the implementation of chatbot technology to assist policyholders in managing their active policies. This study analyses the drivers and necessary conditions for their acceptance by employing a technological acceptance model based on the widely used UTAUT, including four explanatory variables: PE, EE, SI, and TR. The proposed model explains nearly 70% of the variance in the sample and demonstrates adequate predictive capability. PLS-SEM analysis reveals that professionals tend to evaluate chatbot services more favorably than regular users do. However, being professional does not significantly moderate the impact of PE, EE, SI, and TR. Additionally, while the variable with the strongest impact on IU is EE, SI and TR are also significant.

NCA provided a complementary perspective on how the analyzed drivers influence the formation of usage intention. All the explanatory variables are necessary conditions for acceptance. However, there are differences between how consumers and professionals perceive the existence of bottlenecks in the acceptance. Common policyholders display only a high necessity size effect on EE, whereas for the other variables, it is medium. In contrast, in the subsample of industry professionals, these effects vary from high to very high. Furthermore, while the greatest perceived necessity effect size by common policyholders comes from EE, for professionals, it originates from TR and SI.

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Availability of data

By request to the authors, by e-mail.

Ethical approval

The study adhered to the following principles: (1) all participants received comprehensive written information about the study and its procedure; (2) no data pertaining to the subjects' health, either directly or indirectly, were gathered; hence, the Declaration of Helsinki was not specifically mentioned during subject notification; (3) the confidentiality of the collected data was upheld at all stages; and (4) the research received a favorable evaluation from the Ethics Committee of the researchers' institution (CEIPSA-2022-PR-0005).

Informed consent

Permission was obtained from all the respondents.

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References

Acemoglu, D., and P. Restrepo. 2020. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128 (6):2188–244. doi: 10.1086/705716.

Ajzen, I. 2002. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology* 32 (4):665–83. doi: 10.1111/j.1559-1816.2002.tb00236.x.

Akbar, V. R., H. Zainal, A. Basriani, and R. Zainal. 2021. Moderate effect of financial literacy during the COVID-19 pandemic in technology acceptance model on the adoption of online banking services. *Budapest International Research and Critics Institute-Journal* 4:11904–15. doi: 10.33258/birci.v4i4.3253.

Alsharhan, A., M. Al-Emran, and K. Shaalan. 2023. Chatbot adoption: A multiperspective systematic review and future research agenda. *IEEE Transactions on Engineering Management* 71:10232–44. doi: 10.1109/TEM.2023.3298360.

Alt, M. A., I. Vizeli, and Z. Săplăcan. 2021. Banking with a chatbot-A study on technology acceptance. *Studia Universitatis Babes-Bolyai Oeconomica* 66 (1):13–35. doi: 10.2478/subboec-2021-0002.

Andreou, P. C., and S. Anyfantaki. 2021. Financial literacy and its influence on internet banking behavior. *European Management Journal* 39 (5):658–74. doi: 10.1016/j.emj.2020.12.001.

Andres-Sánchez, J. D., A.-A. Almahameed, M. Arias-Oliva, and J. Pelegrin-Borondo. 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. doi: 10.3390/math10224319.

Andrés-Sánchez, J. D., and J. Gené-Albesa. 2023. Explaining policyholders' chatbot acceptance with an unified technology acceptance and use of technology-based model. *Journal of Theoretical & Applied Electronic Commerce Research* 18 (3):1217–37. doi: 10.3390/jtaer18030062.

Andrés-Sánchez, J. D., and J. Gené-Albesa. 2024. Assessing attitude and behavioral intention toward chatbots in an insurance setting: A mixed method approach. *International Journal of Human-Computing Interaction* 40 (17):4918–33. doi: 10.1080/10447318.2023.2227833.

Andrés-Sánchez, J. D., L. González-Vila, and J. Gené-Albesa. 2023. "Evaluation of conversational robots in insurer-insured communication by professionals of the Spanish insurance industry using a technology acceptance model" [in Spanish]. *Anales del Instituto de Actuarios Españoles* 29:111–35. doi: 10.26360/2023_6.

Araujo-Silva, F., A. S. Shojaei, and B. Barbosa. 2023. Chatbot-based services: A study on customers' reuse intention. *Journal of Theoretical & Applied Electronic Commerce Research* 18 (1):457–74. doi: 10.3390/jtaer18010024.

