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Research Article

Modeling Nonusers' Behavioral Intention towards Mobile Chatbot Adoption: An Extension of the UTAUT2 Model with Mobile Service Quality Determinants

Gatzioufa Paraskevi[1], **Vaggelis Saprikis**[1], **and Giorgos Avlogiaris**[2]

[1]*Department of Management Science and Technology, University of Western Macedonia, Kozani, Greece*
[2]*Department of Statistics and Insurance Science, University of Western Macedonia, Grevena, Greece*

Correspondence should be addressed to Gatzioufa Paraskevi; gatzioyfa@gmail.com

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Artificial intelligence agents (chatbots), which are programs to communicate with users primarily in customer service contexts, are an alternative interaction channel supporting businesses in the digital environment and vital components in customer service. The present empirical paper, which is aimed at identifying and discussing the factors motivating nonusers to adopt the specific technology in mobile contexts, proposes a comprehensive conceptual model, which combines the UTAUT 2 behavioral theory with variables of mobile service quality contexts, such as information quality, privacy concerns, interface, and equipment, as well as trust and mobility factors. Data analysis, based on the partial least squares structural equation modeling (PLS-SEM) statistical method, revealed that performance expectancy, facilitating factors, hedonic motivation, mobility, trust, and service quality positively affect nonusers' behavioral intention to adopt chatbots. In addition, equipment, interface, and trust have a significant impact on users' trust in the context of mobile chatbots. Personal data privacy issues also have a negative effect on trust, in contrast to effort expectancy, which positively affects performance expectancy. As mobile service quality factors have not been investigated before in the context of chatbots, the findings of the present research are expected to provide useful insights both to academia and the business industry.

1. Introduction

Artificial intelligence (AI) agents (voice or text), typical of the specific trend, offer individuals the opportunity of direct communication with businesses at any time and day. More specifically, AI agents integrated in marketing strategy have become an efficient tool for customer service, saving money, time, and human resources. They have also offered various benefits ranging from understanding and responding to customer requests [1, 2] to consistent, agile, and effortless friendly service delivery [3]. By simultaneously responding to various requests and a huge number of queries, chatbot use has increased service efficiency and quality [4]. Overall, conversational voice or text marketing implemented via AI agents is a critical communication and interaction channel, which activates consumers, provides necessary personalized information about products or services, and prompts purchases [5]. Business technology giants, such as Amazon, Google, IBM, and Apple, have already integrated AI agents to increase revenues. Amazon's recommendations and Google's predictive search are examples of AI adoption technologies not widely known to many, despite their frequent use [6]. Notably, the global chatbot market size is forecast to grow from 190.8 million USD in 2016 to 1.25 billion in 2025, with the highest level of acceptance in customer service and customer relationship management [7].

In addition, as the use of mobile phones (smartphones), which have become an integral part of daily life, especially for young people, has considerably increased, the investigation of AI adoption factors has become more imperative than before, prompting businesses to foster consumer attraction at any time and place [8]. It is worth noting that since

2010, communication carried out via smartphones and messenger apps has offered online businesses significant opportunities to increase revenues and promote interaction with customers [9].

In this framework, the investigation of the adoption factors and use of AI agents as an alternative communication channel has been variously researched in healthcare [10, 11], financial services [12, 13], social media [14], the tourism industry [15, 16], customer service [3, 17–21], mobile commerce [22], the business industry [23, 24], insurance [25, 26], and education [27, 28].

The present research is an exploratory approach to the factors motivating nonusers' adoption of AI agents on smartphones. More specifically, it is aimed at contributing to understanding the factors affecting chatbot nonusers to adopt the specific leading innovation technology. It is worth noting that in popular online academic databases, such as Science Direct, Emerald, Taylor and Francis, Elsevier, Research Gate, Wiley, IEEE Explore, ACN Digital Libraries, and Google Scholar, the factors affecting the adoption and use of AI agents among nonusers were investigated only in 16 empirical surveys over the last 6 years. As mobile service quality variables have been examined in a mobile context but have not yet been tested in the context of chatbots, the present research provides valuable information on the specific topic and is the first to explore variables, such as information quality, privacy concerns, interface, and equipment, in terms of their effect on the preadopters' intention to adopt and use AI agents.

In detail, the present empirical research is organized as follows: the first section discusses the increasing use of AI agents and investigates the relevant factors affecting nonusers' behavioral intention to adopt chatbots, by employing the UTAUT 2 theory developed by Venkatesh et al. [29], in combination with variables of mobile service quality, namely, information quality, interface, privacy concerns, and equipment, accompanied with trust and mobility variables to explore nonusers' behavioral intention to adopt chatbots. The second part includes a theoretical overview of the extant literature, and the third part is a discussion of the theoretical model followed by the formulation of the relevant research hypotheses. The fourth and fifth parts describe the research methodology and analysis, respectively, whereas the sixth part includes a detailed discussion of the outcomes. Finally, the last part includes a discussion of the research conclusions as well as the theoretical and practical implications, the potential limitations, and suggestions for future research.

2. Theoretical Background

In recent years, there has been growing interest in text and text-to-speech artificial intelligence (AI) agents to improve customer service and offer benefits to modern businesses. AI agents have been variously defined as follows: (a) "software agents that facilitate automated conversation through natural language processing" ([30], p.1); (b) "natural language processing systems acting as a virtual conversational agent mimicking human interactions" ([31], p.4).

They have been incorporated in business digital marketing strategies and perceived as an essential additional communication and interaction channel [32], answering to customer requests and questions on a 24-hour basis and, thus, saving human resources and money [18]. Hlee et al. [33] also hold that, in customer service, users' behavior towards adopting AI agents is significantly affected by both emotional and functional interaction features.

Notably, in modern times, the significance of AI agents has been enhanced by the easy and convenient use of smartphones for all online interactions and communication with businesses [34] despite the privacy and security issues, which have been generally raised, as various mobile apps request disclosure of users' personal data [35]. AI agents, used as an innovative and effective communication channel in online environments, have offered great benefits in various fields. Melian-Gonzalez et al. [36] emphasized the significance of AI agents in the tourism industry, whereas Fryer et al. [27] and Quah and Chua [37] in education settings and banking, respectively. In addition, the use of AI agents was mostly highlighted in the healthcare industry [10, 38, 39], the social media [14], customer service [3, 18], and online shopping using mobile phones [22].

The present research is aimed at contributing to the ongoing research investigating the factors affecting the behavioral intention to adopt and use AI agents in customer service, which have already been researched in previous studies focused on relevant AI agent areas and applications, with special emphasis on chatbot use in the business industry. In detail, customer service, a most common and popular research topic [17, 18, 20, 40], was examined in qualitative or quantitative surveys and, based on theoretical behavioral models, was explored in terms of the factors driving users and/or nonusers to interaction and customer service via AI agents. In addition, the contribution and innovative approach of the present research involves the integration and examination of factors related to mobile service quality. These factors, namely, quality of information, privacy issues, interface, and mobile network equipment, examined for the first time in the chatbot intention literature, promote a deeper understanding of mobile service quality variables, which, combined with UTAUT 2 factors, as well as mobility and trust, will offer scholars and practitioners a profound insight into further research and improvement of mobile customer service.

3. Conceptual Model and Research Hypotheses

The proposed conceptual model (Figure 1), based on the unified theory of acceptance and use of technology 2 (UTAUT 2) by Venkatesh et al. [29] and including additional variables, is aimed at investigating the factors affecting behavioral intention towards chatbot adoption. In detail, it comprises three groups of variables: (i) UTAUT 2 variables, (ii) mobile service quality variables, and (iii) trust and mobility variables.

The UTAUT 2 approach, which was preferred to other behavioral models, is the newest, well-known, and widely applied behavioral paradigm, based on theories, such as the technology acceptance model (TAM), the theory of reasoned

