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Do I Desire Chatbots to be like Humans? Exploring Factors for Adoption of Chatbots for Financial Services

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ABSTRACT

AI-powered chatbots are gaining traction across various industries, especially in the financial sector. Despite these implementations, chatbot adoption and usage among consumers is still low. Grounding on the unified theory of acceptance and use of technology 2 (UTAUT2) model and the Belief Desire Intentions (BDI) model, this study explores factors influencing the adoption of chatbots for financial sectors by emphasizing on the role of user desires in addition to human beliefs. Explicitly, the research hypothesizes the role of the humanness in chatbots influencing consumer adoption in the financial services sector. The suggested research model was tested via a sample of possible adopters from India, the USA, and Singapore. Results highlight the key role of consumer desires to make artificial machines indistinguishable from human beings. Implications for research and practice are also presented.

Keywords: chatbots, customer service, humanness, technology adoption, UTAUT2, BDI model, financial services

INTRODUCTION

Artificial Intelligence (AI) has been gaining momentum over the past few years due to the advancement in machine learning and deep learning algorithms. In September 2018, more than 600 industry professionals were surveyed in the Euromonitor International Digital Consumer Industry Insights report. Nearly 60 percent of respondents ranked AI as the most impactful technology. With more than 40 percent of the businesses planning to invest more resources in AI, it is indisputable that this technology is revolutionizing how businesses operate (Euromonitor, 2020).

AI performs human cognitive functions like perceiving, interpreting sensory information, and learning (Gams et al., 2019).

AI is already used in various capacities today. For example, AI is being used by Gmail to filter out spam emails, and Netflix leverages AI to suggest video content to users based on their preferences. It is used in smartphone cameras where faces of people in the frame are identified and enhanced (Svenningsson & Faraon, 2019). With expedited digitalization across sectors amidst the pandemic, there is now a growing need to leverage AI towards the development of more innovative chatbots (Følstad & Brandtzaeg, 2017).

Chatbots are AI-powered human-like agents that can simulate human behavior. Many industries have incorporated chatbots on their websites and customer-facing applications. Chatbots are emerging as marketing and consumer engagement tools and integrate with messaging applications such as Facebook, Slack, KIK & Viber (Brandtzaeg & Følstad, 2017). The chatbot industry is expected to grow at a rate of around 9 percent (Nguyen, 2020). Discussing the financial sector alone, chatbots are gaining momentum in their usage for claim submissions, thereby keeping the claim managers free to provide better customer service (Bassett, 2018). Though companies like Google, Facebook, and Microsoft have been optimistic about chatbots, some critics have noted that consumer acceptance of existing chatbots is less significant than expected (Simonite, 2017). A recent survey report by LivePerson reflects low adoption rates of chatbots even in technologically advanced countries such as USA (LivePerson, 2019). Motivated by the low adoption rates of chatbots by consumers, in this research, we aim to explore the factors that are key for consumer acceptance. We contextualize this research to the adoption of chatbots by financial institutions such as banks and insurance companies as, despite the vast potential of artificial technologies in the financial sector (Lui & Lamb, 2018), chatbots have not yet sparked enough interest of the consumers from this stratum.

Organizations are actively seeking to incorporate new technologies such as chatbots to develop their business and provide better customer service. Implementation and integration of chatbots in any organization is an extensive process involving consumer reception that contributes to its success (Ramachandran, 2019). Though organizations spend a significant amount of money on in-service personnel to provide consistent customer care, they are unsure if the aspired value-proposals on chatbot investment would prevail over the investment costs (Barba-Sánchez et al., 2007). Because of the huge implementation costs involved, organizations carefully assess the need to incorporate this AI technology and how it is adding value to the strategic growth of the organization (Nili et al., 2019). Though higher implementation costs trigger companies to look for returns on these investments, the returns are currently limited because of the lower usage of chatbots among consumers (Euromonitor, 2020).

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Motivated by this compelling research gap, the key research question we explore here is:

RQ: *What factors are significant for the intention to adopt and accept chatbots by consumers in the financial sector?*

