Telematics and Informatics 54 (2020) 101473

Contents lists available at ScienceDirect

Telematics and Informatics

journal homepage: www.elsevier.com/locate/tele

I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents

Muhammad Ashfaq[a], Jiang Yun[a], Shubin Yu[b,*], Sandra Maria Correia Loureiro[c]

[a] School of Business Administration, Dongbei University of Finance and Economics, China
[b] HSBC Business School, Peking University, China
[c] Department of Marketing and Operations, Instituto Universitário de Lisboa (ISCTE-IUL) and Business Research Unit (BRU- IUL), Portugal

ARTICLE INFO

Keywords:
Chatbots
Satisfaction
Continuance intention
The need for interaction
ECM
ISS model
TAM

ABSTRACT

Chatbots are mainly text-based conversational agents that simulate conversations with users. This study aims to investigate drivers of users' satisfaction and continuance intention toward chatbot-based customer service. We propose an analytical framework combining the expectation-confirmation model (ECM), information system success (ISS) model, TAM, and the need for interaction with a service employee (NFI-SE). Analysis of data collected from 370 actual chatbot users reveals that information quality (IQ) and service quality (SQ) positively influence consumers' satisfaction, and that perceived enjoyment (PE), perceived usefulness (PU), and perceived ease of use (PEOU) are significant predictors of continuance intention (CI). The need for interaction with an employee moderates the effects of PEOU and PU on satisfaction. The findings also revealed that satisfaction with chatbot e-service is a strong determinant and predictor of users' CI toward chatbots. Thus, chatbots should enhance their information and service quality to increase users' satisfaction. The findings imply that digital technologies services, such as chatbots, could be combined with human service employees to satisfy digital users.

1. Introduction

In this digital era, artificial intelligence (AI) is expected to take over jobs (Letheren et al., 2020), especially for text-based conversational agents (chatbots). Chatbots are dramatically changing the customer service profession for the enhancement of users and businesses (Cath et al., 2018; Wirtz et al., 2018). At present, chatbots provide 24/7 services in several fields, such as sales, support, and marketing. More specifically, chatbots are most commonly used to perform the sales function (41%), followed by support (37%), and marketing (17%). More importantly, it enhanced sales by an average of 67%, along with 26% of all sales is handled by chatbots interaction (Forbes, 2019a).

Chatbots are automated programs used to communicate with humans through text or chat exchange (Przegalinska et al., 2019; Radziwill & Benton, 2017; Sivaramakrishnan et al., 2007). Users interact with these programs to obtain the product or service-related information, place an online order for products, or order food in real-time (Sivaramakrishnan et al., 2007; Luo et al., 2019). Such programs are used for the ease of both end-users and companies, due to their accessibility, flexibility, and low cost (Przegalinska et al., 2019; Radziwill & Benton, 2017). For this reason, almost 80% of businesses today use or plan to incorporate chatbots soon (Forbes, 2019b) to communicate with their users 24/7 and solve their problems.

* Corresponding author at: Office 631, Peking University HSBC Business School, University Town, Nanshan, Shenzhen 518055, China.
E-mail addresses: muhammad.ashfaq0209@gmail.com (M. Ashfaq), jiang.yun@dufe.edu.cn (J. Yun), Shubin.Yu@phbs.pku.edu.cn (S. Yu), sandramloureiro@netcabo.pt (S.M.C. Loureiro).

https://doi.org/10.1016/j.tele.2020.101473
Received 14 April 2020; Received in revised form 2 July 2020; Accepted 16 July 2020
Available online 22 July 2020
0736-5853/

Chatbots use natural language to interact with users and answers their queries effectively (Ciechanowski et al., 2019; Luo et al., 2019; Sivaramakrishnan et al., 2007). According to a recent report issued by PointSource, chatbots will deal with 85% of customer service jobs by 2020, which will help to reduce annual costs by over $8 billion by 2022 (PointSource, 2018). If chatbots are well-systematized, their use can produce excellent results, such as resource and time savings (PointSource, 2018).

With the increase in human–chatbot interaction in recent years, users can now communicate with chatbots using a variety of devices—smartphones, laptops, tablets, or desktops (Araujo, 2018; Luo et al., 2019). Many platforms, including Facebook, Skype, Amazon, WeChat, and eBay have already rolled out chatbots for e-service (Luo et al., 2019). In addition to a chatbot for e-service and in an effort to embrace the chatbot craze, Domino's now offers a chatbot to order pizza online via Facebook Messenger (Luo et al., 2019). These digital assistants serve as a company representative whose aim is to assist consumers on the internet at any time from any location (Chung et al., 2018; Holzwarth et al., 2006). For instance, consumers may expect to have the same interpersonal interaction as in an offline store when they visit an online platform (Sivaramakrishnan et al., 2007). Hence, these automated programs not only provide the information to consumers but also interact with them like a personal assistant; one such example is Coca-Cola's "Hank" (Sivaramakrishnan et al., 2007). Many major luxury players, such as Gucci, Burberry, and Louis Vuitton, are also using chatbots to provide 24-hour customer service (Chung et al., 2018). Chatbots for e-service offer an entirely new way to satisfy users (Chung et al., 2018) because such programs "serve a range of roles, from personal assistant, to intelligent virtual agent, to companion" (Radziwill & Benton, 2017, p. 4). Virtual agents can be used to provide uninterrupted customer service and reduce time-to-response, important factors in enhancing customer satisfaction (Radziwill & Benton, 2017).

Regardless of the extensive use of chatbots by several business leaders in recent years, consumers' acceptance and its continuance usage remain relatively low. For example, recent research argues that 87% of consumers still prefer human interaction to interacting with chatbots (Forbes, 2019a). Respondents agreed that humans are much better than chatbots at answering several queries, specifically in their understanding of complex situations—in other words, they feel that human agents understand them better (Forbes, 2019a). A recent study also shows that customers experience discomfort when they do not believe they are communicating with a human because they think chatbots are less well-informed and less empathetic; thus, they make smaller purchases (Luo et al., 2019).

In spite of users' low satisfaction and continuance intention (CI) regarding chatbots, few studies have explored why consumers are reluctant to continue using them. In light of this, empirical investigation of the users' satisfaction with chatbots and its CI becomes relevant. Understanding the antecedents of chatbot satisfaction and CI can not only extend the growing literature on chatbots in the service context but also help marketers and programmers to adjust the design of chatbot systems. Hence, this study aims to investigate drivers of users' satisfaction and CI toward using chatbot e-service based on three extant models: the expectation–confirmation model (ECM), information system success (ISS) model, and technology acceptance model (TAM).

2. Literature review

2.1. Human-chatbot interaction

A chatbot "is a machine conversation system [that] interacts with human users via natural conversational language" (Shawar & Atwell, 2005, p. 489), or "an artificial construct that is designed to converse with human beings using natural language as input and output" (Brennan, 2006, p. 61). Machine learning and AI technology were used to engage users in conversations automatically (Araujo, 2018). They can be found under different names in the literature, for example, virtual agent (Ciechanowski et al., 2019), intelligent agent (Hill et al., 2015), bot agent or automated program (Edwards et al., 2014), anthropomorphic information agent (Sivaramakrishnan et al., 2007), or e-service agent (Chung et al., 2018). Chatbots work like a personal secretary, supporting users in multiple purposes such as seeking information, search queries, and building social relationships (Chung et al., 2018; Holzwarth et al., 2006; Huang et al., 2007). Companies use such virtual agents as company representatives to satisfy their customers and provide entertainment and information value (Chung et al., 2018; Holzwarth et al., 2006; Radziwill & Benton, 2017). However, a variety of social cues of chatbots, including verbal (e.g., what and how is said), visual (e.g., all body movements of the agent or visual elements that can augment or modify the meaning of a text-based message), auditory (e.g., voice qualities and vocalizations), and invisible (e.g., response time and tactile sensations on the user's body) can result in either positive or negative reactions from users (Feine et al., 2019).

Although chatbots have been widely adopted for e-service, many users still feel reluctant to interact with them due to a lack of personal touch and empathy to handle annoyed users, as well as uncertainty about chatbots' performance (Nguyen, 2019). As a result, some companies are still hesitant to implement them (Nguyen, 2019). Other issues also arise, such as privacy concerns (Zamora, 2017), feelings of discomfort (Luo et al., 2019), and difficulty in interaction (Colace et al., 2017). Thus, this technology sometimes cannot really service consumers without human intervention; human beings usually deliver better customer experience. A person can handle situations and subjects better than a chatbot, particularly in complex situations (Forbes, 2019a; Nguyen, 2019).

Research shows that chatbots enhance customer satisfaction in different contexts (Chung et al., 2018; Holzwarth et al., 2006). For example, Chung et al. (2018) examine chatbots and customer satisfaction in the context of luxury brands. They find that using chatbots for e-service leads to higher customer satisfaction with the brand because chatbots can engage the customer and deliver interactive customer service. Holzwarth et al. (2006) examine the effect of virtual agents on consumer satisfaction, product attitude, and purchase intention in the context of e-commerce. They reveal that virtual agents in online shopping lead to greater consumer "satisfaction with the retailer, a more positive attitude toward the product, and a greater purchase intention" (Holzwarth et al., 2006, p. 1) because such new technologies have the potential to satisfy the user's needs/desire by providing personalized information, making the shopping experience more enjoyable (Holzwarth et al., 2006). Thus, companies can enhance customer satisfaction

Table 1
Previous studies on the chatbot.

Article	Study focus	Theoretical lens	Key findings
(Mou & Xu, 2017)	Whether users' communicative attributes and personality traits are different when they initially interact with human-artificial intelligence (i.e., chatbot) and human-human interaction.	The computers-are-social-actors (CASA) paradigm and the cognitive-affective processing system (CAPS) model	Users confirmed different communicative attributes and personality traits when they interact with human-human and human-artificial intelligence, especially when they are interacting with a human, they are "more open, more conscientious, more extroverted, more agreeable, and self-disclosing than AI" (p. 432).
(Hill et al., 2015)	Comparison between human-chatbot and human-human conversations.	Computer-mediated communication (CMC)	People are more likely to communicate with the chatbot for longer time with shorter messages lengths than with another human.
(Crutzen et al., 2011)	Use of chatbot to answer adolescents' questions in the medical field.	No specific theory	A chatbot was more anonymous and faster than search engines and information lines. Specifically, concerning information quality and conciseness, an artificially intelligent assistant outperformed search engines.
(Chung et al., 2018)	The effect of chatbot e-service on customer satisfaction in luxury contexts.	Social Media Marketing Activities model	E-service through chatbot assistances in engaging the customer and delivers interactive customer service. Moreover, using chatbot e-service leads to customer satisfaction with the brand.
(Holzwarth et al., 2006)	The effect of virtual agents on consumer satisfaction with the retailer, product attitude, and purchase intention in e-commerce.	Theory of social response	A virtual agent leads to more satisfaction with the retailer, more attitude toward the product, and more intention to purchase.
(Edwards et al., 2014)	A comparison between a bot and a human agent regarding communication quality on Twitter.	The CASA paradigm	Drawing on the CASA paradigm, findings showed (a) there is no difference between a bot and a human agent regarding source credibility, intentions of interaction, or communication competence; (b) bot is perceived as attractive, credible, and competent both in communication and interactional intentions; and (c) notably, the human agent was perceived as more attractional both in social and task than the bot.
(Ciechanowski et al., 2019)	The uncanny valley effect (UCVE) in human-chatbot interaction	The theory of planned behavior (TPB)	Based on the TPB, users show an interest in interacting with chatbots and intentions to continue the use of chatbots in the future as well. However, UCVE was found more in the human-like chatbots.
(Feine et al., 2019)	Taxonomy categories and subcategories in human-chatbot	Systematic literature review and interpersonal communication theory	A taxonomy that classifies the identified social cues into four major categories, i.e., verbal (expressed with written or spoken words), visual (that can be seen), auditory (that can be heard), and invisible (cannot be seen or heard)

through human–chatbot interaction.