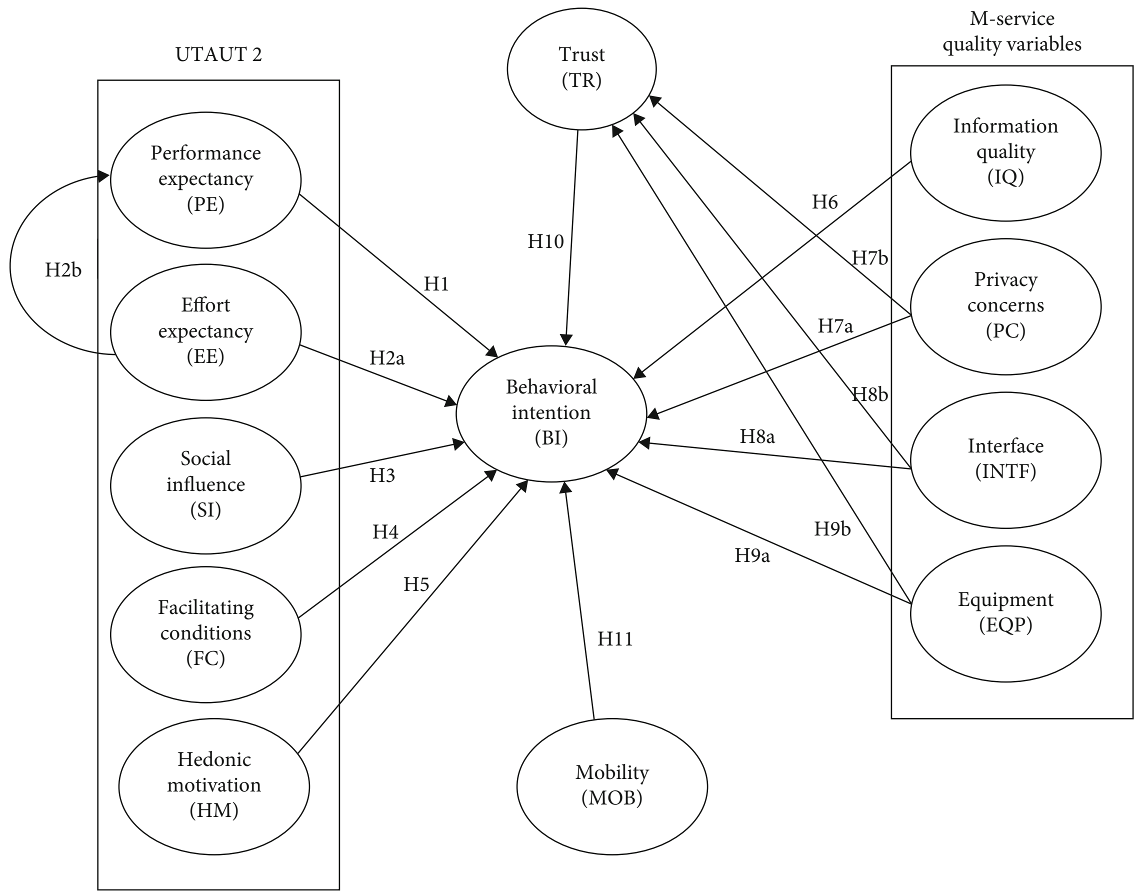


Figure 1: Proposed conceptual model.

action (TRA), the theory of planned behavior (TPB), and the diffusion of innovations (DOI) theory. According to Diekmann and Theuvsen [41], UTAUT 2 is a model suggested for technology nonusers. The specific model is suitable to investigate the factors motivating nonusers' chatbot adoption in mobile contexts as it is considered a better explanatory intention model than other relative paradigms by providing a more comprehensive approach to new technology acceptance [42].

The proposed model was also based on relevant research carried out by Lu et al. [43] and Stiakakis et al. [44], which focus on the quality of mobile contexts and the underlying determinants, given that nowadays smartphones are used as major and fundamental tools for online transactions. Stiakakis et al. [44] discussed the impact of mobile-related dimensions by grouping them into 3 major categories comprising mobile service (m-service) quality. In addition, the determinants of the present research drew on Akter et al. [45] and Ozer et al. [46], who discussed the factors affecting service quality.

Finally, trust and mobility factors were also added to the proposed conceptual model to offer a much more comprehensive approach to the examined topic. Similarly, various other researchers, such as Oliveira's et al. [47], have already utilized the same approach to their empirical studies.

Figure 1 provides a detailed overview of all variables examined in the proposed model.

3.1. UTAUT 2 Variables

3.1.1. Behavioral Intention. Intention to use has been found to have a very significant effect on individuals' attitudes towards new technologies [29, 48, 49]. Behavioral intention is defined as the "degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" ([50], p. 214). Human behavior is affected by individuals' intention to develop a specific attitude [51]. Accordingly, the proposed conceptual model employed behavioral intention based on Venkatesh et al. [29], who describe it as "a person's subjective probability that he/she will adopt and use chatbots through his/her smartphone."

3.1.2. Performance Expectancy. Performance expectancy is "the degree to which using a technology will provide benefits to consumers in performing certain activities" ([29], p.159). In the literature of the behavioral intention to adopt and use chatbots, the specific variable has a significant effect in combination with other predictors of the UTAUT and UTAUT 2 theory. The positive effect of the variable on the intention to use was demonstrated by a number of researchers, such as Kuberkar and Singhal [52], Balakrishnan et al. [17], and Melian-Gonzalez et al. [36]. Based on the assumption that nonusers are expected to use chatbots when they are confident that they will have a positive effect, the following hypothesis is formulated:

H1: performance expectancy (PE) positively affects behavioral intention to adopt chatbots.

3.1.3. Effort Expectancy. Effort expectancy is "the degree of ease associated with consumers' use of technology" ([29], p. 159). Thus, if consumers consider a specific technology easy to use, they perceive it as more useful and valuable [53]. The specific variable, commonly examined in a large number of studies investigating chatbots, was found to have a positive effect on the intention to use [17, 52, 54]. The effect of effort expectancy on performance expectancy was also found in the social (s)-commerce and m-commerce literature [55–57]. Thus, the following hypotheses are made:

H2a: effort expectancy positively (EE) affects behavioral intention to adopt chatbots.

H2b: effort expectancy positively (EE) affects Performance expectancy (PE).

3.1.4. Social Influence. Social influence is the "degree to which individuals perceive that important others believe they should use a new system" ([49], p. 451). Familiar groups, such as family and relatives, friends, colleagues, and fellow students, who influence others to adopt a technology, play a major role in the intention to adopt a new technology [58]. Overall, various studies have confirmed the impact of the specific variable on the behavioral intention to use chatbots [59, 60]. Thus, the following hypothesis is formulated:

H3: social influence positively (SI) affects behavioral intention to adopt chatbots.

3.1.5. Facilitating Conditions. Facilitating conditions are defined as the "degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" ([49], p. 453). This implies that when individuals are competent users of smartphones and applications, they are capable of interacting with chatbots. Kuberkar and Singhal [52] adopted UTAUT 2 and suggested that facilitating conditions positively influence the intention of nonusers to use chatbots. Thus, the following hypothesis was made:

H4: facilitating conditions (FC) positively affects behavioral intention to adopt chatbots.

3.1.6. Hedonic Motivation. Hedonic motivation involves individuals' willingness to engage in a new technology that is expected to induce pleasant experiences, as suggested by Venkatesh et al. [29]. In the case of mobile contexts, the specific variable was found to determine customers' decision to use e-banking [61]. Research on the intention to use and adopt chatbots demonstrated the value of hedonic motivation [36, 60, 62]. Thus, the relevant hypothesis is formulated as follows:

H5: hedonic motivation (HM) positively affects behavioral intention to adopt chatbots.

3.2. Mobile Service Quality Variables. Mobile service quality has been variously investigated [43, 45, 63–65]. The present research, which explores mobile service quality variables, was based on Stiakakis and Georgiadis [64] and Lu et al. [43], who distinguish three categories of mobile service quality. Two of these categories, namely, interaction quality and environment quality, were congruent with the present research purpose, whereas the third category, outcome quality, was rejected as it addresses chatbot users. The variables of the specific two categories, which were assumed to best fit the purpose and type of the research carried out, generated meaningful and consistent results.

3.2.1. Information Quality. Interaction quality includes, among others, the quality of information offered to consumers by m-service providers [43]. E-commerce research demonstrated the significance of information during interaction with companies on service websites [66, 67]. According to Stiakakis and Georgiadis [64], information quality in mobile service environments, which is a sub-dimension of interaction quality, implies accurate and up-to-date information delivery to customers. In addition, the significance of mobile service information was emphasized in other surveys, such as Vlachos and Vrechopoulos [65], Tan and Chou [68], and Chae et al. [69], who suggested that accurate and up-to-date information provided by chatbots on smartphones positively affects intention to use. Therefore, it is hypothesized that

H6: information quality (IQ) positively affects behavioral intention to adopt chatbots.

3.2.2. Privacy Concerns. Privacy concerns have been defined as the users' anxiety of managing personal information online [70]. In online contexts, in which users tend to disclose personal information and data, privacy concerns involve poor management or abuse of personal information [71]. In the context of e-commerce and online customer service, users share sensitive personal and financial data when making purchases or searches [72]. Research on the intention to use chatbots identified privacy concerns as negatively affecting intention [73, 74]. In addition, privacy concerns negatively affect user trust [26]. Thus, the following hypotheses were made:

H7a: privacy concerns (PC) negatively affect behavioral intention to adopt chatbots.

H7b: privacy concerns (PC) negatively affect trust (*T*R).

3.2.3. Interface. Context quality, a dimension which positively affects service quality, was widely researched in the literature for both overall service quality [67, 75–77] and mobile service quality [43, 69]. Tarasewich et al. [78] demonstrated that smartphone design was critical to task completion. Interface is a context variable related to navigation, aesthetics, design, music, and display of objects in mobile devices [43, 64, 78]. Zhao et al. [79] highlighted the significance of interface in understanding and evaluating overall mobile quality service. Research demonstrated that interface affects mobile user trust [80, 81], since well-designed interfaces allow for interactivity and easy navigation and promote trust [81, 82], thus resulting in mobile chatbot adoption and trust. Thus, the following hypotheses are formulated:

H8a: interface (INTF) positively affects behavioral intention to adopt chatbots.

H8b: interface (INTF) positively affects trust (TR).

3.2.4. Equipment. Equipment involves two dimensions, wireless telecommunication delivered by service providers and smartphones [43, 64], which contribute to the assessment of mobile service quality. As users must have access to stable mobile networks and stable connections, as well as to fast, uninterrupted responses to requests [69], mobile telecom service providers' equipment and customers' devices are critical to enabling users to adopt and trust chatbots. Thus, the following hypotheses are formulated:

H9a: equipment (EQP) positively affects behavioral intention to adopt chatbots.

H9b: equipment (EQP) positively affects trust (TR).