Grounding our research on the Unified Theory of Acceptance and Use of Technology2 (UTAUT2) model (Venkatesh et al., 2012), we explore the critical factors for the adoption of chatbots by the consumers of the financial sector. The UTAUT2 model is a well-established model for understanding the factors which guide user beliefs for the adoption of technology (Venkatesh et al., 2012), we need to move beyond user beliefs to user desires for the adoption of technology. Chatbots are artificial machines that aim to think and behave like humans. Human customer service agents are still a preferred choice of consumers as compared to artificial conversational agents as scripted dialogues, and robotic communication styles reflect low *humanness* (Go & Sundar, 2019). Hence, we posit that the adoption of chatbots will be influenced not only by the consumer *beliefs* as proposed by the UTAUT2 model but the consumer *desire* to converse with chatbots as though they were real humans. Steered by the low humanness in AI machines, we integrate the UTAUT2 model with the Belief Desire Intentions (BDI) model (Norling, 2004) to understand the key factors that move beyond the user *beliefs* of providing timely and convenient assistance to achieve their *desires* of conversing with human agents. This study makes four key contributions. *First*, identifying factors that enhance the *humanness* in chatbots would bridge the gap between the offerings and the consumer expectations, thereby motivating the consumers for better chatbots adoption. *Second*, by integrating the BDT with the UTAUT2 model, we offer fresh research perspectives around the factors that are critical to addressing the challenges around chatbot adoption (Malhotra et al., 2008). *Third*, though the design of chatbots is witnessing a transcendental advancement by incorporating emerging trends such as open-source platforms and shared learning, this research contributes towards achieving better chatbot designs in the future by understanding the *desires* of the chatbot users for effective chatbot usage by consumers (Euromonitor, 2020). *Fourth*, this study is contextualized to the adoption of chatbots in the financial industry. The financial sector is notably different from many other sectors because of consumer privacy concerns being fundamental here (Lui & Lamb, 2018). This research aims to strike the interest of chatbot designers and developers working towards replacing human agents with artificial conversational agents in the financial sector.

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THEORETICAL BACKGROUND

Artificial Intelligence

AI was created in the 1950s, and during this period, Alan Turing circulated an article, which for many scientists marks the birth of AI (Gams et al., 2019).
The report suggested the Turing test, which targets to measure the intelligence of machines and to define whether they could persuade a jury that they are human. There are worries concerning to which extent this could specify that a machine is smart, and even Turing highlighted that the emphasis of the examination was for machines to reproduce a human being (Braga & Logan, 2017). A computer did not manage to pass the Turing test until 2014 (Kevin Warwick & Shah, 2016). The chatbot, nicknamed Eugene Goostman, managed to persuade more than a third of the judges that he was a human being. Imitating human intelligence is not easy for AI since there are many things to consider such as cognitive, social, and psychological factors (Vinciarelli et al., 2015; Kevin Warwick & Shah, 2016). AI technologies can complement and sustain human-run tasks today (Makridakis, 2017). Many researchers believe that if AI is given human-equivalent rights and comprehensive access to decision-making processes, these machines may emerge more potent than humans (Makridakis, 2017). Thus, on the one hand, AI has an immense capability to add to human contributions (Jarrahi, 2018), on the other hand, it raises several concerns such as the morality, openness, and accountability of AI machines (Floridi et al., 2018; Torresen, 2018). AI is already part of our existing lives with inventions. One of them is smart sensor Air Conditioners (E.g. Ambi Climate), autonomous vehicles which use algorithms and sensors for tech-enabled self-driving (E.g. BYD cars). The emerging AI patterns indicate that AI may replace not only in professions requiring mechanical intelligence but also in jobs requiring analytical and cognitive intelligence (e.g., auditors, consultants, managers) (Gams et al., 2019; Huang & Rust, 2018).

Chatbots

While interest in chatbots has increased in recent years, the study and research on natural language interfaces are not new in computer science studies. In the 1960s, Weizenbaum published a groundbreaking thesis with a computer program named ELIZA, designed to replicate a psychotherapist's responses during a therapy session (Weizenbaum, 1966). Dale debates the "return of chatbots" in the current decade is grounded on the earlier research works on the interfaces of natural languages (Dale, 2016).
The growing attention in chatbots is mostly linked to significant developments in computing technology and the wide acceptance of smartphone messaging apps.

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Chatbots can communicate with humans via various modes, such as through text, image, or voice. Text-based chatbots are usually deployed on company websites, where consumers could clarify basic queries, such as FAQs or obtain documents. Image-based algorithms are deployed in searching for products online on e-commerce websites, such as Lazada, Amazon. While voice-based applications are in the likes of Alexa and Siri that act as virtual voice assistants providing user-requested information.

Chatbots are driven by new developments in the field of AI and machine learning (Brandtzaeg & Følstad, 2017). Such developments promise substantial improvements in the understanding and analysis of natural languages, including advances in machine translation (K Warwick et al., 2016). Besides, the growing use of mobile internet and messaging apps has led to an increase in chatbot usage (Følstad & Brandtzaeg, 2017). Chat agents serve a variety of use cases, including consumer service, emotional support, knowledge, social support, entertainment, and interaction with other people or machines (Brandtzaeg & Følstad, 2017). Besides, consumers often feel that chatbot conversations are natural and efficient. Chat agents can respond to queries, place consumer orders, accept purchase proposals, and keep the clients updated on delivery via a natural language interface (Brandtzaeg & Følstad, 2017). They can substitute existing consumer services (A. Xu et al., 2017).