Through an in-depth review of the prior studies on chatbots (peer-reviewed publications in English) conducted through two major databases Web of Science (WOS) and Scopus online libraries using the following query applied to the title, abstract and keywords: ("agent* OR assistant*") OR "chatbot* OR chatterbot* OR chatterbox*"). Table 1 shows that most of the earlier literature has mainly focused on the comparison of human–chatbot, and human–human conversations (e.g., Edwards et al., 2014; Hill et al., 2015; Mou & Xu, 2017), with most studies utilizing the CASA paradigm. In addition, some researchers have studied chatbots in the context of medical-related services (Crutzen et al., 2011) or create a taxonomy of social cues for conversational agents (Feine et al., 2019).

Apart from that, researchers have also studied chatbots in the context of psychotherapy (Weizenbaum, 1966), interviews (Hasler et al., 2013) or investigated how chatbots can help in the e-learning environment (Jia, 2009). However, despite a growing body of literature on chatbots, little attention has been paid to understanding the antecedents that influence customers' satisfaction and CI. Previous studies also investigate consumers' satisfaction (Chung et al., 2018) and CI (Ciechanowski et al., 2019) toward chatbots. However, these studies have not revealed the underlying mechanism or antecedent of satisfaction and continuance.

Thus, in order to extend the growing literature on chatbots in the service context, the present study serves to fill this gap. On the basis of the ECM, ISS model, and TAM, the current study proposes a model that employs a post-adoption view to better understand the factors that are associated with users' satisfaction and CI regarding chatbots. This model also includes a new construct: the need for interaction with a service employee (NFI-SE). To the best of our knowledge, past studies have not investigated the moderating effect of NFI-SE in the context of chatbots for e-service. The inclusion of NFI-SE will also increase the reliability of the model, as NFI-SE is highly relevant both for chatbots and the service sector.

2.2. Theoretical foundation

A major portion of the foundation of this study is Bhattacherjee's (2001) ECM of information technology. Bhattacherjee (2001) initially developed the ECM by incorporating expectation–confirmation theory (ECT) (Oliver, 1980) and the TAM (Davis et al., 1989). ECM is a proven success model to explain users' intention to continue using both in the marketing service and information technology (IT) literature (Ashfaq et al., 2019; Gupta et al., 2020; Park, 2020; Joo et al., 2017). ECM has been applied by numerous scholars to understand users' CI, repurchase intention, and behavior, in many fields, ranging from IT usage (Bhattacherjee, 2001) to mobile application use (Tam et al., 2018), and most recently, mobile advertising (Lu et al., 2019). A recent meta-analysis (Ambalov, 2018) based on 51 ECM studies report the ECM is appropriate to study users' satisfaction and CI.

The ECM is the most commonly used model to understand users' satisfaction toward a product or service and post-usage behavior. The ECM suggests three prominent determinants in explaining the users' CI, namely, confirmation, perceived usefulness (PU), and satisfaction (Bhattacherjee, 2001). Essentially, users' satisfaction and PU are key predictors of CI, whereas users' confirmation of expectation and PU are key antecedents of their satisfaction (Bhattacherjee, 2001). Potential users are likely to use new technologies, such as chatbots, if they perceive such technologies as likely to be useful and beneficial to them (Bhattacherjee, 2001; Bölen, 2020).

Hence, Bhattacherjee's (2001) model is based on Oliver's (1980) ECT. The ECT is one of the most extensively studied models in marketing, particularly in the consumer behavior literature (Espejel et al., 2009). According to Oliver (1980) and Espejel et al. (2009, p. 18), "satisfaction occurs when expectations are confirmed." In agreement with this, we only use the three most relevant constructs— PU, satisfaction, and CI —into the conceptual framework using the ECM. The use of a few constructs from the ECM is possible and even has been done by Hsiao et al. (2016), who use only PU, satisfaction, and CI. Excluding confirmation can make the model more parsimonious. We followed a similar approach and developed our proposed model with the exception of the construct confirmation.

In addition to the ECM, another well-accepted theory in explaining post-stage usage behavior is DeLone and McLean's (2003) ISS model, initially developed by DeLone and McLean (1992). The IS success model comprises six variables: "system quality, information quality (IQ), IS use, user satisfaction, individual impact, and organization impact" (p. 87). In a follow-up study, DeLone and McLean (2003) extend the ISS model by incorporating one new variable: service quality (SQ). Past studies claim that IQ and SQ are crucial determinates of any information system platform's success (e.g., Gao et al., 2015; Teo et al., 2008; Veeramootoo et al., 2018). Accordingly, in the chatbot e-service context, the current study incorporates the two most relevant constructs— IQ and SQ —into the conceptual framework. If a chatbot provides quality information and service, it will stimulate a user to continue using chatbots in the future.

Concomitantly, PEOU and perceived enjoyment (PE) from TAM have been regarded as crucial factors to enhance customer satisfaction and CI, especially in the technological context (Choi et al., 2019; Hong et al., 2006; Thong et al., 2006). The more easy and enjoyable to use a system or service is, the more positive the attitude of customers toward it. These two antecedents found to be a better predictor for IT-based services (Davis, 1989; Davis et al., 1992; Oghuma et al., 2016). Thus, the current study incorporates PEOU and PE into the research model in the context of chatbots, as we expect such factors to drive chatbot users' satisfaction and CI. Notably, some chatbots are difficult to use (e.g., complex interface, ambiguous information, or need to download web plug-in), which we believe can have a negative impact on customer decision making. Since e-service using chatbots is a recent advancement in the technological arena, we use the ECM, ISS model, and TAM as the theoretical foundation for the current study.

However, simply combining the three models may fail to explain individual differences in chatbot satisfaction and CI. Therefore, we incorporate NFI-SE as a moderating variable. Seeking human–human interaction is part of human nature. Some users may not enjoy interactions with chatbots or machines because such technologies reduce their interaction with other people (Evanschitzky et al., 2015; Kokkinou & Cranage, 2015). Thus, NFI-SE may play an essential role in the effect of PU, PEOU, and PE on satisfaction. For people who prefer human–human interaction to technology-based services (Dabholkar & Bagozzi, 2002; Demoulin & Djelassi, 2016), interacting with a chatbot may remove the (desirable) opportunity to interact with a human, leading them to perceive technology-based services as less useful (Dabholkar, 1996; Evanschitzky et al., 2015). Notably, previous studies (e.g., Dabholkar, 1996) on IT-based self-service or self-service technologies (SSTs) suggest that NFI-SE is an essential and pertinent factor in interaction with human beings. Thus, we expect that NFI-SE is also a crucial determinant of users' satisfaction and CI related to chatbot e-service.

3. Hypotheses development and conceptual model

3.1. IQ, SQ, and satisfaction

The metric of IQ is first proposed by DeLone and McLean's (1992) ISS model. According to Setia et al. (2013, p. 268), IQ can be defined as "the accuracy, format, completeness, and currency of information produced by digital technologies." IQ reveals "information accuracy, relevance, sufficiency, and timeliness" (Gao et al., 2015, p. 254). Access to sufficient, precise, accurate, up-to-date, and reliable information plays a decisive role in users' satisfaction (Teo et al., 2008; Veeramootoo et al., 2018). DeLone and McLean's (1992) original ISS model also suggests that the quality of information stimulates users' satisfaction.

Users spend considerable time and effort to seek out product information, latest offers, or usage instruction via chatbot e-service. Therefore, the information provided by the chatbot should be personalized, completed, easy to understand, and well-formatted (Teo et al., 2008), because IQ is one of the most important quality components to measure the success of a system (DeLone and McLean, 2003), and one which leaves a positive impact on users' satisfaction (Chung & Kwon, 2009). Poor quality information will provide a poor user experience: if the information provided by a chatbot is not up-to-date, irrelevant, or is otherwise incorrect, users may need

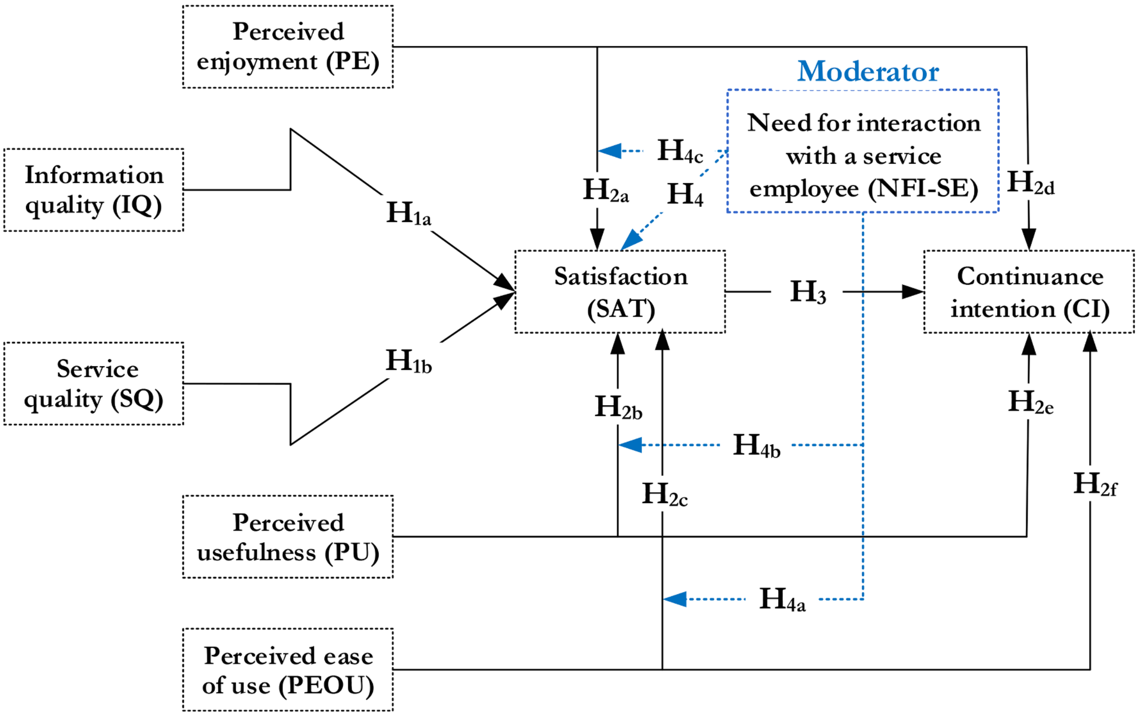

Fig. 1. The conceptual framework.

to seek alternative sources to find information, which will require more time and effort on their part (Gao et al., 2015). In that case, users may perceive the company is unable to provide them with quality service, which may reduce their level of satisfaction. In contrast, service providers who provide appropriate, precise, timely, and relevant information to users can enhance chatbot users' satisfaction.