Balan, C. 2023. Chatbots and voice assistants: Digital transformers of the company-customer interface—A systematic review of the business research literature. *Journal of Theoretical & Applied Electronic Commerce Research* 18 (2):995–1019. doi: 10.3390/jtaer18020051.

Balasubramanian, R., A. Libarikian, and D. McElhaney. 2018. *Insurance 2030—the impact of AI on the future of insurance*. McKinsey Company. https://www.mckinsey.com/industries/financial-services/our-insights/insurance-2030-the-impact-of-ai-on-the-future-of-insurance.

Balasubramnian, B., and C. Springer Sargent. 2020. Impact of inflated perceptions of financial literacy on financial decision making. *Journal of Economic Psychology* 80:102306. doi: 10.1016/j.joep.2020.102306.

Belanche, D., L. V. Casaló, and M. Flavián. 2024. Human versus virtual influences, a comparative study. *Journal of Business Research* 173:114493. doi: 10.1016/j.jbusres.2023.114493.

Bohnert, A., A. Fritzsche, and S. Gregor. 2019. Digital agendas in the insurance industry: The importance of comprehensive approaches†. *The Geneva Papers on Risk and Insurance-Issues and Practice* 44 (1):1–19. doi: 10.1057/s41288-018-0109-0.

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

Camilleri, M. A., and C. Troise. 2023. Live support by chatbots with artificial intelligence: A future research agenda. *Service Business* 17 (1):61–80. doi: 10.1007/s11628-022-00513-9.

Cezar, A. 2024. A province-level configurational analysis of fixed and mobile broadband adoption. *Journal of Organizational Computing and Electronic Commerce* 34 (1):27–45. doi: 10.1080/10919392.2024.2303942.

Chiu, C.-M., P. Jen-Hwa Hu, J. Shih-Chieh Hsu, and Y.-C. Lin. 2024. The facilitators and inhibitors of customer adoption of pure internet banking: Trust transfer and status quo bias. *Journal of Organizational Computing and Electronic Commerce* 34 (2):85–107. doi: 10.1080/10919392.2024.2315714.

Çiğdem, Ş., I. Meidute-Kavaliauskiene, and B. Yıldız. 2023. Industry 4.0 and industrial robots: A study from the perspective of manufacturing company employees. *Logistics* 7 (1):17–18. doi: 10.3390/logistics7010017.

Davis, F. D., R. P. Bagozzi, and P. R. Warshaw. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science* 35 (8):982–1003. doi: 10.1287/mnsc.35.8.982.

DeAndrade, I. M., and C. Tumelero. 2022. Increasing customer service efficiency through artificial intelligence chatbot. *Revista de Gestão* 29 (3):238–51. doi: 10.1108/REGE-07-2021-0120.

de Cicco, R., S. Iacobucci, A. Aquino, F. Romana, F. Alparone, and R. Palumbo. 2022. Understanding users' acceptance of chatbots: An extended TAM approach. In Chatbot research and design. CONVERSATIONS 2021. Lecture notes in computer science, 13171. Springer Cham. doi: 10.1007/978-3-030-94890-0_1.

Du, L., and B. Lv. 2024. Factors influencing students' acceptance and use generative artificial intelligence in elementary education: An expansion of the UTAUT model. *Education and Information Technologies*. doi: 10.1007/s10639-024-12835-4.

Dul, J. 2016. Necessary condition analysis (NCA) logic and methodology of "necessary but not sufficient" causality. *Organizational Research Methods* 19 (1):10–52. doi: 10.1177/1094428115584005.

Dul, J., S. Hauff, and R. B. Bouncken. 2023. Necessary condition analysis (NCA): Review of research topics and guidelines for good practice. *Review of Managerial Science* 17 (2):683–714. doi: 10.1007/s11846-023-00628-x.

Dul, J., E. van der Laan, and R. Kuik. 2020. A statistical significance test for necessary condition analysis. *Organizational Research Methods* 23 (2):385–95. doi: 10.1177/1094428118795272.

Eckert, C., C. Neunsinger, and K. Osterrieder. 2022. Managing customer satisfaction: Digital applications for insurance companies. *The Geneva Papers on Risk and Insurance-Issues and Practice* 47 (3):569–602. doi: 10.1057/s41288-021-00257-z.

Euromonitor International Voice of the Consumer. 2024. *Ask AI*. https://lp.euromonitor.com/white-paper/2024-global-consumer-trends/ask-ai.