3.3. Additional Variables

3.3.1. Trust. Trust involves being willing to have confidence in others, in mediated or interactive processes [83], and implies integrity, reliance, and beneficial influence. Trust becomes more significant in settings of high uncertainty, such as digital environments [84]. Corritore et al. [85] suggested that the major determinants of trust in digital environments are perceptions of reliability, ease of use, and risk of interaction. There have also been several empirical studies investigating the positive effect of trust on the behavioral intention to use chatbots [26, 52]. The above considerations contribute to the following hypothesis:

H10: trust (TR) positively affects behavioral intention to adopt chatbots.

3.3.2. Mobility. A critical dimension of service quality on mobile phones is mobility, namely, access to information, communication, and services from any place using mobile devices and wireless networks beyond the time limit [86, 87]. In the relevant literature, mobility was demonstrated to affect intention to use. The impact of mobility has been studied in the context of mobile payment services [88, 89] and mobile shopping [88, 90]. More specifically, it was argued that mobility affects customers' behavioral intention to use smartphones. Moreover, Almahri et al. [54] assumed that there is a positive and significant effect of mobility on the intention to use m-commerce. Thus, the following hypothesis is made:

H11: mobility (MOB) positively affects the intention to adopt chatbots.

4. Research Methodology

4.1. Variable Operationalization. Based on an extensive review of the relevant literature, the research variables were measured on a five-point Likert scale (Table 1). In detail, 4 items were used to measure interface and effort expectancy; 3 items for performance expectancy, social influence, facilitating conditions, behavioral intention, trust, mobility, information quality, and privacy concerns; and 2 items for equipment and hedonic motivation.

4.2. Data Collection and Sampling. Data collection was based on an e-questionnaire to be answered via Google Forms from September to October 2022. The e-questionnaire was first drafted in English, and afterwards, it was translated into Greek. It was also followed by a pilot study on a sample of 20 people to discover possible failures or inaccuracies and test item and variable validity and reliability.

Data collection was based on convenience sampling and focused on students (undergraduate, postgraduate, and doctoral candidates) of 3 Greek public universities, who were chatbot nonusers. University students, often used in primary research sampling, enable making valuable findings [103–106]. Notably, students have been widely used in research investigating the intention to use chatbots [28] as they are representative for their strong tendency to adopt new technologies [107]. Overall, young people tend to use mobile phone applications and other modern technologies more frequently to interact with businesses [108].

The research was organized by sending a hyperlink to 1,280 students on the university's asynchronous e-class student platform from September to October 2022. The e-questionnaire was accompanied by a short text explaining the purpose of the research. During the first month of the research, 285 individuals answered the questionnaire, and after a follow-up notification, the total number of responses was 411. To test for nonresponse bias between the first and second-round response groups, the Kolmogorov-Smirnov test was applied. The sample distributions did not exhibit any statistical difference; thus, there was no nonresponse bias [57]. Therefore, the final sample of the present empirical study includes 411 answers, accounting for 32.1% of the response rate, which is acceptable [109].

As regards the participants' demographic information, Table 2 demonstrates that the majority of the respondents are female (57.2%), whereas male respondents are 42.8%. In terms of age, 45% of them are 18-21 years old, and 57.9% are aged 22-25.

4.3. Data Analysis. To investigate the conceptual research model and its hypotheses (Figure 1), the structural equation modeling (SEM) using maximum likelihood estimation was carried out. SEM combines the attributes of a measurement model and a structural model; thus, it is considered a proper method for examining the underlying hypothesized structural relations between multiple independent and dependent variables, using estimated regression parameters. It is primarily applied when the scope of the study is the validation of an established theory [110]. Its statistical objective is to estimate model parameters that minimize the differences between the observed sample covariance matrix and the covariance matrix estimated after the revised theoretical model is confirmed [111]. IBM SPSS Amos 24 version software was used to apply SEM.

Regarding measurement, the model enables the evaluation of the latent variables reflecting constructs of interest. Remarkably, the dimensions for all twelve (12) constructs were first measured via confirmatory factor analysis (CFA). In addition, they were also measured for reliability and convergent validity purposes. Based on the extant literature, convergent validity uses two basic recommended standards, among others, for evaluating the measuring model: (1) all indicator factor loading values should be more than 0.4 [111]; (2) composite reliability (CR) should exceed 0.6

Table 1: Operational definitions of research variables.

Research variables	Operational definition	Sources
Performance expectancy (PE)	PE1: by using chatbots, I will have more opportunities to find solutions to issues I am interested in. PE2: using chatbots will make me more competent. PE3: generally, I think that I will get benefits from chatbot use.	Venkatesh et al. [29]
Effort expectancy (EE)	EE1: I believe learning how to use chatbots will be easy. EE2: I believe that chatbot use will be simple and easy to understand. EE3: I believe that it is easy for me to become skillful at using chatbots. EE4: generally, I expect that chatbots are easy to use.	Venkatesh et al. [29]
Social influence (SI)	SI1: I believe that people who influence my behavior use chatbots. SI2: I believe that the people who are important to me use chatbots. SI3: I think that the people whose opinion I value use chatbots.	Venkatesh et al. [29]
Facilitating conditions (FC)	FC1: I think my smartphone can be used for interaction with chatbots. FC2: I believe I know how to interact with chatbots. FC3: I think that I can interact with chatbots on my smartphone.	Venkatesh et al. [29]
Hedonic motivation (HM)	HM1: I think using chatbots will be fun. HM2: I think using chatbots will be enjoyable.	Venkatesh et al. [29]
Information quality (IQ)	IQ1: I believe that I will find chatbot information clear. IQ2: I believe that I will find chatbot information sufficient. IQ3: I believe that chatbot information will help me with decision-making.	Chae [69]; Su et al. [91]; Cheng et al. [4]; Lu et al. [43]; Stiakakis et al. [44]
Privacy concerns (PC)	PC1: I am worried that the information I will disclose to chatbots may be used for a different (abusive) purpose. PC2: I am worried that providers (companies) will use chatbot information improperly. PC3: I am worried about malware when I will disclose information to chatbots.	Shaw et al. [92]; De Cosmo et al. [93]; Xu et al. [94]
Interface (INTF)	INTF1: I feel that chatbot interface will make a positive impression on me. INTF2: I feel that chatbot interface will serve its purpose. INTF3: I feel that chatbot interface will be aesthetically pleasant. INTF4: I feel that chatbot graphical interface will be uniform.	Lu et al. [43]; Chae et al. [69]
Equipment (EQP)	EQP1: I believe that my mobile network offers stable connection. EQP2: I believe that my mobile network connectivity will be stable.	Lu et al. [43]; Chae et al. [69]
Trust (TR)	TR1: I think chatbots will be reliable. TR2: I think I will trust chatbot use. TR3: Overall, I will trust chatbots.	Ashforth [95]; Shaw [96]; Cheng and Jiang [97]; Coopamootoo [73]
Mobility (MOB)	MOB1: I believe I will be able to interact with chatbots from anywhere. MOB2: I believe I will be able to interact with chatbots any time. MOB3: I believe I will be able to interact with chatbot anyplace.	Schierz et al. [88]; Leong et al. [98]; Ali and Arshad [99]; Mohammadi [100]; Wilman and Sardjono [101]; Kim et al. [90]

Table 1: Continued.

Research variables	Operational definition	Sources
Behavioral intention (BI)	BI1: I am going to use chatbots in the future. BI2: I am confident that I will use chatbots in the future. BI3: I will probably use chatbots in the future.	Venkatesh et al. [29]; Davis [53]; Belanger and Carter [102]

Table 2: Sample demographics.

Demographic information	Respondents
Sex	
Male	176
Female	235
University rank	
Undergraduate students	256
MSc students	126
PhD students	29
Age	
18-21	185
22-25	53
26-29	20
>30	153

[112], when the specific measurement scale is applied. Finally, factor analysis was applied utilizing principal component analysis (PCA) and orthogonal rotation (VARIMAX). The factor analysis was carried out to identify the usual method bias and check whether data variance can be principally related to a single factor [113].

Subsequently, when the constructs reached the prerequisite measurement standards, the relationships between the constructs were calculated. This establishes the structural model, which is applied to test the strength and direction of the relationships among the theoretical constructs. To estimate the overall goodness-of-fit model, a combination of measures should be applied. In detail, the chi-square/df ratio should be lower than 5 [114]; the goodness-of-fit index (GFI), the comparative fit index (CFI), the normed fit index (NFI), the incremental fit index (IFI), and the Tucker-Lewis index (TLI) values should exceed 0.90 [115], and the root mean square error of approximation (RMSEA) should be lower than 0.08 [116].

5. Results

This section discusses the results of the SEM procedure used to investigate the hypothesized variable relationships, thus providing an examination of the measurement and structural models. The confirmatory factor analysis (CFA) model involves 36 items that represent the 12 underlying constructs (Table 3). More specifically, factor analysis that uses PCA and VARIMAX was employed to examine the validity of the variables to group measurement items into latent factors and calculate factor loadings. To investigate the suitability of the data for factor analysis, however, various measures were applied as well. In detail, Bartlett's tests of sphericity ($\text{chi}-\text{square} = 11151.364$, $p < 0.001$) proved that the correlation matrices had significant correlations among the variables. The Kaiser-Meyer-Olkin (KMO) result was -0.888, and the measurement of sampling adequacy (MSA) ranged from 0.723 to 0.949, indicating that both values were acceptable. The MSA values were all higher than 0.50 [117]. The results showed the suitability of factor analysis. The values of all factor loading indicators ranged from 0.469 to 0.903 (Table 3), exceeding the threshold [117, 118], whereas composite reliability (CR) also exceeded 0.6 [112], ranging from 0.672 to 0.930 (Table 3). Consequently, convergent validity was satisfied. Moreover, to investigate the reliability of the questionnaire items, Cronbach's alpha test was used. The results (Table 3), ranging from 0.731 to 0.954, exceeded the threshold of 0.7 [117]. Finally, the twelve (12) latent factors can interpret 81.780% of the variance of the measurement items (Table 3).