The updated ISS model posits that the quality of service also influences users' satisfaction (e.g., DeLone and McLean, 2003; Chung & Kwon, 2009; Veeramootoo et al., 2018). SQ relies upon prompt responses and individual attention, which may have a favorable impact on the users' satisfaction (Chung & Kwon 2009; Veeramootoo et al., 2018; Roca et al., 2006), and reflect upon the service provider's goodwill, ability, and reliability (Gao et al., 2015). If a chatbot system is designed well and understands users' concerns and addresses their problems by providing a prompt response, the quality of service may enhance users' satisfaction level, which may enhance their CI. On the other hand, if a system is slow and users encounter service interruption, has a poor interface design, does not respond in a timely manner or offer individualized attention, users' trust is reduced (Gao & Waechter, 2017), which may reduce their satisfaction level. As such, we argue that quality information and quality service will affect users' overall satisfaction with chatbots. Therefore, we hypothesize (see Fig. 1):

H1. *IQ **(H1a)** and SQ **(H1b)** positively influence users' satisfaction with chatbot e-service.*

3.2. PE, PU, PEOU, satisfaction, and CI

TAM predicts an individual's attitudes toward using technologies and considers two key determinants: PU and PEOU (Davis et al., 1989). PEOU and PU represent the users' belief that using a technology will enhance their experience (Bhattacherjee, 2001). PE is another essential determinant of primary relevance to technology acceptance behavior (Davis et al., 1992). Such TAM constructs are crucial determinants of satisfaction and CI for any technological service (Hong et al., 2006; Lin et al., 2017; Oghuma et al., 2016; Roca et al., 2006; Thong et al., 2006).

Using the subsequent version of TAM (Venkatesh & Bala, 2008), scholars assert that PE, as an intrinsic motivation, is one of the fundamental determinants for end-users' acceptance of a technology system (McLean et al., 2020). In this context, PE is defined as "the activity of using a specific system which is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000, p. 351). Literature has established that users who do experience intrinsic enjoyment and find a system enjoyable during their use could influence both user satisfaction and CI, as users sometimes use technologies for entertainment and fun instead of performance enrichment (Davis et al., 1992; McLean et al., 2020). Several lines of evidence also suggest that PE is a significant predictor of users' satisfaction and CI, particularly in technological settings (Davis et al., 1992; Lin et al., 2017; Oghuma et al., 2016). When consumers interact with a chatbot, a fun and pleasant experience can induce a positive feeling (Chung et al., 2018), which will contribute to overall satisfaction (Park, 2020). Therefore, we expect that when users have enjoyable experiences using a chatbot, they will feel more satisfied and willing to continue using chatbots.

Adding to the TAM, Bhattacherjee's (2001) ECM suggests that users' satisfaction and CI for technology is mainly based on the PU, or the degree to which a user feels that using the new technology (e.g., a chatbot e-service) is useful for supporting his/her activities as well as helps perform some specific tasks effectively (e.g., getting information and making an online order). To this point, the term "performance" is to be perceived as relating to some benefits attained by using chatbot e-service, such as problem-solving by getting instant service support and time saving by receiving real-time information. IT users tend to demonstrate a considerable amount of satisfaction and CI if they perceive such technologies as useful (e.g., Davis et al., 1992; Lin et al., 2017; Roca et al., 2006). Thus, PU influences satisfaction (Roca et al. (2006) and CI for technologies such as social networking sites (Lin et al., 2017)—it is the main motivation of technology acceptance (Bhattacherjees, 2001).

In the case of chatbots, users may expect that chatbots may improve their performance or productivity. According to social exchange theory (Emerson, 1976), if users perceive the value of interacting with a chatbot is higher than its cost, they will be satisfied with the chatbot (Shiau & Luo, 2012). For example, when users ask a question about shipping or return policies, if they receive a response that solves their problem, they will be satisfied with the performance of the chatbot. However, if a user does not obtain help from the chatbot, he/she may perceive the value of such an interaction as lower than its cost. As a result, the user will feel less satisfied and stop using it. Therefore, a higher level of PU will lead to a higher level of satisfaction and a higher CI.

Social exchange theory also suggests that satisfaction depends on the perceived cost. Therefore, PEOU is a relevant construct to predict user satisfaction with chatbots. PEOU is an essential determinant in technology studies (Davis et al., 1989; Hong et al., 2006), one which refers to "the degree to which the prospective user expects the target system to be free of effort" (Davis, 1989, p. 320). In accordance with Davis et al. (1989), to enhance users' satisfaction, technology services such as chatbots should be understandable and clear as well as enable users to complete their tasks effortlessly. These features are positively be related to CI (Ashfaq et al., 2019; Roca et al., 2006; Thong et al., 2006). In the context of chatbots, PEOU decreases the perceived cost. For example, some chatbot systems require the installation of plug-ins, creating a barrier for the user. Others have very complex settings or a chaotic interface design, which requires users to expend cognitive effort and time to initiate a chat. We argue that if chatbot e-service is easy to use, consumers will have a higher level of satisfaction and CI because the perceived cost of using a chatbot is reduced. Accordingly, we suggest the following hypothesis:

H2. *PE, PU, and PEOU will positively influence users' satisfaction with* ***(H2a, H2b, H2c)*** *and CI toward* ***(H2d, H2e, H2f)*** *chatbot e-service.*

3.3. Satisfaction and CI

Bhattacherjee's (2001) ECM predicts that satisfaction is a critical determinant of users' CI toward technology. It is also considered the core antecedent in the marketing literature (Brill et al., 2019), plays an important role in creating and retaining long-term loyal customers (Ashfaq et al., 2019; Nascimento et al., 2018), and is shown to be a key construct for users' CI (Boakye et al., 2014; Nascimento et al., 2018) in multiple research settings (Alghamdi et al., 2018; Bhattacherjee, 2001; Gao et al., 2015; Joo et al., 2017; Lin et al., 2017). In line with this evidence, we argue that satisfied users will be more likely to continually use chatbot e-service:

H3. *Satisfaction will positively influence users' CI toward chatbot e-service.*

3.4. The moderating role of NFI-SE

IBM's CEO Rometty claims that "man and machine always get a better answer than man alone or machine alone" (Loftis, 2018), indicating the role of human–human interaction in the technological context (e.g., chatbots), cannot be ignored. Thus, inspired by the study of Dabholkar and Bagozzi, NFI-SE, meaning "the importance of human interaction to the customer in service encounters" (2002, p. 188) is considered as a moderator. According to Dabholkar (1996), NFI-SE is an appropriate, relevant, and crucial determinant for IT-based self-service or SSTs. Users with a high NFI-SE will avoid IT-based self-service, and therefore, for them, such services reduce intrinsic motivation (Dabholkar & Bagozzi, 2002). For instance, Kokkinou and Cranage (2015) find that NFI-SE of the respondents that selected self IT-based service is lower than for those that chose a service employee. In contrast, users with low NFI-SE will search for technological options (Dabholkar & Bagozzi, 2002). In the technological environment, NFI-SE is considered an essential factor in understanding users' needs (Dabholkar & Bagozzi, 2002; Kokkinou & Cranage, 2015; Mimoun et al., 2017). Indeed, NFI-SE tends to reduce the use of SSTs by people with a stronger need for human contact (Kokkinou & Cranage, 2015); the use of service employees is more valued by users with a high need for human contact (Mimoun et al., 2017). However, for the consumers who look for technological-based service, the choices should be more comfortable, much more reliable, easier to use, and much more interesting (Dabholkar & Bagozzi, 2002). Indeed, for the buyers with strong NFI-SE, the SSTs and its features need to be much more humanized, useful, and interesting (Dabholkar & Bagozzi, 2002). Additionally, Kokkinou and Cranage (2015) reveal that high NFI-SE customers are less likely to choose SSTs. Similarly, Lee (2017) finds an inverse relationship between NFI-SE and desire to use SSTs, because, non-users of SSTs are more likely to interact with retail employees rather than machines. Hence, the users who do not have much experience interacting with computers (or chatbots) or non-users of SSTs may feel less confident, more uncertain, and less comfortable than other experienced users (Mou et al., 2019). Yet, less experienced human–computer interaction users may feel more confident, more comfortable, and more determined to interact with a human service employee rather than a chatbot. In this regard, Mou and Xu (2017) claim that users show different personality traits when they interact with human–human and human-AI agents. They further argue that when users interact with a human, they are "more open, more conscientious, more extroverted, more agreeable, and self-disclosing than AI agent" (Mou & Xu, 2017, p. 432).

In this vein, we anticipate that people with high NFI-SE prefer human–human over human–machine interaction. They may feel more comfortable and find it more convenient to negotiate with a service employee. If those with strong NFI-SE perceive a chatbot as too simple, it may be interpreted as a lack of interaction and human touch (Nguyen, 2019). Hence, the effect of PEOU on chatbot e-service satisfaction negatively moderates through NFI-SE for users with a high need for human interaction. For people with higher NFI-SE, higher PEOU (e.g., limited functions and options, the absence of personalized and customized services, an oversimplified interface) may lead to lower satisfaction; to cater to them, SSTs and their features must be more humanized, useful, and interesting (Dabholkar & Bagozzi, 2002). For people with lower NFI-SE, higher PEOU will lead to higher satisfaction; technologies targeting this group should be more comfortable, reliable, easier to use, and more interesting (Dabholkar & Bagozzi, 2002).

We also argue that NFI-SE will moderate the effect of PU on satisfaction. As people with higher NFI-SE may have a very low expectation of chatbot services, increasing the PU (e.g., providing highly relevant information, showing personalized recommendations, solving problems in a timely manner) of these users can enhance their satisfaction. Thus, for people with higher NFI-SE, higher PU will lead to higher satisfaction. For people with lower NFI-SE, such a positive effect will be less prominent.

Correspondingly, we further expect that NFI-SE will moderate the effect of PE on satisfaction. Generally speaking, higher PE leads to higher satisfaction. When people feel comfortable and enjoy a service, they are likely to exhibit a higher level of satisfaction (Davis et al., 1992; Lin et al., 2017; Oghuma et al., 2016). However, users with higher NFI-SE tend to avoid using SSTs because they do not enjoy the service as much as interacting with a human service agent. In this case, increasing the PE of the chatbot service (e.g., adding relaxing background music, providing a stylish interface) can have a stronger positive effect on satisfaction for these users. Thus, drawing on this discussion, in the chatbot e-service context, we suggest the following hypotheses:

H4. *NFI-SE will negatively influence users' satisfaction with using chatbot e-service. Additionally, NFI-SE will moderate the relationships among PEOU, PU, PE, and satisfaction toward chatbot e-service.*

H4a. *NFI-SE will moderate the effect of PEOU on satisfaction. For users with higher (lower) NFI-SE, the relationship between PEOU and satisfaction toward using chatbot e-service will be negative (positive).*

H4b. *NFI-SE will moderate the effect of PU on satisfaction. For users with higher (lower) NFI-SE, the positive relationship between PU and satisfaction toward using chatbot e-service will be stronger (weaker).*

H4c. *NFI-SE will moderate the effect of PE on satisfaction. For users with higher (lower) NFI-SE, the positive relationship between PE and satisfaction toward using chatbot e-service will be stronger (weaker).*

4. Methodology

4.1. Data collection and procedure

Data for this study were collected using Amazon's Mechanical Turk (MTurk) in the United States. Scholars from several disciplines, including social science, psychology, and marketing, use MTurk to collect data from participants (Sheehan, 2018; Yu et al., 2018). The MTurk sample is more diverse than a traditional student sample (Sheehan, 2018).