Faul, F., E. Erdfelder, A. Buchner, and A.-G. Lang. 2009. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods* 41:1149–60. doi: 10.3758/BRM.41.4.1149.

Fishbein, M., and I. Ajzen. 1975. *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading: Addison-Wesley.

Fornell, C., and D. F. Larcker. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18 (1):39–50. doi: 10.1177/002224378101800104 .

Fotheringham, D., and M. A. Wiles. 2023. The effect of implementing chatbot customer service on stock returns: An event study analysis. *Journal of Academy Marketing Science* 51 (4):802–22. doi: 10.1007/s11747-022-00841-2.

Gansser Oliver, A., and C. S. Reich. 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. doi: 10.1016/j.techsoc.2021.101535.

Gatzioufa, P., and V. Saprikis. 2022. A literature review on users' behavioral intention toward chatbots' adoption. *Applied Computing & Informatics*. doi: 10.1108/ACI-01-2022-0021.

Gebert-Persson, S., M. Gidhagen, J. E. Sallis, and H. Lundberg. 2019. Online insurance claims: When more than trust matters. *International Journal of Bank Marketing* 37 (2):579–94. doi: 10.1108/IJBM-02-2018-0024.

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

Gkinko, L., and A. Elbanna. 2022. Hope, tolerance and empathy: Employees' emotions when using an ai-enabled chatbot in a digitalized workplace. *Information Technology & People* 35 (6):1714–43. doi: 10.1108/ITP-04-2021-0328.

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

Gopinath, K., and D. Kasilingam. 2023. Forthcoming. "Antecedents of intention to use chatbots in service encounters: A meta-analytic review. *International Journal of Consumer Studies* 47 (6):2367–95. doi: 10.1111/ijcs.12933.

Guiso, L. 2021. Trust and insurance. *Geneva Papers on Risk and Insurance: Issues and Practice* 46 (4):509–12. doi: 10.1057/s41288-021-00241-7.

Ha, D., A. Şensoy, and A. Phung. 2023. Empowering mobile money users: The role of financial literacy and trust in Vietnam. *Borsa Istanbul Review* 23 (6):1367–79. doi: 10.1016/j.bir.2023.10.009.

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

Hair, J. F., Jr., G. Thomas, M. Hult, C. M. Ringle, and M. Marko Sarstedt. 2022. *A primer on partial least squares structural equation modeling (PLS-SEM)*. 3rd ed. Thousand Oaks: Sage.

Hair, J., C. L. Hollingsworth, A. B. Randolph, and A. Yee Loong Chong. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems* 117 (3):442–58. doi: 10.1108/IMDS-04-2016-0130.

Harvey, W. S., and T. Morris. 2012. A labor of love? Understanding the influence of corporate reputation in the labor market. In *The oxford handbook of corporate reputation*, ed. T. G. Pollock, and M. L. Earnett, 341–60. Oxford: Oxford University Press.

Hasan, S., E. R. Godhuli, S. Rahman, and A. Al Mamun. 2023. The adoption of conversational assistants in the banking industry: Is the perceived risk a moderator? *Heliyon Elsevier* 9 (9):e20220. doi: 10.1016/j.heliyon.2023.e20220.

Henseler, J., C. M. Ringle, and M. Sarstedt. 2016. Testing measurement invariance of composites using. *International Marketing Review* 33 (3):405–31. doi: 10.1108/IMR-09-2014-0304.

Huang, S., C.-J. Lee, and S.-C. Lee. 2021. Toward a unified theory of customer continuance model for financial technology chatbots. *Sensors (Switzerland)* 21 (17):5687. doi: 10.3390/s21175687.

Ivanov, S., M. Kuyumdzhiev, and C. Webster. 2020. Automation fears: Drivers and solutions. *Technology in Society* 63:101431. doi: 10.1016/j.techsoc.2020.101431.

Jain, S., A. Mukhopadhyay, and S. Jain. 2023. Can cyber risk of health care firms be insured? A multinomial logistic regression model. *Journal of Organizational Computing and Electronic Commerce* 33 (1–2):41–69. doi: 10.1080/10919392.2023.2244386.

Janssen, A., L. Grützner, and M. H. Breitner. 2021. Why do Chatbots fail? A critical success factors analysis. *ICIS 2021 Proceedings*, 6. https://aisel.aisnet.org/icis2021/hci_robot/hci_robot/6.