As regards the structural model, the results (Table 4) demonstrate a good model fit. The model's overall goodness-of-fit was assessed using a combination of measures. The data fit the model well, as suggested by these measures, the recommended values of which are shown in Table 4. Thus, an adequately fitted model should have a chi-square/df ratio less than 5 [114]; the comparative fit index (CFI) and incremental fit index (IFI) values should be greater than 0.90 [115], and a root mean square error of approximation (RMSEA) should be less than 0.08 [116]. The structural model, illustrated in Figure 2, was suitable (Table 4) as the basic model indicators are satisfactory according to the recommended values in the literature. Moreover, the strength and direction of the relationships between the theoretical constructs of the structural model were investigated. The full model results are demonstrated in Table 5 and Figure 2, which demonstrate the path diagram with the occurring standardized regression coefficients, presenting the direction and magnitude of relationships among variables. The structural model reveals that 10 out of the 15 hypotheses were confirmed (Table 5), and five, namely, effort expectancy, social influence, privacy concerns, interface, and equipment (H2a, H3, H7a, H8a, and H9a) were rejected. On the contrary, as anticipated, performance expectancy has a positive impact on behavioral intention (H1; $\beta = 0.25$, $p < 0.001$), and effort expectancy has a positive impact on performance expectancy (H2b; $\beta = 0.17$, $p < 0.01$). In addition, facilitating conditions and hedonic motivation have a positive impact on behavioral intention (H4; $\beta = 0.19$, $p < 0.001$ and H5; $\beta = 0.32$, $p < 0.001$, respectively). Information quality has a positive impact on behavioral intention (H6; $\beta = 0.23$, $p < 0.1$), and privacy

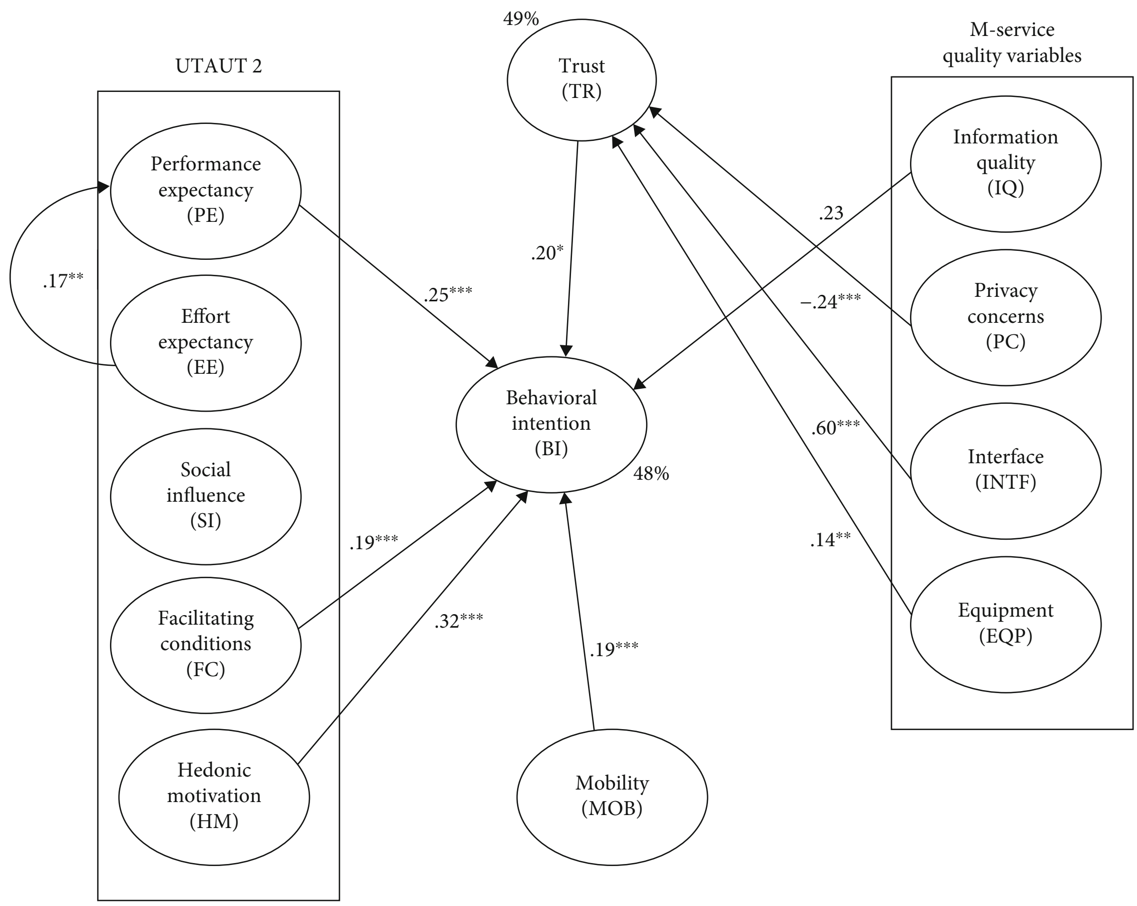
Table 3: Factor loadings, convergent validity, and reliability.

	Item	Loading	Mean	SD	CR	Cronbach's α
Performance expectancy (PE)	PE1	.682	3.22	.948	.786	.871
	PE2	.776	3.19	1.009		
	PE3	.767	2.99	.973		
Effort expectancy (EE)	EE1	.469	3.96	.993	.872	.915
	EE2	.893	3.88	1.082		
	EE3	.868	3.91	1.009		
	EE4	.891	3.90	1.069		
Social influence (SI)	SI1	.892	2.75	1.157	.930	.954
	SI2	.914	2.68	1.195		
	SI3	.902	2.74	1.189		
Facilitating conditions (FC)	FC1	.885	3.73	1.109	.891	.902
	FC2	.816	3.60	1.212		
	FC3	.865	3.79	1.167		
Hedonic motivation (HM)	HM1	.653	3.15	.939	.672	.731
	HM2	.768	3.07	.980		
Mobility (MOB)	MOB1	.823	3.58	1.077	.861	.821
	MOB2	.801	3.87	1.073		
	MOB3	.839	3.81	1.080		
Trust (TR)	TR1	.555	3.08	1.014	.735	.812
	TR2	.753	3.35	.984		
	TR3	.762	3.23	1.041		
Equipment (EQ)	EQ1	.902	3.66	1.070	.862	.786
	EQ2	.837	3.55	.990		
Interface (INTF)	*INT*F1	.494	3.49	.909	.768	.779
	INTF2	.643	3.52	.903		
	INTF3	.815	3.53	.867		
	INTF4	.721	3.60	.887		
Privacy concerns (PC)	PC1	.901	3.37	1.172	.927	.896
	PC2	.903	3.25	1.143		
	PC3	.895	3.14	1.186		
Information quality (IQ)	IQ1	.723	3.61	.881	.782	.804
	IQ2	.776	3.29	.953		
	IQ3	.713	3.20	.989		
Behavioral intention (BI)	BI1	.646	3.46	1.078	.762	.863
	BI2	.780	3.42	1.019		
	BI3	.725	3.57	.974		
Total variance explained = 81.780%						

Table 4: Evaluation of model goodness-of-fit.

Measures	Recommended value	Structural model
χ^2/df	≤5.00	3.006
CFI	≥0.90	0.904
IFI	≥0.90	0.905
RMSEA	≤0.08	0.07

concerns have a negative impact on trust (H7b; $\beta = -24$, $p < 0.001$). Moreover, interface has a strong positive impact on trust (H8b; $\beta = 0.60$, $p < 0.001$), and equipment has a positive impact on trust (H9b; $\beta = 0.14$, $p < 0.01$). Finally, trust has a positive impact on behavioral intention (H10; $\beta = 0.20$, $p < 0.05$), and mobility demonstrates to have a positive impact on behavioral intention (H11; $\beta = 0.19$, $p < 0.001$). Overall, 49% of the variance in behavioral



$p < .1$. $^{*}p < .05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

Figure 2: Validated conceptual model.

Table 5: Structural equation model results and standardized coefficients.

Factor	Performance expectancy	Trust	Behavioral intention
Effort expectancy	0.17**		NS
Social influence			NS
Facilitating conditions			0.19***
Hedonic motivation			0.32***
Mobility			0.19***
Equipment		0.14**	NS
Interface		0.60***	NS
Privacy concerns		-0.24***	NS
Information quality			.23
Performance expectancy			0.25***
Trust			0.20*
R^2	2.9%	49%	48%

intention is explained by all involved factors ($R^2 = 0.49$, Table 5).