On the MTurk platform, a link asking users to participate in a study on chatbots for customer service was sent to respondents. When they opened the link of the questionnaire, they were requested to read an introductory text defining a text-based chatbot for customer service. We only targeted text-based customer service chatbots in this study, as this is the most common type of chatbots. Then we asked them to recall their last experience interacting with a text-based chatbot for customer service and to complete the survey with that experience in mind. The questionnaire was created using the Qualtrics platform. We targeted only participants who previously interacted with chatbots, screening with the question, "have you ever interacted with a chatbot before?".

In total, we received 551 responses (including both male and female respondents), but 181 were removed. We eliminated all respondents who did not read the questions carefully, using an attention filter (e.g., "please select strongly disagree") as suggested by Yu et al. (2018), as well as those who indicated they did not have relevant experience with chatbots. A final sample of 370 valid responses was further analyzed.

Respondents' mean age was 29.75 (SD = 7.06; minimum = 29; maximum 70), including five missing values. In contrast with Chung et al. (2018), the current study did not focus only on a particular age group; we recruited respondents from all age groups to gain a broader understanding regarding users' satisfaction and CI toward chatbot e-service. As Chattaraman et al. (2019) show, older adults (65 and older) are increasingly digitally connected. Most respondents (58 responses; 15.7%) reported a monthly household income of $2001–3000. There were more male respondents (233 responses; 63%) than female (137; 37%). Most respondents held a Bachelor's degree (266 responses; 71.9%) (Table 2).

4.2. Measurement and procedure

In this study, "a seven-point Likert scale was used to measure all indicators except satisfaction." To measure satisfaction, a seven-point bipolar scale containing four bipolar items was used (Oghuma et al., 2016). First, IQ was measured using seven items adapted from Teo et al. (2008). To measure SQ, we used six items from Roca et al. (2006). CI was examined using the instrument developed by Bhattacherjee (2001). To measure PE, five items from Lee and Choi (2017) were adopted. The scale developed by Oghuma et al. (2016) was employed to measure PU, and PEOU was estimated based on four items adapted from Liao et al. (2007). Finally, NFI-SE was assessed based on four items from Dabholkar and Bagozzi (2002).

Table 2
Profile of the respondents.

Characteristics	Distribution	Frequency	%	Mean	SD
Gender	Male	233	63.0	1.37	0.484
	Female	137	37.0		
Chatbot experience?	Yes	370	100.0		
Frequency	1–3 times per year	165	44.6	2.88	0.958
	4–9 times per year	113	30.5		
	10–15 times per year	63	17.0		
	> 15 times per year	29	7.8		
Educational background	High School	40	10.8	3.60	0.909
	Bachelor degree	266	71.9		
	Master's degree	62	16.8		
	Doctoral degree	2	0.5		
Monthly household income	$0 - $1000	13	3.5	5.41	2.721
	$1001 - $2000	47	12.7		
	$2001 - $3000	58	15.7		
	$3001 - $4000	36	9.7		
	$4001 - $5000	48	13.0		
	$5001 - $6000	47	12.7		
	$6001 - $7000	28	7.6		
	$7001 - $8000	25	6.8		
	$8001 - $9000	21	5.7		
	Above $9000	47	12.7		
Age	20–30	270	73.0	29.76	7.064
	31–40	69	18.6		
	41–50	13	3.5		
	> 50	13	3.5		
	Missing	5	1.4		

4.3. Control variables

Following the previous studies (e.g., Li et al., 2020; Zafar et al., 2019), particularly in the technological context (e.g., Cheng & Mitomo, 2017), some commonly controlled variables such as age, gender, and education are included as control variables in our study to confirm that the results from the empirical analysis are not because of variance with these demographic variables. In the technological environment, previous (academic) literature relating to these specific variables asserted that such variables might influence the empirical results (Cheng & Mitomo, 2017; Fang et al., 2014). In conjunction with this, we have included them as control variables in our model.

5. Data analysis and results

5.1. Common method bias (CMB)

We used a principal component analysis method with "Harman's one-factor test" (Harman, 1976) using SPSS software (version 25) following the approach of previous studies to analyze CMB (Chang et al., 2019). According to Harman's approach, if the value of a single construct is higher than 50% of the variance, then CMB exists in the data (Harman, 1976). Our results indicated that the percent of the variance of a single construct was 47.46, below 50% of the variance, indicating there is no CMB.

5.2. Measurement model analysis

The present study employs the partial least squares structural equation modeling (PLS-SEM) approach. According to Hair et al. (2019), the measurement model should assess the loading of the items, reliability (Cronbach's alpha), convergent validity, and discriminant validity. Indicators (i.e., items) with loadings greater than 0.708 are considered satisfactory (Hair et al., 2019). In this study, all items' loadings are above the suggested level (except for two items, NFI-SE 4 and SQ 3—see Table 3), demonstrating they satisfied this criterion.

In addition, following the approach of Hair et al. (2010), alpha was used to assess the constructs' reliability using a cut-off level of 0.70. The values of alpha range from 0.778 to 0.910, above Hair's suggested minimum. To measure validity, we used two widely accepted forms: convergent validity and discriminant validity (Hair et al., 2010). The average variance extracted (AVE) (Hair et al., 2019; Usakli & Kucukergin, 2018) and composite reliability (Fornell & Larcker, 1981) were employed to measure convergent validity. The values of composite reliability (ideally > 0.70) and AVE (ideally > 0.50) for our sample were both acceptable (Table 3). The square root of the AVE was used to measure the discriminant validity (Fornell & Larcker, 1981). The results are presented in Table 4.

Lastly, before examining the structural model, we assessed the overall model. Model fit can be evaluated using the standardized root mean square residual (SRMR) (Hu and Bentler, 1999), and the root mean square covariance (RMS_{theta}) (Lohmoeller, 1989). The

Table 3
The reliability and validity of the measurement.

Construct/ Source	Items	FL	VIF	α	CR	AVE
Information quality (Teo et al., 2008)	1. This chatbot provides sufficient information.	0.802	2.186	0.894	0.916	0.610
	2. Through this chatbot, I get the information I need on time.	0.763	1.848			
	3. Information provided by this chatbot is in a useful format.	0.760	1.887			
	4. Information provided by this chatbot is clear.	0.766	1.930			
	5. Information provided by this chatbot is accurate.	0.775	1.931			
	6. Information provided by this chatbot is up-to-date.	0.767	2.011			
	7. Information provided by this chatbot is reliable.	0.833	2.454			
Service quality (Roca et al., 2006)	1. The chatbot has a modern-looking interface.	0.722	1.513	0.860	0.895	0.590
	2. The chatbot provides the right solution to my request.	0.826	2.157			
	3. The chatbot gives me a prompt response.	0.616	1.409			
	4. The chatbot has visually appealing materials.	0.765	1.871			
	5. The chatbot gives me individual attention.	0.773	1.845			
	6. The chatbot has an excellent interface to communicate my needs.	0.837	2.321			
Perceived enjoyment (Lee & Choi, 2017)	1. I enjoy a conversation with the chatbot.	0.868	2.631	0.910	0.933	0.735
	2. It is fun and pleasant to share a conversation with the chatbot.	0.862	2.588			
	3. The conversation with the chatbot is exciting.	0.874	2.843			
	4. I enjoy choosing products more if they are recommended by the chatbot than if I choose them myself.	0.849	2.459			
	5. I was absorbed in the conversation with the chatbot.	0.832	2.268			
Perceived usefulness (Oghuma et al., 2016)	1. I find the chatbot useful in my daily life.	0.866	2.388	0.893	0.926	0.757
	2. Using the chatbot helps me to accomplish things more quickly.	0.869	2.457			
	3. Using chatbot increases my productivity.	0.882	2.583			
	4. Using the chatbot helps me to perform many things more conveniently.	0.863	2.432			
Perceived ease of use (Liao et al., 2007)	1. My interaction with the chatbot is clear and understandable.	0.833	1.776	0.802	0.870	0.627
	2. Interaction with the chatbot does not require a lot of my mental effort.	0.730	1.472			
	3. It is easier to use the chatbot to find products that I want to buy.	0.807	1.629			
	4. I find the chatbot to be easy to use.	0.794	1.753			
Need for interaction with a service employee (Dabholkar & Bagozzi, 2002)	1. Human contact in providing services makes the process enjoyable for me.	0.867	2.018	0.818	0.873	0.636
	2. Personal attention by the service employee is very important to me.	0.758	1.676			
	3. I like interacting with the person who provides the service.	0.891	1.938			
	4. It bothers me to use a chatbot when I could talk to a person instead.	0.651	1.457			
Satisfaction (Oghuma et al., 2016)	How do you feel about your overall experience of using the chatbot?					
	1. Very dissatisfied — very satisfied.	0.848	2.176	0.877	0.916	0.731
	2. Very displeased — very pleased.	0.828	2.002			
	3. Very frustrated — very contented.	0.872	2.471			
	4. Very unpleasant — very pleasant.	0.870	2.440			
Continuance intention (Bhattacherjee, 2001)	1. I intend to continue using this chatbot in the future.	0.875	1.942	0.778	0.870	0.692
	2. I will always try to use this chatbot in my daily life.	0.847	1.616			
	3. I will strongly recommend others to use it.	0.769	1.705			

Factor loadings (FL); Cronbach's alpha (α); Composite reliability (CR); Average variance extracted (AVE); Variance inflation factor (VIF).

Table 4
Descriptive statistics, correlations, and discriminant validity.

	Mean	SD	1	3	4	5	6	7	8	9
CI	5.35	1.23	**0.832**							
IQ	5.43	0.92	0.778	**0.781**						
NFI-SE	5.32	1.09	0.447	0.451	**0.797**					
PE	5.11	1.27	0.786	0.687	0.499	**0.857**				
PEOU	5.31	1.03	0.698	0.755	0.417	0.613	**0.792**			
PU	5.31	1.15	0.764	0.737	0.456	0.776	0.698	**0.870**		
SAT	5.59	1.12	0.695	0.719	0.279	0.690	0.586	0.705	**0.855**	
SQ	5.39	0.94	0.814	0.855	0.470	0.786	0.749	0.755	0.738	**0.768**

The square root of the AVE in diagonal (bold values) and off-diagonal values are correlations among constructs.

SRMR is the most frequently used measure for model fit assessment (Henseler et al., 2016), especially when scholars use SmartPLS 3 software (Ringle et al., 2015). The SRMR value should be below 0.08 (Hu and Bentler, 1999). Henseler et al. (2014) indicate that RMS_{theta} can also be an approximate model fit criterion. However, the cut-off value for RMS_{theta} is not yet established (Henseler et al., 2016). As expected, in the current study, the SRMR value is 0.06, below the suggested maximum of 0.08 (Hu and Bentler, 1999), suggests an adequate model fit.