Jenneboer, L., C. Herrando, and E. Constantinides. 2022. The impact of chatbots on customer loyalty: A systematic literature review. *Journal of Theoretical & Applied Electronic Commerce Research* 17 (1):212–29. doi: 10.3390/jtaer17010011.

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

Kim, Y., H. Kim, R. Murphy, S. Lee, and C. R. Ahn. 2022. Delegation or collaboration: Understanding different construction stakeholders' perceptions of robotization. *Journal of Management in Engineering* 38. 1. doi: 10.1061/(ASCE)ME.1943-5479.0000994.

Koetter, F., M. Blohm, J. Drawehn, M. Kochanowski, J. Goetzer, D. Graziotin, and S. Wagner. 2019. Conversational agents for insurance companies: From theory to practice. In *Agents and artificial intelligence. ICAART 2019. Lecture notes in computer science*, J. van den Herik, A. Rocha, and L. Steels, vol. 11978, 338–62. Berlin: Springer-Verlag. doi: 10.1007/978-3-030-37494-5_17.

Kopplin, C. S. 2023. Chatbots in the workplace: A technology acceptance study applying uses and gratifications in coworking spaces. *Journal of Organizational Computing and Electronic Commerce* 32 (3–4):232–57. doi: 10.1080/10919392.2023.2215666.

Kovacs, O. 2018. The dark corners of industry 4.0-grounding economic governance 2.0. *Technology in Society* 55:140–45. doi: 10.1016/j.techsoc.2018.07.009.

Lappeman, J., S. Marlie, T. Johnson, and S. Poggenpoel. 2023. Trust and digital privacy: Willingness to disclose personal information to banking chatbot services. *Journal of Financial Services Marketing* 28 (2):337–57. doi: 10.1057/s41264-022-00154-z.

Latorre Guillem, M. Á. 2022. Insurance brokers' behaviour: The effect of policy collection on management decisions. *International Humanities Review* 13 (3):1–10. doi: 10.37467/revhuman.v11.4035.

Lee, C., and R. Hallak. 2018. "Investigating the moderating role of education on a structural model of restaurant performance using multigroup PLS-SEM analysis2. *Journal of Business Research* 88:298–305. doi: 10.1016/j.jbusres.2017.12.004.

Leesakul, N., A.-M. Oostveen, I. Eimontaite, M. L. Wilson, and R. Hyde. 2022. Workplace 4.0: Exploring the implications of technology adoption in digital manufacturing on a sustainable workforce. *Sustainability* 14 (6):3311. doi: 10.3390/su14063311.

Leung, S. O. 2011. A comparison of psychometric properties and normality in 4-, 5-, 6-, and 11-point likert scales. *Journal of Social Service Research* 37 (4):412–21. doi: 10.1080/01488376.2011.580697.

Mahlow, N., and J. Wagner. 2016. Evolution of strategic levers in insurance claims management: An industry survey. *Risk Management and Insurance Review* 19 (2):197–223. doi: 10.1111/rmir.12061.

Meher, J. R., R. K. Mishra, R. R. Panigrahi, G. Patel, and L. K. Jena. 2023. Does learning culture enhance organizational performance? A serial mediator with knowledge management and organizational intelligence. *Knowledge Management Research & Practice* 1–12. doi: 10.1080/14778238.2023.2278729.

Modliński, A., P. Fortuna, and B. Rożnowski. 2023. Human-machine trans roles conflict in the organization: How sensitive are customers to intelligent robots replacing the human workforce? *International Journal of Consumer Studies* 47 (1):100–17. doi: 10.1111/ijcs.12811.

Mogaji, E., J. Balakrishnan, A. C. Nwoba, and N. P. Nguyen. 2021. Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics* 65:101711. doi: 10.1016/j.tele.2021.101711.

Morgan, R. M., and S. D. Hunt. 1994. The commitment-trust theory of relationship marketing. *Journal of Marketing* 58 (3):20–38. doi: 10.1177/002224299405800302.

Mostafa, R. B., and T. Tamara Kasamani. 2022. Antecedents and consequences of chatbot initial trust. *European Journal of Marketing* 56 (6):1748–71. doi: 10.1108/EJM-02-2020-0084.