6. Discussion

Data analysis demonstrated that most variables of the UTAUT 2 theory were established, except for effort expectancy and social influence, which proved to be nonstatistically significant for behavioral intention to adopt chatbots (H2a and H3). In the extant literature, effort expectancy was found not to affect the intention to use chatbots [14, 24, 119]. Students, as early adopters of new and AI technologies, find it easy to use chatbots, especially on smartphones. However, despite its significance as regards new technology acceptance, ease of use is not critical to developing attitudes [120]. Effort expectancy involves specific learning curve technologies, which do not include chatbots; their use is not considered difficult, as it implies simply typing questions on mobile applications [119]. However, effort expectancy is found to have a positive effect on performance expectancy, which, thus supports H2b hypothesis of the model.

Social influence did not affect the adoption of chatbots (H3) in customer service, which was also demonstrated by Balakrishnan et al. [17]. This finding is supported by the theory of Gupta et al. [121], who argue that a powerful information system (IS) is based on social influence rather than cognitive response. The use of online chats is a daily routine for most people who visit a website or social networking platforms using a mobile application. This implies familiarity and, thus, no impact on the intention to use chatbots.

Regarding the effect of performance expectancy on the behavioral intention to use chatbots (H1), it was demonstrated that it had a positive impact on the behavioral intention to adopt and use chatbots [17, 52, 54, 59, 60, 119]. AI agents enable users to increase productivity, enjoy better and more effective service delivery, and receive responses to requests saving time and effort.

Facilitating conditions (smartphone device and knowing how to use applications) positively affect the intention to use chatbots (H4). The present research endorses this positive relationship in line with similar research carried out on chatbots, such as Mogaji et al. [59], Kuberkar and Singhal [52], Trapero et al. [60], Balakrishnan et al. [17], and Sitthipon et al. [11]. Notably, Sitthipon et al. [11] highlighted that facilitating factors have the highest predictive power in the behavioral intention to use health chatbots.

In addition, hedonic motivation was found to have a positive impact on the intention to adopt chatbots (H5). When users "talk" to chatbots, they tend to ask questions they would not often ask a human personal assistant. Thus, for a pleasant user experience, chatbots frequently include entertaining elements or games in their programming environments [122]. The specific assumption is also corroborated by De Cicco et al. [123], Nyagadza et al. [13], Kasillingam [124], Selamat and Windasari [24], and Melian-Gonzalez et al. [36].

Trust positively affects the intention to use chatbots (H10). The specific hypothesis was substantiated in the proposed research model and is congruent with similar research carried out by Cardona et al. [26], Coopamooto et al. [73], Kassilingam [124], Kuberkar and Singhal [52], Murtarelli et al. [40], and Pillai and Sivathanu [125]. Trust is a key factor affecting the intention to use AI technologies, such as chatbots [126].

As regards mobility, it was found that mobility positively affects the behavioral intention to adopt chatbots, thus establishing hypothesis H11 of the proposed conceptual model. Notably, in the digital environment, mobility is particularly valued and is an integral component of chatbots. In several studies, mobility is a variable with a positive effect on the behavioral intention to adopt and use in m-commerce, on account of the easy access to information and communication via wireless networks, beyond time and place limits [98, 101, 127].

Finally, the impact of mobile-related variables on the intention to use chatbots was also established. To our knowledge, it is the first time the examined variables have been investigated in mobile service contexts in the framework of AI agents' adoption intention.

In addition, concerns about the privacy of information and personal data in online transactions have been variously raised in the relevant literature [71]. Surprisingly, H7a hypothesis about the negative effect of privacy issues was not established in the survey, thus demonstrating that young people are not concerned with privacy violation caused by chatbot use. However, the research highlighted that the negative effect of privacy issues in terms of user trust was established (H7b). As demonstrated, when potential users do not trust this new technology, the intention to adopt is negatively affected. The specific considerations are emphasized in several surveys on chatbot use [20, 26, 73, 74, 93]. When users are uncertain of information privacy in their interaction with chatbots, there is no intention to adopt and use.

Notably, information quality integrated in mobile interaction quality involves offering accurate and correct information to users [68]. Interaction quality also includes information quality and implies the degree of effective communication of m-service providers with customers to enable problem-solving [63]. Information quality was found to significantly affect customer satisfaction and loyalty to a company [69], which was also established in the specific research (*H*6).

In terms of equipment, namely, the devices used for communication with AI agents and mobile network stability, as well as in terms of response speed, the relevant research demonstrated that these are significant components of mobile service perceived quality [43, 64, 69, 77], which affect trust [91]. Equipment was not found to positively affect the intention to use chatbots (H9a). As telecommunication network systems and bandwidth have considerably improved, users do not assume that this is a problem. As they can always have stable connections, fast speed, and network stability, chatbot adoption is not affected, unless it is examined in terms of trust (H9b). When users trust new technology, equipment has a positive effect on adoption.

With regard to interface and its effect on mobile communication quality, it was demonstrated that smartphone user interface (UI), good navigation, and unbroken display affect perceived service quality and task completion as well as user trust [43, 64, 78, 91]. In the present research, interface did not positively affect the intention to use, which rejects hypothesis H8a. However, it affects intention indirectly, when combined with trust, which, thus, confirms hypothesis H8b. Nowadays, as interface quality is enhanced and there are no significant differences among chatbot applications, users are more familiar with all interface types. Moreover, chatbot developers follow high-quality UI standards to offer the best user experience.

6.1. Theoretical Implications. The present research contributes to the extant literature of investigating the behavioral intention to adopt and use AI agents on smartphones. To our knowledge, no previous research has integrated mobile service quality variables in behavioral variables, as those suggested by UTAUT 2, and examined them in terms of their effect on the intention to adopt chatbots and trust. Despite the fact that several model variables (mobility, trust, and privacy concerns) were examined in the context of using chatbots, no research has investigated the combination of all the specific variables in mobile contexts. The positive effect of effort expectancy on performance expectancy in mobile chatbot contexts is a fundamental finding of the present research.

In addition, a small number of studies have been conducted only on nonusers of AI agents. The majority of studies involve AI users or comparison of users and nonusers. Notably, it is the first time that relationships between mobile phone service quality and intention to adopt have been investigated and established in a sample of nonusers of chatbots. Thus, the specific theoretical model can be employed to research other topics, such as m-commerce and s-commerce.

6.2. Managerial and Practical Implications. The findings of the present research corroborate the theoretical background and provide valuable managerial insights into the relevance of chatbots in the business industry. Businesses, realizing the importance of fast and immediate service delivery, have adopted chatbots as communication tools, which contribute to enhancing customer satisfaction and loyalty and create a competitive advantage to achieve a higher market share. By understanding the advantages deriving from the adoption and use of chatbots, enterprises are aimed at service quality. The growing use of smartphones, especially among young people, requires that marketing policies make efforts to improve mobile features and information, such as interface design and information quality. Information privacy and perceived trust in interaction with chatbots are also significant, as they promote intention to use, on which managers should focus. As customers provide information to enterprises via conversational commerce, chatbots are used as tools for gathering and using personal information to the benefit of enterprises. The less effort users make to interact with chatbots, the higher the impact of perceived performance. Thus, to motivate nonusers to communicate with companies and achieve good service delivery via chatbots, managers should seriously consider chatbot ease of use, possibly by improving algorithms and quality of communication.

The increasing use of chatbots can help marketers design and promote relevant messages and delivery methods on mobile phones to enable offering customers a pleasant user experience and satisfaction and stimulate the continuous use of this technology and the creation of added value for enterprises.

Overall, the results of the present research can contribute to stimulating managers, marketers, and businesses to formulate mobile-related policies and strategies and provide valuable guidelines about the strategy and policy design of modern organizations based on the great potential of chatbots.

7. Limitations and Future Research

Despite the significant findings of the present research, there are several limitations to be considered. First, as the study was carried out in only 3 Greek universities, future research could focus on comparing relevant findings from other Greek or international universities and explore potential similarities or differences. Further research could also be conducted on a sample of different age groups to investigate the impact of the examined factors. Second, the present research used only a sample of nonusers of AI agents. Thus, it would be interesting to carry out a comparative study on a sample of both users and nonusers of chatbots. Additionally, apart from mobility and trust, other variables, such as satisfaction with using chatbots and recommendation, could be considered in future research among chatbot users.

Finally, in the framework of the specific conceptual model, further considerations should be made, such as other facilitating factors for the intention to adopt and use chatbots in mobile contexts (anthropomorphic elements, perceived intelligence, attitude, degree of innovation, and problem-solving) as well as constraints to their behavioral intention (technology anxiety, low information reliability, complexity, and compatibility).

8. Conclusion

AI agents or chatbots are a promising leading innovation technology applied in customer service, which has reshaped communication and interaction in e-/m-commerce. Focusing on smartphones and chatbot use quality, the present research explored the motivating factors for nonusers to adopt chatbots on their mobile phones. By using the UTAUT 2 theory combined with variables of mobile service quality and additional variables, such as trust, mobility, and privacy concerns, the research attempted to investigate the impact of these variables on behavioral intention to adopt chatbots. The research outcomes demonstrate the impact of performance, facilitating factors, hedonic motivation, mobility, trust, equipment, interface, and information quality on the behavioral intention to adopt chatbots. Social influence and effort expectancy were not found to influence intention to use. Overall, the research contributes to providing valuable information to the relevant literature and generating significant advantages both for the academia and the business industry.