Table 5
Structural model analysis for all five models.

Path	Model-1	Model-2	Model-3	Model-4	Model-5
PU → SAT	0.296***	0.317***	0.240***	0.249***	0.325***
PU → CI	0.546***	0.388***	0.187***	0.187***	0.187***
SAT → CI	0.313***	0.261***	0.158***	0.158***	0.158***
IQ → SAT	0.229**	0.261***	0.272***	0.291***	0.275***
SQ → SAT	0.318***	0.341***	0.251***	0.256***	0.217***
PEOU → SAT	———	−0.088 (ns)	−0.077 (ns)	−0.063 (ns)	−0.104 (ns)
PEOU → CI	———	0.273***	0.238***	0.238***	0.238***
PE → SAT	———	———	0.167**	0.218***	0.214***
PE → CI	———	———	0.386***	0.386***	0.386***
NFI-SE → SAT	———	———	———	−0.169***	−0.126***
PEOU × NFISE → SAT	———	———	———	———	−0.152***
PU × NFI-SE → SAT	———	———	———	———	0.103*
PE × NFI-SE → SAT	———	———	———	———	0.055 (ns)
The value of R^2 throughout the five models in the structural analysis					
		SAT		CI	
Model-1 →	———	0.608	———	0.637	← R^2
Model-2 →	———	0.611	———	0.668	← R^2
Model-3 →	———	**0.620**	———	**0.722**	← R^2
Model-4 →	———	0.640	———	0.722	← R^2
Model-5 →	———	**0.661**	———	**0.722**	← R^2

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; not supported (ns).

5.3. Multicollinearity

We further assessed the variance inflation factor (VIF) to check for multicollinearity before structural model analysis (Hair et al., 2017). According to Hair et al. (2017), a VIF above 5.0 is problematic, indicating multicollinearity. Our results show that the values of VIF for all measurement indicators were below this value; the highest VIF value in our model is 2.84 (Table 3), indicating the model is free from multicollinearity.

5.4. Structural model analysis

After confirming adequate reliability and validity of the measurement model and overall model fit, we applied a bootstrapping approach (bootstrapping subsample = 5000) to test the proposed hypothesis and path coefficients. Before examining the full model, we first tested the model in each stage (model 1 to model 5). For example, in model 1, we added the ISS model constructs of IQ and SQ to the ECM. In models 2 and 3, we added the TAM constructs PEOU and PE to the previous model. The results are provided in Table 5. All models were significant at the $p < 0.001$, $p < 0.01$, and $p < 0.05$ levels. Model 3 explained 62% of the variance in users' satisfaction toward chatbot e-service and 72.2% in CI, indicating it a much better model than models 1–2 (incorporating all constructs but without NFI-SE as a moderator). Finally, the full model incorporating NFI-SE as a moderator was tested (model 5). The overall results (including hypothesis testing, path coefficients, t-values, p-values, and decisions) are presented in Table 6.

The full model (Fig. 5) showed that, first, the effect of IQ ($\beta = 0.275$; $t = 3.404$; $p < 0.001$) and SQ ($\beta = 0.217$; $t = 2.607$; $p < 0.001$) on satisfaction were confirmed. These results are statistically significant and in favor of H1a and H1b; hence, H1 is fully supported. Second, the influence of PE ($\beta = 0.214$; $t = 2.869$; $p < 0.001$), and PU ($\beta = 0.325$; $t = 5.072$; $p < 0.001$) on

Table 6
Hypothesis testing (full model).

Hypo	Path	Beta	T-values	P-values	Decision
H1a	Information quality → satisfaction	0.275***	3.404	0.001	Accepted
H1b	Service quality → satisfaction	0.217***	2.607	0.009	Accepted
H2a	PE → satisfaction	0.214***	2.869	0.004	Accepted
H2b	PU → satisfaction	0.325***	5.072	0.000	Accepted
H2c	PEOU → satisfaction	−0.104 (ns)	2.020	0.043	Rejected
H2d	PE → continuance intention	0.386***	6.316	0.000	Accepted
H2e	PU → continuance intention	0.187***	2.840	0.005	Accepted
H2f	PEOU → continuance intention	0.238***	4.828	0.000	Accepted
H3	Satisfaction → continuance intention	0.158***	3.326	0.001	Accepted
H4	NFI-SE → satisfaction	−0.126***	2.982	0.003	Accepted
H4a	PEOU × NFI-SE → satisfaction	−0.152***	2.955	0.003	Accepted
H4b	PU × NFI-SE → satisfaction	0.103*	2.059	0.040	Accepted
H4c	PE × NFI-SE → satisfaction	0.055 (ns)	1.006	0.314	Rejected

***$p < 0.001$; *$p < 0.05$; not supported (ns).

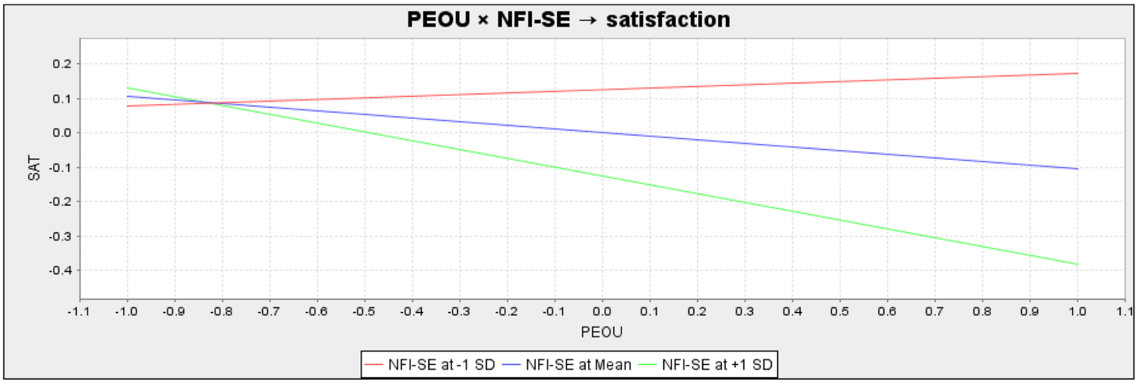

Fig. 2. Interaction plot of NFI-SE.

satisfaction and CI ($\beta = 0.386$; $t = 6.316$; $p < 0.001$; $\beta = 0.187$; $t = 2.840$; $p < 0.001$) offer support to H2a, H2b, H2d, and H2e, respectively. Similarly, PEOU has a positive impact on CI ($\beta = 0.238$; $t = 4.828$; $p < 0.001$), but not on satisfaction ($\beta = -0.104$; $t = 2.020$; $p < 0.05$), supporting only H2f, as a negative significant relationship was observed between PEOU and satisfaction. Hence, H2c is rejected. Third, satisfaction has a strong direct positive influence on CI ($\beta = 0.158$; $t = 3.326$; $p < 0.001$). Therefore, H3 is supported. Finally, to examine the potential influence of demographic variables such as education, age, and gender, we run a series analysis controlling for these variables. The results suggest that these variables did not produce a significant influence on the proposed model. To make the model more parsimonious, we exclude them from our model.

5.5. Moderating analysis

The moderating effect of NFI-SE between PEOU, PU, PE, and satisfaction was checked in two steps (Table 5; models 4 and 5). First, we checked the direct effect of NFI-SE on satisfaction as an independent variable without an interaction effect. Second, we checked its moderating effect among the constructs. A strong significant negative effect of NFI-SE on users' satisfaction toward using chatbot e-service was found ($\beta = -0.126$; $t = 2.982$; $p < 0.001$), supporting H4. The findings further confirmed that NFI-SE moderates the effect of PEOU on satisfaction ($\beta = -0.152$; $t = 2.955$; $p < 0.001$). Hence, H4a was accepted. Likewise, the moderating effect of NFI-SE was found on the relationship between PU and satisfaction ($\beta = 0.103$; $t = 2.059$; $p < 0.05$). Therefore, H4b was also statistically supported. However, NFI-SE did not moderate the effect of PE on satisfaction ($\beta = 0.055$; $t = 1.006$; $p > 0.05$). Hence, H4c is rejected. Furthermore, model 5 (the full model) explains 66.1% of the variance in users' satisfaction toward chatbot e-service, indicating that including the effect of moderation by NFI-SE creates a better model. The moderation effect of NFI-SE among the constructs is shown in Figs. 2–4, and the full model is shown in Fig. 5.

6. Discussions and implications

Chatbots can play a significant role in consumers' experience of companies. The current study mainly focuses on chatbot e-service, which is already extensively employed by many retailers and marketers. The findings suggest the following four significant outcomes.

First, in the context of chatbot e-service, if a chatbot provides up-to-date, reliable information (i.e., offers high IQ), prompt responses, and offers individualized attention (i.e., high SQ), this has a positive influence on users' satisfaction, which in turn affects their CI. The results of this study provide valuable insight that IQ and SQ are key predictors of satisfaction, which ultimately has a

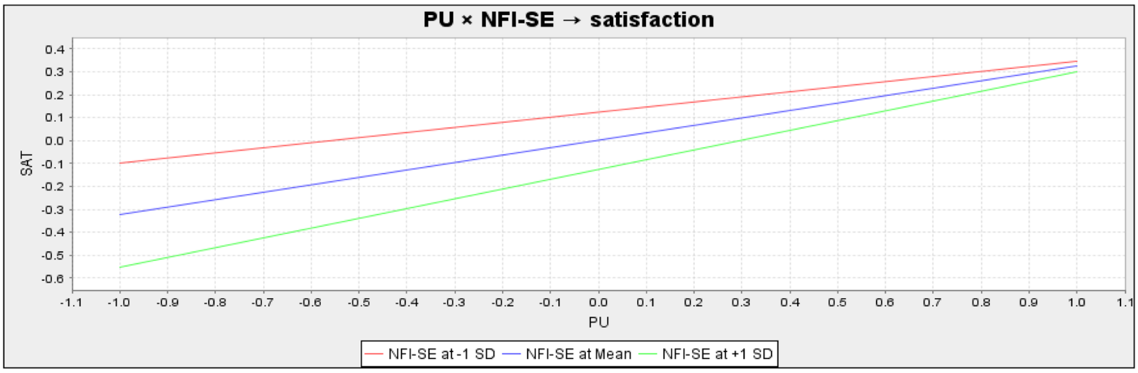

Fig. 3. Interaction plot of NFI-SE.

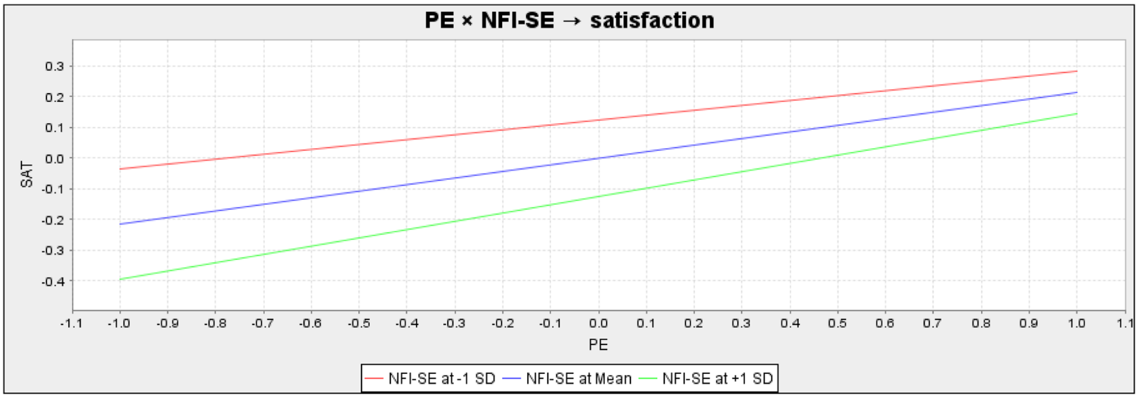

Fig. 4. Interaction plot of NFI-SE.