Nguyen, D. M., Y.-T. H. Chiu, and H. D. Le. 2021. Determinants of continuance intention toward banks' chatbot services in Vietnam: A necessity for sustainable development. *Sustainability* 13 (14):7625. doi: 10.3390/su13147625.

Nicoletti, B. 2021. *Insurance 4.0: Benefits and challenges of digital transformation*. Cham, Switzerland: Palgrave Macmillan. doi: 10.1007/978-3-030-58426-9_2.

Ong, W. L. K., V. Gauhar, D. Castellani, and J. Y. C. Teoh. 2023. Tips and pitfalls in using social media platforms for survey dissemination. *Société Internationale d'Urologie Journal* 4 (2):118–24. doi: 10.48083/PERG3137.

Ostrowska, M. 2021. Does new technology put an end to policyholder risk declaration? The impact of digitalization on insurance relationships. *The Geneva Papers on Risk and Insurance-Issues and Practice* 46:573–92. doi: 10.1057/s41288-020-00191-6.

Paluch, S., S. Tuzovic, H. F. Holz, A. Kies, and M. Jörling. 2022. My colleague is a robot"-exploring frontline employees' willingness to work with collaborative service robots. *Journal of Service Management* 33 (2):363–88. doi: 10.1108/JOSM-11-2020-0406.

Panigrahi, R. R., D. Jena, J. Ranjan Meher, and A. K. Shrivastava. 2023. Assessing the impact of supply chain agility on operational performances-a PLS-SEM approach. *Measuring Business Excellence* 27 (1):1–24. doi: 10.1108/MBE-06-2021-0073.

Phan, T. C., L. Minh, T. T. Tao Nguyen, and H. Tu Phan. 2024. Digital financial literacy and mobile banking behavior: Empirical evidence from an emerging market. *11th International Conference on Emerging Challenges: Smart Business and Digital Economy 2023 (ICECH 2023)*, Ninh Binh, Vietnam, 164–78, Atlantis Press. https://doi.org/10.2991/978-94-6463-348-1_15.

Pooser, D. M., and M. J. Browne. 2018. The effects of customer satisfaction on company profitability: Evidence from the property and casualty insurance industry. *Risk Management and Insurance Review* 21 (2):289–308. doi: 10.1111/rmir.12105.

PromTep, S., M. Arcand, L. Rajaobelina, and L. Ricard. 2021. From what is promised to what is experienced with intelligent bots. *Advances Information and Communication: Proceedings of the 2021 Future of Information and Communication Conference (FICC)*, vol. 1, 560–65, Berlin: Springer-Verlag. https://doi.org/10.1007/978-3-030-73100-7_40.

Rajaobelina, L., S. PromTep, M. Manon Arcand, and L. Ricard. 2021. Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing* 38 (12):2339–56. doi: 10.1002/mar.21548.

Richter, N. F., S. Schubring, S. Hauff, C. M. Ringle, and M. Sarstedt. 2020. When predictors of outcomes are necessary: Guidelines for the combined use of PLS-SEM and NCA. *Industrial Management & Data Systems* 120 (12):2243–67. doi: 10.1108/IMDS-11-2019-0638.

Riikkinen, M., H. Saarijärvi, P. Sarlin, and I. Lähteenmäki. 2018. Using artificial intelligence to create value in insurance. *International Journal of Bank Marketing* 36 (6):1145–68. doi: 10.1108/IJBM-01-2017-0015.

Rodríguez-Cardona, D., A. Janssen, N. Guhr, M. H. Breitner, and J. Milde. 2021. A matter of trust? Examination of chatbot usage in insurance business. *Proceedings of the 54th Hawaii International Conference on System Sciences*, Cancun, Mexico, 556–65. https://doi.org/10.24251/HICSS.2021.068.

Rodríguez-Cardona, D., O. Werth, S. Schönborn, and M. H. Breitner. 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.

Saihi, A., M. Ben-Daya, and M. Hariga. 2024. The moderating role of technology proficiency and academic discipline in ai-chatbot adoption within higher education: Insights from a PLS-SEM analysis. *Education and Information Technologies*. doi: 10.1007/s10639-024-13023-0.

Shaikh, I. A. K., S. Khan, and S. Faisal. 2023. Determinants affecting customer intention to use chatbots in the banking sector. 19 (4):257–68. doi: 10.21511/im.19(4).2023.21.