Data Availability

The data will be available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] P. R. Daugherty, H. James Wilson, and P. Michelman, "Revisiting the jobs artificial intelligence will create," *MIT Sloan Management Review*, vol. 60, no. 4, pp. 1–8, 2019.

[2] L. Gkinko and A. Elbanna, "Hope, tolerance and empathy: employees' emotions when using an AI-enabled chatbot in a digitalised workplace," *Information Technology & People*, vol. 35, no. 6, pp. 1714–1743, 2022.

[3] X. Luo, S. Tong, Z. Fang, and Z. Qu, "Frontiers: machines vs humans: the impact of artificial intelligence chatbot disclosure on customer purchases," *Marketing Science*, vol. 38, no. 6, pp. 937–947, 2019.

[4] X. Cheng, Y. Bao, A. Zarifis, W. Gong, and J. Mou, "Exploring consumers' response to text-based chatbots in e-commerce: the moderating role of task complexity and chatbot disclosure," *Internet Research*, vol. 32, no. 2, pp. 1066–2243, 2022.

[5] L. Lo Presti, G. Maggiore, and V. Marino, "The role of the chatbot on customer purchase intention: towards digital relational sales," *Italian Journal of Marketing*, vol. 2021, no. 3, pp. 165–188, 2021.

[6] J. W. Hong, "Artificial intelligence (AI), don't surprise me and stay in your lane: an experimental testing of perceiving humanlike performances of AI," *Human Behavior and Emerging Technologies*, vol. 3, no. 5, pp. 1023–1032, 2021.

[7] Statista 2023, *Chatbot Market Worldwide 2021-2030*, Bergur Thormundsson, 2023, (accessed at 14 April 2023), https://www.statista.com/statistics/656596/worldwide-chatbot-market/.

[8] J. H. R. Wang, C. E. Malthouse, and L. Krishnamurthi, "On the go: how mobile shopping affects customer purchase behavior," *Journal of Retailing*, vol. 91, no. 2, pp. 217–234, 2015.

[9] M. Sarwar and T. R. Soomro, "Impact of smartphones on society," *European Journal of Scientific Research*, vol. 98, no. 2, pp. 216–226, 2013.

[10] T. Nadarzynski, O. Miles, A. Cowie, and D. Ridge, "Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: a mixed-methods study," *Digital Health*, vol. 5, 2019.

[11] T. Sitthipon, S. Siripipatthanakul, B. Phayaphrom, S. Siripipattanakul, and P. Limna, "Determinants of customers' intention to use healthcare chatbots and apps in Bangkok, Thailand," *International Journal of Behavioral Analytics*, vol. 2, no. 2, pp. 1–15, 2022.

[12] V. Bharathi, D. Pramod, and R. Raman, "Intention to Use Artificial Intelligence Services in Financial Investment Decisions," in *2022 International Conference on Decision Aid Sciences and Applications (DASA)*, pp. 560–566, Chiangrai, Thailand, 2022.

[13] B. Nyagadza, A. Muposhi, G. Mazuruse et al., "Prognosticating anthropomorphic chatbots' usage intention as an e-banking customer service gateway: cogitations from Zimbabwe," *PSU Research Review*, 2022.

[14] B. Zarouali, E. Van den Broeck, M. Walrave, and K. Poels, "Predicting consumer responses to a chatbot on Facebook," *Cyberpsychology, Behavior and Social Networking*, vol. 21, no. 8, pp. 491–497, 2018.

[15] D. Cai, H. Li, and R. Law, "Anthropomorphism and OTA chatbot adoption: a mixed methods study," *Journal of Travel & Tourism Marketing*, vol. 39, no. 2, pp. 228–255, 2022.

[16] A. Cheriyan, R. K. Sharma, A. Joseph, and S. R. Kappil, "Consumer acceptance towards AI-enabled chatbots; case of travel and tourism industries," *Journal of Positive School Psychology*, vol. 6, no. 3, pp. 3880–3889, 2022.

[17] J. Balakrishnan, S. S. Abed, and P. Jones, "The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?," *Technological Forecasting and Social Change*, vol. 180, no. 3, article 121692, 2022.

[18] M. Chung, E. Ko, H. Joung, and S. J. Kim, "Chatbot e-service and customer satisfaction regarding luxury brands," *Journal of Business Research*, vol. 117, pp. 587–595, 2020.

[19] C. V. Misischia, F. Poecze, and C. Strauss, "Chatbots in customer service: their relevance and impact on service quality," *Procedia Computer Science*, vol. 201, pp. 421–428, 2022.

[20] I. Roozen, M. Raedts, and G. Waetermans, "Does a chatbot's location influence consumer attitude and intentions," *International Journal of Internet Marketing and Advertising*, vol. 1, no. 1, p. 1, 2022.

[21] M. Song, X. Xing, Y. Duan, J. Cohen, and J. Mou, "Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention," *Journal of Retailing and Consumer Services*, vol. 66, article 102900, 2022.

[22] M. Van Eeuwen, *Mobile Conversational Commerce: Messenger Chatbots as the Next Interface between Businesses and Consumers, [M.S. thesis]*, University of Twente, 2017.

[23] F. Brachten, T. Kissmer, and S. Stieglitz, "The acceptance of chatbots in an enterprise context – a survey study," *International Journal of Information Management*, vol. 60, no. C, article 102375, 2021.

[24] A. M. Selamat and N. A. Windasari, "Chatbot for SMEs: integrating customer and business owner perspectives," *Technology in Society*, vol. 66, article 101685, 2021.

[25] D. R. Cardona, O. Werth, S. Schonborn, and M. H. Breitner, "A mixed methods analysis of the adoption and diffusion of chatbot technology in the german insurance sector," in *Twenty-fifth Americas Conference on Information System*, pp. 1–10, Cancun, Mexico, 2019.

[26] D. R. Cardona, A. Janssen, N. Guhr, M. H. Breitnet, and J. Milde, "A Matter of Trust? Examination of Chatbot Usage in Insurance Business," in *Proceedings of the 54th Hawaii International Conference on System Sciences*, pp. 556–565, Maui, Hawaii, 2021.

[27] L. Fryer, K. Nakao, and A. Thompson, "Chatbot learning partners: connecting learning experiences, interest and competence," *Computers in Human Behavior*, vol. 93, pp. 279–289, 2019.

[28] U. Gnewuch, S. Morana, M. T. P. Adam, and A. Maedche, "Opposing effects of response time in human–chatbot interaction," *Business & Information Systems Engineering*, vol. 64, no. 6, pp. 773–791, 2022.

[29] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: extending the

unified theory of acceptance and use of technology," *MIS Quarterly*, vol. 36, no. 1, pp. 157–178, 2012.

[30] A. Følstad and P. B. Brandtzaeg, "Chatbots and the new world of HCI," *Interactions*, vol. 24, no. 4, pp. 38–42, 2017.

[31] M. Ivanovic and M. Semnic, "The role of agent technologies in personalized medicine," in *2018 5th International Conference on Systems and Informatics (ICSAI)*, pp. 299–304, Nanjing, China, 2018.

[32] V. Kumar, B. Rajan, R. Venkatesan, and J. Lecinski, "Understanding the role of artificial intelligence in personalized engagement marketing," *California Management Review*, vol. 61, no. 4, pp. 135–155, 2019.

[33] S. Hlee, J. Park, H. Park, C. Koo, and Y. Chang, "Understanding customer's meaningful engagement with AI-powered service robots," *Information Technology & People*, vol. 36, no. 3, pp. 1020–1047, 2023.

[34] D. C. Ukpabi, B. Aslam, and H. Karjaluoto, "Chatbot adoption in tourism services: a conceptual exploration," in *Robots, Artificial Intelligence, and Service Automation in Travel, Tourism and Hospitality*, S. Ivanov and C. Webster, Eds., pp. 105–121, Emerald Publishing Limited, 2019.

[35] J. A. Martínez-Román, J. Gamero, J. A. Tamayo, and L. Delgado-González, "Empirical analysis of organizational archetypes based on generation and adoption of knowledge and technologies," *Technovation*, vol. 96, no. 97, 2020.

[36] S. Melian Gonzalez, D. Gutierrez Tano, and J. Bulchand Gidumal, "Predicting the intentions to use chatbots for travel and tourism," *Current Issues in Tourism*, vol. 24, no. 2, pp. 192–210, 2021.

[37] J. T. Quah and Y. W. Chua, "Chatbot assisted marketing in financial service industry," in *Services Computing – SCC 2019*, pp. 107–114, Springer, Cham, Switzerland, 2019.

[38] Y. C. Lee and L. A. Malcein, "Users' mental models forcomputer-mediatedcommunication: theorizing emerging technology and behavior ineHealthapplications," *Human Behavior and Emerging Technologies*, vol. 2, no. 4, pp. 354–366, 2020.

[39] S. C. Paul, N. Bartmann, and J. L. Clark, "Customizability in conversational agents and their impact on health engagement," vol. 3, no. 5, pp. 1141–1152, 2021.

[40] G. Murtarelli, C. Collina, and S. Romenti, "Hi! How can I help you today?: investigating the quality of chatbots–millenials relationship within the fashion industry," *The TQM Journal*, vol. 35, no. 3, 2022.

[41] M. Diekmann and L. Theuvsen, "Non-participants' interest in CSA–insights from Germany," *Journal of Rural Studies*, vol. 69, pp. 1–10, 2019.