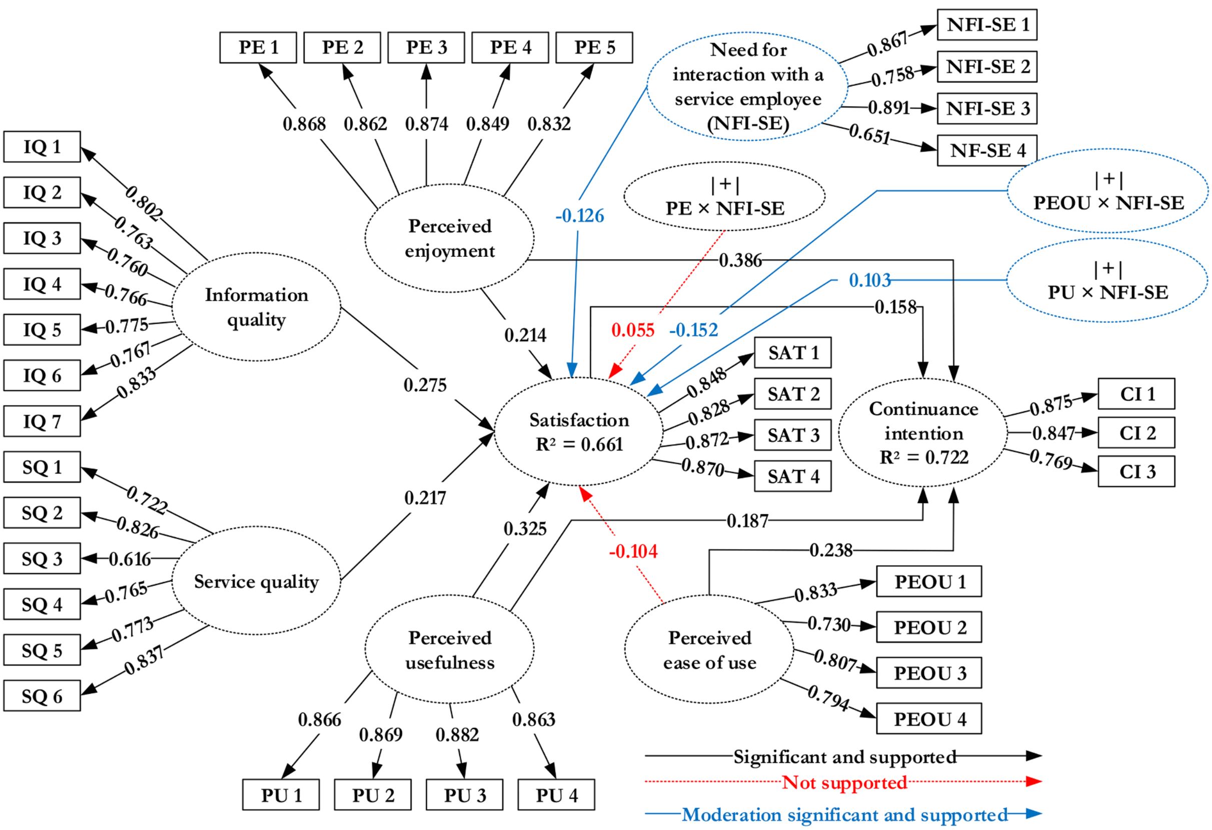

Fig. 5. The structural model with path coefficients (full model).

positive effect on users' CI toward chatbots. These findings gain support from the original ISS models (DeLone and McLean, 1992, 2003), which suggests that IQ and SQ enhance users' satisfaction.

Second, if users find a chatbot easy to use, useful, and enjoyable, they are more satisfied and more willing to continue using it. The detailed results reveal that PE is a crucial predictor for satisfaction and CI, gain support from the TAM theory (Davis et al., 1992) and in line with Ashfaq et al.'s (2019) findings in the context of second-hand products. Similarly, this study finds that PU is a necessary antecedent for satisfaction and CI, a finding supported by Bhattacherjee's (2001) ECM. Our results further suggest that PEOU positively affects CI, which is consistent with the findings of Hong et al. (2006) and Thong et al. (2006). Our results also show no positive significant relationship between PEOU and satisfaction, in line with the findings of Ashfaq et al. (2019). Third, we find satisfaction with chatbot e-service is a strong determinant and predictor of users' CI toward chatbots. This finding finds support from Bhattacherjee's (2001) original ECM.

Fourth, we show that NFI-SE plays a moderating role between PEOU, PU, PE, and users' satisfaction. Mou and Xu (2017) claim that users demonstrate different personality traits when interacting with an AI (e.g., chatbot) or a human agent. They further argue that users feel much more comfortable and are much more open during human–human than human–AI interactions. This suggests that the need for human interaction is still an essential determinant in the technological context. Thus, the present study attempts to explore the moderating role of NFI-SE between PEOU, PU, PE, and users' satisfaction in the chatbot e-service context.

As expected, the direct relationship between NFI-SE and satisfaction (H4) was negative and statistically significant. On the other hand, the relationship between PEOU and users chatbot e-service satisfaction diminishes through NFI-SE for strong human interaction (H4a). In addition, the relationship between PU and satisfaction escalates through NFI-SE (H4b). However, the results show an insignificant moderating effect of NFI-SE on the relationship between PE and satisfaction (H4c). Here, we may claim that interaction with human employees does not strengthen or weaken the relationship between the activity of using chatbots, which is perceived to be enjoyable, and users' satisfaction when doing so. Consumers who find chatbots enjoyable tend to feel more satisfied with them, and do not always require direct interaction with human employees. Consequently, higher PE generally implies satisfaction. Yet, consumers also tend to expect that some interactions with employees may add to the service provided by a chatbot, in helping users to perform some tasks more easily or rapidly. Concomitantly, (some) consumers consider that when the use of chatbots is too easy and does not require substantial mental effort, they may feel unhappy or otherwise unpleasant, resulting in a slight decrease in satisfaction.

6.1. Theoretical implications

This paper contributes to the advancement of theory regarding the acceptance and use of chatbots in several ways. First, this study is one of the early attempts to explore actual chatbot users' satisfaction and CI through the lens of the ECM (Bhattacherjee, 2001) ISS model (DeLone & McLean, 1992, 2003), and TAM (Davis, 1989). In other words, these three models (ECM, ISS model, TAM) are integrated into a new, simplified model to investigate drivers of users' satisfaction and CI of chatbot e-service. Second, the current study further extends three primary bodies of literature by incorporating the construct of NFI-SE into the model. More importantly, we demonstrate how NFI-SE moderates the relationships between PEOU, PU, and satisfaction.

Third, although extensive research has been carried out on chatbots in recent years, no single study exists which adequately assessed the key factors affecting users' satisfaction and CI toward chatbots, this research sheds new light on the role of quality information and quality service delivered by chatbots in strengthening the users' satisfaction level from the perspective of the ECM (Bhattacherjee, 2001) and ISS model (DeLone & McLean, 1992, 2003).

Fourth, our empirical results show that users' satisfaction level and intention to continue are determined by PU, PE, PEOU. In addition, the current work establishes the role of NFI-SE in strengthening users' satisfaction levels in the digital context. In this sense, this study extends Bhattacherjee's (2001) ECM and Davis's (1989) TAM in two ways. First, by confirming the new relationship between NFI-SE and users' satisfaction toward chatbot e-service in the technological environment. Second, by showing its moderating role between users' satisfaction toward chatbot based service and its antecedents.

Taken together, to this end, we propose an analytical framework combining the ECM, ISS model, TAM, and the NFI-SE to investigate drivers of users' satisfaction and CI toward chatbot-based customer service based on the data collected from actual chatbot users.

6.2. Managerial implications

Several managerial implications need to be noted regarding the present study. First, service managers should take care when developing chatbot e-service systems; such systems must provide relevant, reliable, personalized, precise, and up-to-date information in a useful format. Among these important components of IQ, chatbot e-service systems should deliver the quality of information by providing information that highly related to chatbot users' needs and according to current trends. If chatbot users cannot get the information that they actually want from the chatbot e-service systems, they could consider such systems as useless. In such a case, the chatbot e-service leaves a negative impact on users' satisfaction, which, in turn, discourages to continue using it. In a similar vein, when service providers deliver high IQ, plenty of benefits can be achieved, such as positive image and reputation (Butler et al., 2002). On the other hand, when the quality of information is not up to the mark (or low-quality information), it not only distracts chatbot users, but also increases information-processing costs, effort, and more importantly time to reading useless messages (Gu et al., 2007; Zheng et al., 2013). Thus, this impacts the business, reduces user satisfaction, and increases cost.

Second, although IQ is found one of the important predictors of users' satisfaction toward chatbot-based service, another important predictor of users' satisfaction is service quality, indicating that such systems must offer prompts response to users' queries at the same time. Thus, the overall support offered by the chatbot-based service should be of high quality and prompt. Conversely, if chatbot e-service provides low SQ (such as slow service, not paying attention to users' quires, or break in flow), the satisfaction level is reduced. In line with this reasoning, service managers should be careful when developing chatbot systems.

Third, although digital technologies can offer efficiency and effectiveness, such technologies can sometimes cause users to become frustrated by failing to fulfill their needs/desires. In this study, one of the more significant findings is that NFI-SE exerts a powerful influence upon chatbot users' satisfaction, which ultimately leads to higher CI. Thus, we suggest that digital technologies services, such as chatbots, could work together with human service employees to satisfy digital users. To this point, the human channel is more a supplement of chatbot e-service than a replacement because it is costly and also because of the advance of AI technologies in recent years. For example, chatbots-based customer service will help to save annual costs of over $8 billion by 2022 (PointSource, 2018), and therefore it is expected that 85% of all customer interactions will be handled without a service employee or human agent by 2020

(Schneider, 2017). However, managers must consider that different users have different levels of NFI-SE.

Fourth, our findings reveal that users tend to be satisfied with a simple and relevant service that they regard as useful. However, retailers should create some diversity and include enjoyable tasks to enhance users' satisfaction. Consumers will not feel satisfied if they are frustrated, displeased, or bored. For people with high NFI-SE, chatbots should not merely provide simple answers; a more complex system that requires more mental effort may be more effective for them. Even if users tend to regard the service provided by current chatbots as enjoyable and satisfactory, from time to time, they may be even more satisfied by interacting with employees, as long as doing so increases the user's productivity.

Finally, the service provider should ensure that chatbot e-service is trouble-free, useful, and enjoyable. Additionally, retailers ensure that the whole process should be very simple and useful. Further, our findings show that users find chatbot enjoyable, useful in day-to-day life, and that they intend to continue to use them in the future. Thus, retailers should use chatbots to provide 24-hour customer service to their users.