Sharma, P. N., B. D. Liengaard, J. F. Hair, M. Sarstedt, and C. M. Ringle. 2023. Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing* 57 (6):1662–77. doi: 10.1108/EJM-08-2020-0636.

Shmueli, G., S. Ray, J. Manuel Velasquez Estrada, and S. Babu Chatla. 2016. The elephant in the room: Predictive performance of PLS models. *Journal of Business Research* 69 (10):4552–64. doi: 10.1016/J.JBUSRES.2016.03.049.

Singh, A., R. Karthik, and S. Shrey. 2019. Processes in the banking and insurance industries. In *Building an enterprise chatbot*, ed. A. Singh, K. Ramasubramanian, and S. Shivam, 1–18. Berkeley, CA: Apress. doi: 10.1007/978-1-4842-5034-1_1.

Sitar-Taut, D.-A., and D. Mican. 2021. Mobile learning acceptance and use in higher education during social distancing circumstances: An expansion and customization of UTAUT2. *Online Information Review* 45 (5):1000–19. doi: 10.1108/OIR-01-2021-0017.

Sitar-Taut, D.-A., D. Mican, L. Frömbling, and M. Sarstedt. 2023. Digital socialligators? Social media-induced perceived support during the transition to the COVID-19 lockdown. *Social Science Computer Review* 41 (3):748–67. doi: 10.1177/08944393211065872.

Sonntag, M., J. Mehmann, and F. Teuteberg. 2023. Deriving trust-supporting design knowledge for ai-based chatbots in customer service: A use case from the automotive industry. *Journal of Organizational Computing and Electronic Commerce* 33 (3–4):178–210. doi: 10.1080/10919392.2023.2276631.

Stoeckli, E., C. Dremel, and F. Uebernickel. 2018. Exploring characteristics and transformational capabilities of InsurTech innovations to understand insurance value creation in a digital world. *Electronic Markets* 28 (3):287–305. doi: 10.1007/s12525-018-0304-7.

Toh, T.-J., and L.-Y. Tay. 2022. Banking chatbots: A study on technology acceptance among millennials in Malaysia. *Journal of Logistics, Informatics and Service Science* 9 (3):1–15. doi: 10.33168/LISS.2022.0301.

Ullah, S., U. Safdaf Kiani, B. Raza, and A. Mustafa. 2022. Consumers' intention to adopt m-payment/m-banking: The role of their financial skills and digital literacy. *Frontiers in Psychology* 13:873708. doi: 10.3389/fpsyg.2022.873708.

Van Pinxteren, M. M. E., M. Pluymaekers, and J. G. A. M. Lemmink. 2020. Human-like communication in conversational agents: A literature review and research agenda. *Journal of Service Management* 31:203–25. ht tps://1 0.1108/JOSM-06-2019-0175.

Vassilakopoulou, P., A. Haug, L. Martin Salvesen, and I. O. Pappas. 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. doi: 10.1080/0960085X.2022.2096490.

Venkatesh, V. 2022. Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research* 108 (1–2):641–52. doi: 10.1007/s10479-020-03918-9.

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

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27 (3):425–78. doi: 10.2307/30036540.

Wang, W.-T., and C.-C. Lu. 2014. Determinants of success for online insurance web sites: The contributions from system characteristics, product complexity, and trust. *Journal of Organizational Computing and Electronic Commerce* 24 (1):1–35. doi: 10.1080/10919392.2014.866501.

Wong, K.-K.-K. 2016. Mediation analysis, categorical moderation analysis, and higher-order constructs modeling in structural equation modeling (PLS-SEM): A B2B example using SmartPLS. *Marketing Bulletin* 26 (1):1–22. doi: 10.13140/RG.2.1.1643.0562.

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

Yoshino, N., P. J. Morgan, and L. Q. Trinh. 2020. Financial literacy and fintech adoption in Japan (no. 1095). *ADBI Working Paper Series*. https://www.adb.org/publications/financial-literacy-fintech-adoption-japan.

Zarifis, A., and X. Cheng. 2022. A model of trust in fintech and trust in Insurtech: How artificial intelligence and the context influence it. *Journal of Behavioural and Experimental Finance* 36:100739. doi: 10.1016/j.jbef.2022.100739.

Zhou, T., Y. Lu, and B. Wang. 2010. Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior* 26 (4):760–67. doi: 10.1016/j.chb.2010.01.013.