[42] S. Kim, K. H. Lee, H. Hwang, and S. Yoo, "Analysis of the factors influencing healthcare professionals' adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital," *BMC Medical Informatics and Decision Making*, vol. 16, no. 1, pp. 1–12, 2015.

[43] Y. Lu, L. Zhang, and B. Wang, "A multidimensional and hierarchical model of mobile service quality," *Electronic Commerce Research and Applications*, vol. 8, no. 5, pp. 228–240, 2009.

[44] E. Stiakakis, C. K. Georgiadis, and K. Petridis, "Analyzing M-service quality dimensions using multivariate statistical techniques," in *Proceedings of the AIS-affiliated conference 12th International Conf. on Mobile Business 2013 (ICMB 2013*, pp. 1–7, Berlin, Germany, 2013.

[45] S. Akter, J. D'Ambra, and P. Ray, "User Perceived Service Quality of M-Health Services in Developing Countries," in *Paper Presented at the 18th European Conference on Information Systems*, pp. 1–12, Pretoria, South Africa, 2010.

[46] A. Ozer, T. M. Argan, and M. Argan, "The effect of mobile service quality dimensions on customer satisfaction," *Procedia-Social and Behavioral Sciences*, vol. 99, pp. 428–438, 2013.

[47] T. Oliveira, M. Thomas, G. Baptista, and F. Campos, "Mobile payment: understanding the determinants of customer adoption and intention to recommend the technology," *Computers in Human Behavior*, vol. 61, pp. 404–414, 2016.

[48] I. Ajzen, "The theory of planned behavior," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179–211, 1991.

[49] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.

[50] P. R. Warshaw and F. D. Davis, "Disentangling behavioral intention and behavioral expectation," *Journal of Experimental Social Psychology*, vol. 21, no. 3, pp. 213–228, 1985.

[51] M. Fishbein and I. Ajzen, *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA, USA, 1975.

[52] S. Kuberkar and T. K. Singhal, "Factors influencing adoption intention of AI powered chatbot for public transport services within a smart city," *International Journal of Emerging Technologies*, vol. 11, no. 3, pp. 948–958, 2020.

[53] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," *Management Science*, vol. 35, no. 8, pp. 982–1003, 1989.

[54] F. Almahri Amer Jid, D. Bell, and M. Merhi, "Understanding student acceptance and use of chatbots in the United Kingdom universities: a structural equation modeling approach," in *6th IEEE International Conference on Information Management*, pp. 284–288, UK, 2020.

[55] S. Abed, "An empirical examination of Instagram as an s-commerce channel," *Journal of Advances in Management Research*, vol. 15, no. 2, pp. 146–160, 2018.

[56] V. Saprikis, G. Avlogiaris, and A. Katarachia, "Determinants of the intention to adopt mobile augmented reality apps in shopping malls among university students," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 16, no. 3, pp. 491–512, 2021.

[57] V. Saprikis and G. Avlogiaris, "Modeling users' acceptance of mobile social commerce: the case of 'Instagram checkout'," *Electronic Commerce Research*, vol. 23, no. 2, pp. 1–30, 2023.

[58] T. Zhou, Y. Lu, and B. Wang, "Integrating TTF and UTAUT to explain Mobile banking user adoption," *Computers in Human Behavior*, vol. 26, no. 4, pp. 760–767, 2010.

[59] E. Mogaji, J. Balakrishnan, C. A. Nwoba, and P. Nguyen, "Emerging-market consumers' interactions with banking chatbots," *Telematics and Informatics*, vol. 65, article 101711, 2021.

[60] H. Trapero, J. Ilao, and R. Lacaza, "An Integrated Theory for Chatbot Use in Air Travel: Questionnaire Development and Validation," in *IEEE Region 10 Conference (TENCON)*, pp. 652–657, Osaka, Japan, 2020.

[61] A. Alalwan, Y. Dwivedi, and M. Williams, "Examining factors affecting customer intention and adoption of Internet banking,"

in *Jordan UK Academy for Information Systems Conference Proceedings 2014*, p. 3, 2014, https://aisel.aisnet.org/ukais2014/3.

[62] E. Svikhnushina and P. Pu, "PEACE: a model of key social and emotional qualities of conversational chatbots," *ACM Transactions on Interactive Intelligent Systems*, vol. 12, no. 4, pp. 1–29, 2022.

[63] J. Y. Heo, C. H. Lim, and K. J. Kim, "Scales for measuring mobile service quality: a literature review and identification of key dimensions," *International Journal of Services and Operations Management*, vol. 27, no. 4, pp. 524–548, 2017.

[64] E. Stiakakis and C. K. Georgiadis, "A model to identify the dimensions of mobile service quality," in *Proceedings of the 10th International Conference on Mobile Business*, pp. 195–204, Como, Italy, 2011.

[65] P. A. Vlachos and A. P. Vrechopoulos, "Determinants of behavioral intentions in the mobile Internet services market," *Journal of Services Marketing*, vol. 22, no. 4, pp. 280–291, 2008.

[66] L. Martínez Caro and J. A. Martínez García, "Measuring perceived service quality in urgent transport service," *Journal of Retailing and Consumer Services*, vol. 14, no. 1, pp. 60–72, 2007.

[67] H. McKnight, V. Choudhury, and C. Kacmar, "The impact of initial consumer trust on intentions to transact with a web site: a trust building model," *Journal of Strategic Information Systems*, vol. 11, no. 3–4, pp. 297–323, 2002.

[68] F. B. Tan and J. P. C. Chou, "The relationship between mobile service quality, perceived technology compatibility, and users' perceived playfulness in the context of mobile information and entertainment services," *International Journal of Human-Computer Interaction*, vol. 24, no. 7, pp. 649–671, 2008.

[69] M. Chae, J. Kim, H. Kim, and H. Ryu, "Information quality for mobile Internet services: a theoretical model with empirical validation," *Electronic Markets*, vol. 12, no. 1, pp. 38–46, 2002.

[70] G. Aiello, R. Donvito, D. Acuti et al., "Customers' willingness to disclose personal information throughout the customer purchase journey in retailing: the role of perceived warmth," *Journal of Retailing*, vol. 96, no. 4, pp. 490–506, 2020.

[71] Y. B. Limbu, M. Wolf, and D. L. Lunsford, "Consumers' perceptions of online ethics and its effects on satisfaction and loyalty," *Journal of Research in Interactive Marketing*, vol. 5, no. 1, pp. 71–89, 2011.

[72] S. Roman and P. J. Cuestas, "The perceptions of consumers regarding online retailers' ethics and their relationship with consumers' general Internet expertise and word of mouth: a preliminary analysis," *Journal of Business Ethics*, vol. 83, no. 4, pp. 641–656, 2008.

[73] N. M. Coopamootoo, E. Toreini, M. Aitken, K. Elliot, and A. Van Moorse, "Simulating the effects of social presence on trust, privacy concerns & usage intentions in automated bots for finance," in *2020 IEEE European Symposium on Security and Privacy Workshops (EuroS & PW)*, pp. 190–199, Genoa, Italy, 2020.

[74] A. Rese, L. Ganster, and D. Baier, "Chatbots in retailers' customer communication: how to measure their acceptance?," *Journal of Retailing and Consumer Services*, vol. 56, article 102176, 2020.

[75] M. K. Brady and J. Cronin, "Some new thoughts on conceptualizing perceived service quality: a hierarchical approach," *Journal of Marketing*, vol. 65, no. 3, pp. 34–49, 2001.

[76] V. A. Zeithaml, L. L. Berry, and A. Parasuraman, "Communication and control processes in the delivery of service quality," *Journal of Marketing*, vol. 52, no. 2, pp. 35–48, 1988.

[77] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "A conceptual model of service quality and its implications for future research," *Journal of Marketing*, vol. 49, no. 4, pp. 41–50, 1985.

[78] P. Tarasewich, R. Nickerson, and M. Warkentin, "Issues in mobile e-commerce," *Communications of the Association for Information Systems*, vol. 8, no. 1, p. 3, 2002.

[79] L. Zhao, Y. Lu, L. Zhang, and P. Y. K. Chau, "Assessing the effects of service quality and justice on customer satisfaction and the continuance intention of mobile value-added services: an empirical test of a multidimensional model," *Decision Support Systems*, vol. 52, no. 3, pp. 645–656, 2012.

[80] Y. Li and Y. Yeh, "Increasing trust in mobile commerce through design aesthetics," *Computers in Human Behavior*, vol. 26, no. 4, pp. 673–684, 2010.

[81] S. Vaithilingam, M. Nair, and B. K. Guru, "Do trust and security matter for the development of M-banking? Evidence from a developing country," *Journal of Asia-Pacific Business*, vol. 14, no. 1, pp. 4–24, 2013.

[82] S. Sarkar, S. Chauhan, and A. Khare, "A meta-analysis of antecedents and consequences of trust in mobile commerce," *International Journal of Information Management*, vol. 50, pp. 286–301, 2020.

[83] S. X. Komiak and I. Benbasat, "Understanding customer trust in agent-mediated electronic commerce, web-mediated electronic commerce, and traditional commerce," *Information Technology and Management*, vol. 5, no. 1/2, pp. 181–207, 2004.

[84] R. Riedl, P. Mohr, P. Kenning, F. Davis, and H. Heekeren, *Trusting Humans and Avatars: Behavioral and Neutral Evidence*, ICIS 2011 Proceedings- AIS eLibrary, Shanghai, China, 2011, https://aisel.aisnet.org/icis2011/proceedings/hci/7.