7. Limitations and future research directions

This study has several limitations that suggest fruitful avenues for future studies. First, like prior research on the topic (Chung et al., 2018), we included only those respondents who had previously interacted with chatbots. Further research should investigate whether the findings differ among other groups of people, such as those who are not familiar with digital assistants (Chung et al., 2018). Additionally, although we only included participants who reported having interacted with a chatbot before, some respondents may not be aware that they had actually interacted with a chatbot. For example, they were considering they had interacted with a human service agent rather than a chatbot agent. Moreover, the intensity of the use of chatbots for e-service can also be played a crucial role and may influence the results as well; thus, should be considered these limitations in the future study.

Second, the research model developed in this study heavily relies on three well-known models aggregated in a simplified manner. In addition to the constructs analyzed, some personality-related determinants such as technology optimism, novelty-seeking, and technology self-efficacy may also play important roles in meeting customer satisfaction and CI. However, chatbots can also be used as a companion or virtual assistant. Thus, researchers should further consider the role of perceived risk and privacy concern in the adoption of new technologies, as such technologies' lack of personal touch and lack of empathy to handle frustrated users. We suggest the incorporation of relationship constructs, such as brand attachment (the emotional ties between humans and technology) or subjective well-being.

Third, we employed only NFI-SE as a moderator in the proposed model. The potential moderating influence of demographic variables has not been analyzed and should be done in the future. In addition, the questionnaires were collected using an online method—MTurk in the United States. However, the popularity of chatbots varies across different areas, and country-level and cultural differences may also affect our findings. Future research should investigate whether including people from different countries or with different cultural backgrounds affect the findings.

Finally, future research should be devoted to understanding what aspects of communication properties are effectively perceived as key features of chatbots in the domain of customer service. Thus, the factorial design experiment should be prepared to understand if customers give more importance to one-way vs. two-way, static vs. dynamic, text vs. voice, or AI or human in the domain of customer service.

8. Conclusion

We set out to develop a model for human–chatbot interaction to gain a better understanding of users' satisfaction and CI toward chatbots. Although human–chatbot interaction technologies can offer efficiency and effectiveness, such technologies can sometimes cause users to become frustrated by failing to fulfill their needs/desires. In this study, one of the more significant findings is that NFI-SE exerts a powerful influence upon chatbot users' satisfaction, which ultimately leads to higher CI. Thus, we suggest that digital technologies services, such as chatbots, could be combined with human service employees to satisfy digital users. The second significant finding is that the quality of information and the quality of service provided by chatbots also play significant roles in improving users' level of satisfaction. Information quality, service quality, and NFI-SE are important factors affecting users' satisfaction, whereas satisfaction, PU, PE, PEOU are significant predictors of users' CI toward chatbots.

Funding

National Natural Science Foundation of China "Link TMT Creativity to Strategic Change: an Integration Based on Views of Upper Echelon and Ambidexterity" (71672025), Planning Program of Liaoning Educational Science "Research on Micro-media in the Innovation of Business Administration Teaching Mode" (JG14DB155), Innovation Team Project of DUFE "Study on the Strategy of Chinese Enterprises Under the Background of Social Innovation" (DUFE2017T02), and Dalian Science and Technology Innovation Fund Project "Research on Dalian Science and Technology Plan Project and Policy Performance Evaluation" (2020JJ27FZ118).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Alghamdi, A., Elbeltagi, I., Elsetouhi, A., Yacine Haddoud, M., 2018. Antecedents of continuance intention of using Internet banking in Saudi Arabia: a new integrated model. Strategic Change 27 (3), 231–243.
Ambalov, I.A., 2018. A meta-analysis of IS continuance: an evaluation of the expectation-confirmation model. Telematics Inform. 35 (6), 1561–1571.
Araujo, T., 2018. Living up to the chatbot hype: the influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. Comput. Hum. Behav. https://doi.org/10.1016/j.chb.2018.03.051.
Ashfaq, M., Yun, J., Waheed, A., Khan, M.S., Farrukh, M., 2019. Customers' expectation, satisfaction, and repurchase intention of used products online: empirical evidence From China. SAGE Open 9 (2). https://doi.org/10.1177/2158244019846212.
Bhattacherjee, A., 2001. Understanding information systems continuance: an expectation-confirmation model. MIS Q. 351–370.
Boakye, K.G., McGinnis, T., Prybutok, V.R., Paswan, A.K., 2014. Development of a service continance model with IT service antecedents. J. Retailing Consumer Serv. 21 (5), 717–724.
Bölen, M.C., 2020. Exploring the determinants of users' continuance intention in smartwatches. Technol. Soc. https://doi.org/10.1016/j.techsoc.2019.101209.
Brennan, K., 2006. The managed teacher: emotional labour, education, and technology. Educ. Insights 10 (2), 55–65.
Brill, T.M., Munoz, L., Miller, R.J., 2019. Siri Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. J. Mark. Manage. https://doi.org/10.1080/0267257X.2019.1687571.
Butler, B., Sproull, L., Kiesler, S., Kraut, R., 2002. Community effort in online groups: who does the work and why. In: Weisband, S., Atwater, L. (Eds.), Leadership at a Distance. Lawrence Erlbaum, Publishers, Mahwah, NJ.
Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., Floridi, L., 2018. Artificial Intelligence and the 'Good Society': the US, EU, and UK approach. Sci. Eng. Ethics 24, 505–528. https://doi.org/10.1007/s11948-017-9901-7.
Chang, Y.-W., Hsu, P.-Y., Lan, Y.-C., 2019. Cooperation and competition between online travel agencies and hotels. Tourism Manage. 71, 187–196.
Chattaraman, V., Kwon, W.-S., Gilbert, J.E., Ross, K., 2019. Should AI-Based, conversational digital assistants employ social-or task-oriented interaction style? A task-competency and reciprocity perspective for older adults. Comput. Hum. Behav. 90, 315–330.
Cheng, J.W., Mitomo, H., 2017. The underlying factors of the perceived usefulness of using smart wearable devices for disaster applications. Telematics Inform. https://doi.org/10.1016/j.tele.2016.09.010.
Choi, K., Wang, Y., Sparks, B., 2019. Travel app users' continued use intentions: it'sa matter of value and trust. J. Travel Tourism Marketing 36 (1), 131–143.
Chung, M., Ko, E., Joung, H., Kim, S.J., 2018. Chatbot e-service and customer satisfaction regarding luxury brands. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2018.10.004.
Chung, N., Kwon, S.J., 2009. Effect of trust level on mobile banking satisfaction: a multi-group analysis of information system success instruments. Behav. Inf. Technol. 28 (6), 549–562.
Ciechanowski, L., Przegalinska, A., Magnuski, M., Gloor, P., 2019. In the shades of the uncanny valley: an experimental study of human–chatbot interaction. Future Generation Comput. Syst. 92, 539–548.
Colace, F., De Santo, M., Pascale, F., Lemma, S., Lombardi, M., 2017. BotWheels: A petri net based Chatbot for recommending tires. In: DATA 2017 - Proceedings of the 6th International Conference on Data Science, Technology and Applications, https://doi.org/10.5220/0006491903500358.
Crutzen, R., Peters, G.-J.-Y., Portugal, S.D., Fisser, E.M., Grolleman, J.J., 2011. An artificially intelligent chat agent that answers adolescents' questions related to sex, drugs, and alcohol: an exploratory study. J. Adolesc. Health 48 (5), 514–519.
Dabholkar, P.A., 1996. Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. Int. J. Res. Mark. 13 (1), 29–51.
Dabholkar, P.A., Bagozzi, R.P., 2002. An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. J. Acad. Mark. Sci. 30 (3), 184–201.
Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319–340. https://doi.org/10.2307/249008.
Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of computer technology: a comparison of two theoretical models. Manage. Sci. 35 (8), 982–1003.
Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1992. Extrinsic and intrinsic motivation to use computers in the workplace 1. J. Appl. Soc. Psychol. 22 (14), 1111–1132.
DeLone, W.H., McLean, E.R., 1992. Information systems success: the quest for the dependent variable. Inf. Syst. Res. 3 (1), 60–95. https://doi.org/10.1287/isre.3.1.60.
DeLone, W.H., McLean, E.R., 2003. The DeLone and McLean model of information systems success: a ten-year update. J. Manage. Inf. Syst. 19 (4), 9–30. https://doi.org/10.1080/07421222.2003.11045748.
Demoulin, N.T.M., Djelassi, S., 2016. An integrated model of self-service technology (SST) usage in a retail context. Int. J. Retail Distrib. Manage. https://doi.org/10.1108/IJRDM-08-2015-0122.
Edwards, C., Edwards, A., Spence, P.R., Shelton, A.K., 2014. Is that a bot running the social media feed? Testing the differences in perceptions of communication quality for a human agent and a bot agent on Twitter. Comput. Hum. Behav. 33, 372–376.
Emerson, R.M., 1976. Social exchange theory. Ann. Rev. Sociol. https://doi.org/10.1146/annurev.so.02.080176.002003.
Espejel, J., Fandos, C., Flavián, C., 2009. The influence of consumer degree of knowledge on consumer behavior: the case of Spanish olive oil. J. Food Prod. Marketing. https://doi.org/10.1080/10454440802470565.
Evanschitzky, H., Iyer, G.R., Pillai, K.G., Kenning, P., Schütte, R., 2015. Consumer trial, continuous use, and economic benefits of a retail service innovation: the case of the personal shopping assistant. J. Prod. Innov. Manage. https://doi.org/10.1111/jpim.12241.
Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., Lim, K.H., 2014. Trust, satisfaction, and online repurchase intention: the moderating role of perceived effectiveness of e-commerce institutional mechanisms. MIS Q. Manage. Inf. Syst.
Feine, J., Gnewuch, U., Morana, S., Maedche, A., 2019. A taxonomy of social cues for conversational agents. Int. J. Hum.-Comput. St. 132, 138–161. https://doi.org/10.1016/j.ijhcs.2019.07.009.
Forbes, 2019. AI Stats News: Chatbots Increase Sales By 67% But 87% Of Consumers Prefer Humans. Retrieved from https://www.forbes.com/sites/gilpress/2019/11/25/ai-stats-news-chatbots-increase-sales-by-67-but-87-of-consumers-prefer-humans/#61dadfb248a3 (Assessed, December 2019).
Forbes, A.R, 2019. How Businesses Can Begin Using Chatbots The Right Way. Retrieved from https://www.forbes.com/sites/forbestechcouncil/2019/01/18/how-businesses-can-begin-using-chatbots-the-right-way/#1d3b68252183 (Assessed, February 2019).
Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Marketing Res. 18 (1), 39–50.
Gao, L., Waechter, K.A., 2017. Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. Inf. Syst. Front. 19 (3), 525–548.
Gao, L., Waechter, K.A., Bai, X., 2015. Understanding consumers' continuance intention towards mobile purchase: a theoretical framework and empirical study–a case of China. Comput. Hum. Behav. 53, 249–262.
Gu, B., Konana, P., Rajagopalan, B., Chen, H.W.M., 2007. Competition among virtual communities and user valuation: the case of investing-related communities. Inf. Syst. Res. https://doi.org/10.1287/isre.1070.0114.
Gupta, A., Yousaf, A., Mishra, A., 2020. How pre-adoption expectancies shape post-adoption continuance intentions: an extended expectation-confirmation model. Int. J. Inf. Manage. 102094.
Hair, J., Black, W., Babin, B., Anderson, R., 2010. Multivariate Data Analysis, seventh ed. Pearson Prentice Hall.
Hair, J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2017. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), second ed. Sage Publications Limited Inc, London, Thousand Oaks, Calif.
Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24.
Harman, H.H., 1976. Modern Factor Analysis. University of Chicago Press.
Hasler, B.S., Tuchman, P., Friedman, D., 2013. Virtual research assistants: replacing human interviewers by automated avatars in virtual worlds. Comput. Hum. Behav.