Zhu, Y., R. Zhang, Y. Zou, and D. Jin. 2023. Investigating customers' responses to artificial intelligence chatbots in online travel agencies: The moderating role of product familiarity. *Journal of Hospitality & Tourism Technology* 14 (2):208–24. doi: 10.1108/JHTT-02-2022-0041.

Appendix

Table A1. Items of the scales used in the study.

Latent variable	Items
Intention to use (IU) (Gebert-Persson et al. 2019; Toh and Tay 2022; Venkatesh et al. 2003)	IU1. Employing a chatbot to make procedures into regard of my contracts is OK. IU2. I will use chatbots to communicate with my insurance provider. IU3. I will opt for insurance procedures with bots.
Performance expectancy (PE) (Gebert-Persson et al. 2019; Toh and Tay 2022; Venkatesh et al. 2003)	PE1. Procedures linked to my contracts are easier with chatbots. PE2. Chatbots allow solving quicker procedure resolution in my contracts. PE3. By using chatbots implementing procedures does not suppose an effort.
Effort expectancy (EE) (Gebert-Persson et al. 2019; Toh and Tay 2022; Venkatesh et al. 2003)	EE1. Using chatbots to get in touch with the insurance company is easy. EE2. Processing claims with conversational bots is transparent and straightforward. EE3. The assistance by chatbots in administering insurance contracts is accessible and less prone to errors.
Social influence (SI) (Toh and Tay 2022, Andrés-Sánchez and Gené-Albesa 2023; Venkatesh et al. 2003)	SI1. The people who are important to me believe that chatbots make effortless managing insurance policies. SI2. Persons whose opinions I appreciate feel that chatbots are a step forward to manage policies
Trust (TR) (de Cicco et al. 2022; Gebert-Persson et al. 2019; Morgan and Hunt 1994)	TR1. Chatbots provide a secure and trustable service to manage policies. TR2. Interacting with the insurance company via chatbots takes into account the interests of policyholders.

Table A2. Internal consistency of the scales.

	C-α	CR	AVE
Intention to use	0.864	0.917	0.787
Performance expectancy	0.920	0.949	0.862
Effort expectancy	0.903	0.939	0.837
Social influence	0.877	0.942	0.890
Trust	0.779	0.898	0.815

Table A3. Discriminant validity matrix.

	IU	PE	EE	SI	TR	PROF
IU	**0.887**	*0.763*	*0.842*	*0.776*	*0.879*	*0.285*
PE	0.684	**0.929**	*0.838*	*0.771*	*0.893*	*0.125*
EE	0.747	0.766	**0.915**	*0.714*	*0.841*	*0.076*
SI	0.678	0.692	0.639	**0.943**	*0.76*	*0.153*
TR	0.739	0.774	0.727	0.634	**0.903**	0.*268*
PROF	0.264	0.123	0.073	0.145	0.241	**1.000**

The square root of the average variance extracted appears on the principal diagonal. Below the main diagonal, Pearson's correlations are found, and the HTMT ratios are above the principal diagonal.

Table A4. Bottlenecks for CE-FDH and CR-FDH in the group of policyholders.

	CE-FDH				CR-FDH			
IU	PE	EE	SI	TR	PE	EE	SI	TR
0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
20	0	0	0	0	0	33.05	0	0
30	36.44	51.70	0	0	0.00	42.37	0.00	0
40	36.44	61.86	0	0	40.68	53.39	0.00	37.29
50	50.00	73.73	42.37	50.00	48.31	71.19	38.98	47.46
60	79.66	90.68	60.17	83.05	59.32	79.66	51.70	61.86
70	79.66	93.22	60.17	83.05	68.64	88.14	60.17	73.73
80	79.66	93.22	60.17	83.05	77.12	92.37	74.58	80.51
90	79.66	96.61	83.05	88.14	85.59	97.46	79.66	86.44
100	79.66	96.61	83.05	88.14	92.37	99.15	82.20	89.83

Quantities are presented as percentages

Table A5. Bottlenecks for CE-FDH and CR-FDH in the group of professionals.