[85] C. L. Corritore, B. Kracher, and S. Wiedenbeck, "On-line trust: concepts, evolving themes, a model," *International Journal of Human-Computer Studies*, vol. 58, no. 6, pp. 737–758, 2003.

[86] Y. A. Au and R. J. Kauffman, "The economics of mobile payments: understanding stakeholder issues for an emerging financial technology application," *Electronic Commerce Research and Applications*, vol. 7, no. 2, pp. 141–164, 2008.

[87] N. Mallat, "Exploring consumer adoption of mobile payments – a qualitative study," *Journal of Strategic Information Systems*, vol. 16, no. 4, pp. 413–432, 2007.

[88] P. G. Schierz, O. Schilke, and B. W. Wirtz, "Understanding consumer acceptance of mobile payment services: an empirical analysis," *Electronic Commerce Research and Applications*, vol. 9, no. 3, pp. 209–216, 2010.

[89] F. Xu, S. S. Huang, and S. Li, "Time, money, or convenience: what determines Chinese consumers' continuance usage intention and behavior of using tourism mobile apps?," *International Journal of Culture, Tourism, and Hospitality Research*, vol. 13, no. 3, pp. 288–302, 2019.

[90] C. Kim, M. Mirusmonov, and I. Lee, "An empirical examination of factors influencing the intention to use mobile payment," *Computers in Human Behavior*, vol. 26, no. 3, pp. 310–322, 2010.

[91] D. N. Su, N. A. N. Nguyen, L. N. T. Nguyen, T. T. Luu, and D. Q. Nguyen-Phuoc, "Modeling consumers' trust in mobile food delivery apps: perspectives of technology acceptance

model, mobile service quality and personalization-privacy theory," *Journal of Hospitality Marketing & Management*, vol. 31, no. 5, pp. 535–569, 2022.

[92] N. Shaw, B. Eschenbrenner, and B. Brand, "Towards a mobile app diffusion of innovations model: a multinational study of mobile wallet adoption," *Journal of Retailing and Consumer Services*, vol. 64, article 102768, 2022.

[93] L. M. De Cosmo, L. Piper, and A. Di Vittorio, "The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots," *Italian Journal of Marketing*, vol. 2021, no. 1-2, pp. 83–102, 2021.

[94] H. Xu, T. Dinev, H. J. Smith, and P. Hart, "Examining the Formation of individual's Privacy Concerns: Toward an Integrative View," in *Proceedings of the 29th International Conference on Information Systems*, pp. 1–16, Paris, France, 2008.

[95] B. E. Ashforth, *Role Transitions in Organizational Life: An Identity-Based Perspective*, Lawrence Erlbaum Associates, Mahwah, NJ, USA, 2000.

[96] N. Shaw, "The mediating influence of trust in the adoption of the mobile wallet," *Journal of Retailing and Consumer Services*, vol. 21, no. 4, pp. 449–459, 2014.

[97] Y. Cheng and H. Jiang, "Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts," *Journal of Product & Brand Management*, vol. 31, no. 2, pp. 252–264, 2022.

[98] C. M. Leong, K. L. Tan, C. H. Puah, and S. M. Chong, "Predicting mobile network operators users m-payment intention," *European Business Review*, vol. 33, no. 1, pp. 104–126, 2021.

[99] R. A. Ali and M. R. M. Arshad, "Perspectives of students' behavior towards mobile learning (M-learning) in Egypt: an extension of the UTAUT model," *Engineering Technology & Applied Science Research*, vol. 6, no. 4, pp. 1109–1114, 2016.

[100] H. Mohammadi, "Social and individual antecedents of m-learning adoption in Iran," *Computers in Human Behavior*, vol. 49, pp. 191–207, 2015.

[101] A. Wilman and W. Sardjono, "Understanding factors determining the use of mobile apps by customer: customer mobility as an extension construct of UTAUT2," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 4, 2022.

[102] F. Bélanger and L. Carter, "Trust and risk in e-government adoption," *The Journal of Strategic Information Systems*, vol. 17, no. 2, pp. 165–176, 2008.

[103] I. I. Antoniadis, V. S. Saprikis, and E. E. Karteraki, "Consumers' attitudes towards advertisement in YouTube. In Strategic Innovative Marketing and Tourism," in *7th ICSIMAT, Athenian Riviera, Greece, 2018*, pp. 253–261, Springer International Publishing, 2019.

[104] P. Gatzioufa and V. Saprikis, "A literature review on users' behavioral intention toward chatbots' adoption," *Applied Computing and Informatics*, 2022.

[105] V. Saprikis, "Suppliers' behavior on the post-adoption stage of business-to-business e-reverse auctions: an empirical study," *Telematics and Informatics*, vol. 30, no. 2, pp. 132–143, 2013.

[106] N. W. Shead, L. J. Derevensky, W. T. Fong, and R. Gupta, "Characteristics of Internet gamblers among a sample of students at a large, public university in southwestern United States," *Journal of College Student Development*, vol. 53, no. 1, pp. 133–148, 2012.

[107] S. Tuzovic and S. Paluch, "Conversational commerce – a new era for service business development?," in *Service Business Development*, M. Bruhn and K. Hadwich, Eds., pp. 81–100, Springer, Wiesbaden, Germany, 2018.

[108] J. Cho, "The impact of post-adoption beliefs on the continued use of health apps," *International Journal of Medical Informatics*, vol. 87, pp. 75–83, 2016.

[109] U. Sekaran and R. Bougie, *Research Methods for Business: A Skill-Building Approach*, John Wiley & Sons, Haddington, Scotland, 5th edition, 2010.

[110] J. Hair, M. L. Mathews, and L. R. Mathews, "PLS-SEM or CB-SEM: updated guidelines on which method to use," *International Journal of Multivariate Data Analysis*, vol. 1, no. 2, pp. 107–123, 2017.

[111] J. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, "An assessment of the use of partial least squares structural equation modeling in marketing research," *Journal of the Academy of Marketing Science*, vol. 40, no. 3, pp. 414–433, 2012.

[112] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," *Journal of the Academy of Marketing Science*, vol. 16, no. 1, pp. 74–94, 1988.

[113] P. M. Podsakof, S. B. MacKenzie, J. Y. Lee, and N. P. Podsakof, "Common method biases in behavioral research: a critical review of the literature and recommended remedies," *Journal of Applied Psychology*, vol. 88, no. 5, pp. 879–903, 2003.

[114] M. Bentler, "Comparative fit indexes in structural models," *Psychological Bulletin*, vol. 107, no. 2, pp. 238–246, 1990.

[115] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives," *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 6, no. 1, pp. 1–55, 1999.

[116] L. K. Muthén and B. O. Muthén, *Mplus for Windows 731*, Muthén and Muthén, 2015.

[117] J. Hair, W. Black, B. Babin, and R. Anderson, *Multivariate Data Analysis*, Pearson/Prentice Hall, 3rd edition, 2014.

[118] C. Fornell and D. F. Larcker, "Structural equation models with unobservable variables and measurement error: algebra and statistics," *Journal of Marketing Research*, vol. 18, no. 3, pp. 382–388, 1981.

[119] S. Melián-González, D. Gutiérrez-Tañ, and J. Bulchand-Gidumal, "Predicting the intentions to use chatbots for travel and tourism," *Current Issues in Tourism*, vol. 24, no. 2, pp. 192–210, 2021.

[120] T. Rietz, I. Benke, and A. Maedche, "The impact of anthropomorphic and functional chatbot design features in enterprise collaboration systems on user acceptance," in *Proceedings of the 14th International Conference on Wirtschaftsinformatik*, pp. 1–17, Siegen, Germany, 2019.

[121] S. Gupta, A. K. Kar, A. Baabdullah, and W. A. Al-Khowaiter, "Big data with cognitive computing: a review for the future," *International Journal of Information Management*, vol. 42, pp. 78–89, 2018.

[122] H. S. Woods, "Asking more of Siri and Alexa: feminine persona in service of surveillance capitalism," *Critical Studies in Media Communication*, vol. 35, no. 4, pp. 334–349, 2018.

[123] R. De Cicco, S. Iacobucci, A. Aquino, F. Romana Alparone, and R. Palumbo, "Understanding users' acceptance of chatbots: an extended TAM approach," in *Chatbot Research and Design: 5th International Workshop, CONVERSATIONS*

2021, Virtual Event, November 23–24, 2021, Revised Selected Papers, pp. 3–22, Springer International Publishing, Cham, 2022.

[124] D. L. Kasilingam, "Understanding the attitude and intention to use smartphone chatbots for shopping," *Technology in Society*, vol. 62, no. 15, article 101280, 2020.

[125] R. Pillai and B. Sivathanu, "Adoption of AI-based chatbots for hospitality and tourism," *International Journal of Contemporary Hospitality Management*, vol. 32, no. 10, pp. 3199–3226, 2020.

[126] E. Toreini, M. Aitken, K. Coopamootoo, K. Elliott, C. G. Zelaya, and A. Van Moorsel, "The relationship between trust in AI and trustworthy machine learning technologies," in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pp. 272–283, Barcelona, Spain, 2020.

[127] M. A. S. Alrawi, G. N. Samy, R. C. M. Yusoff et al., "Examining factors that effect on the acceptance of mobile commerce in Malaysia based on revised UTAUT," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 3, pp. 1173–1184, 2020.