29 (4), 1608–1616.
Henseler, J., Dijkstra, T.K., Sarstedt, M., Ringle, C.M., Diamantopoulos, A., Straub, D.W., et al., 2014. Common beliefs and reality about PLS: comments on Rönkkö and Evermann (2013). Organ. Res. Methods 17 (2), 182–209.
Henseler, J., Hubona, G., Ray, P.A., 2016. Using PLS path modeling in new technology research: updated guidelines. Ind. Manage. Data Syst. 116 (1), 2–20.
Hill, J., Ford, W.R., Farreras, I.G., 2015. Real conversations with artificial intelligence: a comparison between human–human online conversations and human–chatbot conversations. Comput. Hum. Behav. 49, 245–250.
Holzwarth, M., Janiszewski, C., Neumann, M.M., 2006. The influence of avatars on online consumer shopping behavior. J. Marketing 70 (4), 19–36.
Hong, S., Thong, J.Y., Tam, K.Y., 2006. Understanding continued information technology usage behavior: a comparison of three models in the context of mobile internet. Decis. Support Syst. 42 (3), 1819–1834.
Hsiao, C.H., Chang, J.J., Tang, K.Y., 2016. Exploring the influential factors in continuance usage of mobile social Apps: satisfaction, habit, and customer value perspectives. Telematics Inform. 33 (2), 342–355.
Hu, L.t., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Eq. Modeling 6 (1), 1–55.
Huang, J., Zhou, M., Yang, D., 2007. Extracting chatbot knowledge from online discussion forums. Paper Presented at the IJCAI.
Jia, J., 2009. CSIEC: a computer assisted English learning chatbot based on textual knowledge and reasoning. Knowl.-Based Syst. 22 (4), 249–255.
Joo, Y.J., Park, S., Shin, E.K., 2017. Students' expectation, satisfaction, and continuance intention to use digital textbooks. Comput. Hum. Behav. 69, 83–90.
Kokkinou, A., Cranage, D.A., 2015. Why wait? Impact of waiting lines on self-service technology use. Int. J. Contemporary Hospitality Manage. 27 (6), 1181–1197.
Lee, H.-J., 2017. Personality determinants of need for interaction with a retail employee and its impact on self-service technology (SST) usage intentions. J. Res. Interactive Marketing 11 (3), 214–231.
Lee, S., Choi, J., 2017. Enhancing user experience with conversational agent for movie recommendation: effects of self-disclosure and reciprocity. Int. J. Hum. Comput. Stud. 103, 95–105.
Letheren, K., Russell-Bennett, R., Whittaker, L., 2020. Black, white or grey magic? Our future with artificial intelligence. J. Marketing Manage. https://doi.org/10.1080/0267257X.2019.1706306.
Li, W., Bhutto, T.A., Xuhui, W., Maitlo, Q., Zafar, A.U., Ahmed Bhutto, N., 2020. Unlocking employees' green creativity: the effects of green transformational leadership, green intrinsic, and extrinsic motivation. J. Cleaner Prod. https://doi.org/10.1016/j.jclepro.2020.120229.
Liao, C., Chen, J.-L., Yen, D.C., 2007. Theory of planning behavior (TPB) and customer satisfaction in the continued use of e-service: an integrated model. Comput. Hum. Behav. 23 (6), 2804–2822.
Lin, X., Featherman, M., Sarker, S., 2017. Understanding factors affecting users' social networking site continuance: a gender difference perspective. Inf. Manage. 54 (3), 383–395.
Loftis, L., 2018. The Future of Customer Experience Is AI: Are You Ready? Retrieved from https://www.cmswire.com/customer-experience/the-future-of-customer-experience-is-ai-are-you-ready/ (Assessed January, 2019).
Lohmoeller, J.-B., 1989. Latent Variable Path Analysis with Partial Least Squares. Physica, Heidelberg.
Lu, C.-C., Wu, L., Hsiao, W.-H., 2019. Developing customer product loyalty through mobile advertising: affective and cognitive perspectives. Int. J. Inf. Manage. 47, 101–111.
Luo, X., Tong, S., Fang, Z., Qu, Z., 2019. Frontiers: machines vs. humans: the impact of artificial intelligence chatbot disclosure on customer purchases. Marketing Sci. 38 (6), 937–947.
McLean, G., Osei-Frimpong, K., Al-Nabhani, K., Marriott, H., 2020. Examining consumer attitudes towards retailers' m-commerce mobile applications – an initial adoption vs. continuous use perspective. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2019.08.032.
Mimoun, M.S.B., Poncin, I., Garnier, M., 2017. Animated conversational agents and e-consumer productivity: the roles of agents and individual characteristics. Inf. Manage. 54 (5), 545–559.
Mou, Y., Xu, K., 2017. The media inequality: comparing the initial human-human and human-AI social interactions. Comput. Hum. Behav. 72, 432–440.
Mou, Y., Xu, K., Xia, K., 2019. Unpacking the black box: examining the (de) Gender categorization effect in human-machine communication. Comput. Hum. Behav. 90, 380–387.
Nascimento, B., Oliveira, T., Tam, C., 2018. Wearable technology: what explains continuance intention in smartwatches? J. Retailing Consumer Serv. 43, 157–169.
Nguyen, T., 2019. Potential Effects of Chatbot Technology on Customer Support: A case study. Master's thesis, available at. Aalto University. http://urn.fi/URN:NBN:fi:aalto-201906233987.
Oghuma, A.P., Libaque-Saenz, C.F., Wong, S.F., Chang, Y., 2016. An expectation-confirmation model of continuance intention to use mobile instant messaging. Telematics Inform. 33 (1), 34–47.
Oliver, R.L., 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. J. Mark. Res. 460–469.
Park, E., 2020. User acceptance of smart wearable devices: an expectation-confirmation model approach. Telematics Inform. https://doi.org/10.1016/j.tele.2019.101318.
PointSource, 2018. Finding Common Ground Between Consumers and Artificial Intelligence: A Closer Look at Consumers' Current Relationship with Chatbots. Retrieved from https://digital.pointsource.com/acton/media/21911/2018-artificial-intelligence-and-chatbot-report (Assessed, February 2019).
Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., Mazurek, G., 2019. In bot we trust: a new methodology of chatbot performance measures. Bus. Horiz. 62 (6), 785–797.
Radziwill, N.M., Benton, M.C., 2017. Evaluating Quality of Chatbots and Intelligent Conversational Agents. Available at pdf. Cornell University. http://arxiv.org/abs/1704.04579. pdf.
Ringle, C. M., Wende, S., & Becker, J.-M., 2015. SmartPLS 3. Boenningstedt: SmartPLS GmbH, http://www. smartpls. com.
Roca, J.C., Chiu, C.-M., Martínez, F.J., 2006. Understanding e-learning continuance intention: an extension of the Technology Acceptance Model. Int. J. Hum. Comput. Stud. 64 (8), 683–696.
Schneider, C., 2017. 10 reasons why AI-powered, automated customer service is the future. Retrieved June 24, 2020, from https://www.ibm.com/blogs/watson/2017/10/10-reasons-ai-powered-automated-customer-service-future.
Setia, P., Setia, P., Venkatesh, V., Joglekar, S., 2013. Leveraging digital technologies: how information quality leads to localized capabilities and customer service performance. MIS Q. 565–590.
Shawar, B.A., Atwell, E.S., 2005. Using corpora in machine-learning chatbot systems. Int. J. Corpus Linguistics 10 (4), 489–516.
Sheehan, K.B., 2018. Crowdsourcing research: data collection with Amazon's Mechanical Turk. Commun. Monogr. 85 (1), 140–156.
Shiau, W.L., Luo, M.M., 2012. Factors affecting online group buying intention and satisfaction: a social exchange theory perspective. Comput. Hum. Behav. https://doi.org/10.1016/j.chb.2012.07.030.
Sivaramakrishnan, S., Wan, F., Tang, Z., 2007. Giving an "e-human touch" to e-tailing: the moderating roles of static information quantity and consumption motive in the effectiveness of an anthropomorphic information agent. J. Interactive Marketing 21 (1), 60–75.
Tam, C., Santos, D., Oliveira, T., 2018. Exploring the influential factors of continuance intention to use mobile Apps: extending the expectation confirmation model. Inf. Syst. Front. 1–15.
Teo, T.S., Srivastava, S.C., Jiang, L., 2008. Trust and electronic government success: an empirical study. J. Manage. Inf. Syst. 25 (3), 99–132.
Thong, J.Y., Hong, S.-J., Tam, K.Y., 2006. The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. Int. J. Hum. Comput. Stud. 64 (9), 799–810.
Usakli, Ahmet, Kucukergin, Kemal Gurkan, 2018. Using partial least squares structural equation modeling in hospitality and tourism: do researchers follow practical guidelines? Int. J. Contemp. Hospitality Mngt. 30 (11), 3462–3512.
Veeramootoo, N., Nunkoo, R., Dwivedi, Y.K., 2018. What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. Government Inf. Q. 35 (2), 161–174. https://doi.org/10.1016/j.giq.2018.03.004.

Venkatesh, V., 2000. Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model. Inf. Syst. Res. 11 (4), 342–365.
Venkatesh, V., Bala, H., 2008. Technology acceptance model 3 and a research agenda on interventions. Decis. Sci. 39 (2), 273–315.
Weizenbaum, J., 1966. ELIZA-A computer program for the study of natural language communication between man and machine. Commun. ACM. https://doi.org/10.1145/365153.365168.
Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S., Martins, A., 2018. Brave new world: service robots in the frontline. J. Serv. Manage. https://doi.org/10.1108/JOSM-04-2018-0119.
Yu, S., Hudders, L., Cauberghe, V., 2018. Are fashion consumers like schooling fish? The effectiveness of popularity cues in fashion e-commerce. J. Bus. Res. 85, 105–116.
Zafar, A.U., Qiu, J., Li, Y., Wang, J., Shahzad, M., 2019. The impact of social media celebrities' posts and contextual interactions on impulse buying in social commerce. Comput. Hum. Behav. https://doi.org/10.1016/j.chb.2019.106178.
Zamora, J., 2017. I'm Sorry, Dave, i'm afraid i can't do that: Chatbot perception and expectations. In: HAI 2017 - Proceedings of the 5th International Conference on Human Agent Interaction, https://doi.org/10.1145/3125739.3125766.
Zheng, Y., Zhao, K., Stylianou, A., 2013. The impacts of information quality and system quality on users' continuance intention in information-exchange virtual communities: an empirical investigation. Decis. Support Syst. https://doi.org/10.1016/j.dss.2012.11.008.