	CE-FDH				CR-FDH			
IU	PE	EE	SI	TR	PE	EE	SI	TR
0	0	0	0	0	0	0	0	0
10	31.03	0	0	0	0	0	0	0
20	31.03	20.69	27.59	37.93	0	0	32.76	24.14
30	34.48	20.69	56.90	37.93	34.48	20.69	50.00	34.48
40	34.48	20.69	60.35	37.93	50.00	34.48	60.35	50.00
50	50.00	50.00	75.86	63.79	55.17	50.00	70.69	60.35
60	62.07	91.38	91.38	86.21	68.97	68.97	75.86	67.24
70	89.66	93.10	91.38	91.38	77.59	91.38	84.48	82.76
80	89.66	93.10	91.38	91.38	87.93	93.10	94.83	86.21
90	96.55	96.55	91.38	91.38	89.66	96.55	98.28	98.28
100	96.55	96.55	91.38	91.38	96.55	96.55	98.28	98.28

Quantities are presented as percentages

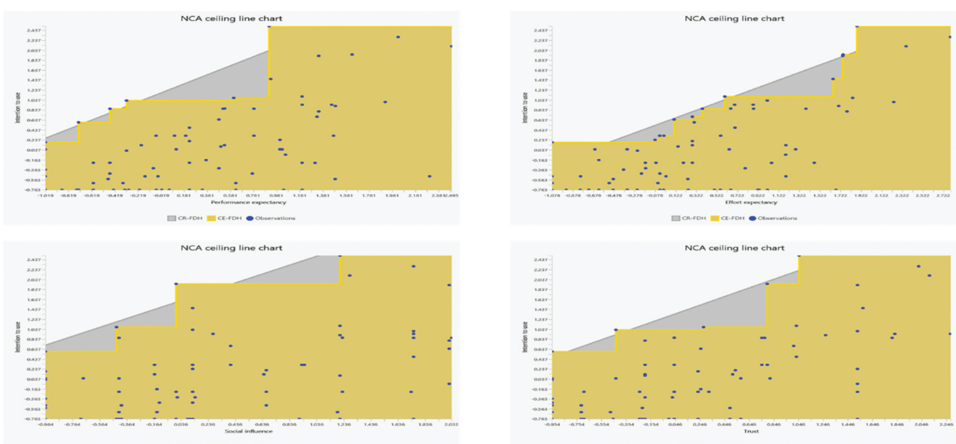

Figure A1. Scatter plots of CE-FDH and CR-FDH for the links between intention to use and performance expectancy, effort expectancy, social influence and trust in the group of policyholders.
Note: From top to bottom and from left to right, we display the scatter plots of IU with PE, EE, SI, and TR.

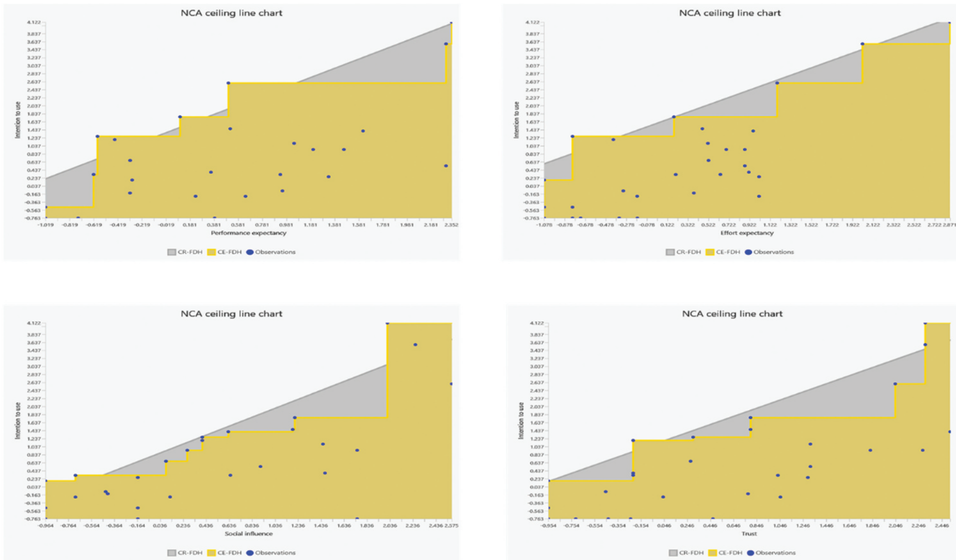

Figure A2. Scatter plots of CE-FDH and CR-FDH for the links between intention to use and performance expectancy, effort expectancy, social influence and trust in the sample of professionals.
Note: From top to bottom and from left to right, we display the scatter plots of IU with PE, EE, SI, and TR.