There are numerous chatbots available today, for example, the insurance company "FWD" in Singapore has recently launched a 24/7 travel insurance claim via chatbot named Faith, the AI is also capable of answering product queries for the company (Olano, 2019). Chat agents like Mitsuku, Jessie, and Humani can satisfy the entertainment and social networking needs of users (Brandtzaeg & Følstad, 2017). Some researchers proposed a classification of chatbots' interaction types, separating chatbots into four categories: (i) dull, in which a chatbot responds with single words and sometimes repeats the same or related phrases; (ii) alternate vocabulary, in which a chatbot has a broader base of variations of the same response; (iii) creating a relationship in which language and topics can shift between easy and professional, and a chatbot can regulate the flow of conversation by giving spontaneous details or making a joke; and (iv) human-like, where a chatbot learns from experience and uses past knowledge to communicate using more subtle and meaningful communication patterns (Paikari & Van Der Hoek, 2018).

Online chat agents possess the prime functions of interchanging responses with users, responding to their inquiries, and assisting users with their concerns (Go & Sundar, 2019).

Because of difficulties in mapping the chatbots' capabilities, users are unable to discern the chatbot capabilities (Jain et al., 2018; Luger & Sellen, 2016).

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When chatbots are unable to meet user expectations, the users tend to get frustrated and disappointed. Past research has identified simple and uncomplicated responses as the key to significant AI interactions (Chakrabarti & Luger, 2015)

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

There are several well-established theories in information systems (IS) research for the adoption of technology (Wade & Hulland, 2004). The unified theory of acceptance and use of technology 2 (UTAUT2) (Venkatesh et al., 2012) is one of the most repeatedly referenced theoretical models for the adoption of technology. Grounded on the review of earlier research works on technology acceptance (Venkatesh et al., 2003), UTAUT's new model was further incorporated and ultimately improved by the authors based on their detailed studies (Owusu Kwateng et al., 2019). UTAUT has served as the reference model for a variety of digital technologies outside and within organizational surroundings. Nevertheless, bearing in mind the numerous technological uses, services, and devices available for customers, it is of prime importance to understand the dominant variables that may persuade customers to accept and consume new technologies (Stofega & Llamas, 2009). The development of the UTAUT2 model was an outcome of this (Venkatesh et al., 2012). UTAUT2 provides the theoretical base for this study.
The UTAUT2 model proposes *effort expectancy*, *performance expectancy*, *social influence*, *hedonic motivation*, and *habit* as the key attributes impacting the behavioral intention of customers to accept and use technology (Venkatesh et al. 2012). E*ffort expectancy* is the belief of the users that technology such as chatbots is easy to use. *Performance expectancy* is the belief of the users that technology such as chatbots is useful for them to increase their efficiency and productivity. *Social influence* is the user's perception that people important to him/her think that s/he should use the particular technology (Venkatesh et al., 2012). The perception of enjoyment that arises from the experience of the technology is the *hedonic motivation* (K. C. Anderson et al., 2014). Behaviors which are automatically exhibited by people due to the act of learning are the *habit* (Venkatesh et al., 2012). The UTAUT2 model also included age, experience, and gender in the model, which we have as controls in the research model (Owusu Kwateng et al., 2019). We did not include facilitating conditions and price value in the research model as they were not relevant to the current context.
While the attributes identified as part of the UTAUT2 model represent the user *beliefs* for technology adoption, the user's desire to view artificial chatbots to be indistinguishable from human beings may influence the adoption intention of chatbots (Go & Sundar, 2019).

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Hence in this research, we integrate the UTAUT2 model with the BDI model to move beyond user beliefs and understand user desires for the adoption of chatbots.

Belief Desire and Intention (BDI) model

The belief Desire and Intention (BDI) model is one of the paradigms used in the development of autonomous human-like agents (Noorunnisa et al., 2019; Norling, 2004). Belief, Desire, and Intention are the three concepts on which the BDI model is based (Noorunnisa et al., 2019). The model has been successful in creating human-like characters (Norling, 2004). The BDI model concerns how an entity makes informed choices about the activities it carries out using *beliefs* about its environments and itself, *desires* that it demands to fulfill, and *intentions* to work in the direction of the accomplishment of specific desires (Noorunnisa et al., 2019). The model takes its roots in the theory of human practical reasoning (Velleman & Bratman, 1991). The interface offered by these chatbots is well-thought-out to be better than the stationary transmission of data, including a list of commonly enquired queries. This is because agents provide a more responsive distribution of information to consumers, answering directly to their queries in such a way that more than a few businesses have started to utilize these chat agents as alternatives for telephonic calls or human agents (Go & Sundar, 2019).

In this research, we integrate the UTAUT2 model with the BDI model to extend the UTAUT2 model with three variables describing *humanness* in chatbots.

The three humanness variables are *anthropomorphism*, *likeability,* and *social presence*. *Anthropomorphism* explains the acknowledgment of a human form, attributes, or actions to objects which are not human, such as robots, computers, and animals (Bartneck et al., 2009). In the last fifty years, researchers and developers have made significant efforts to characterize human-like attributes in intelligent chat agents (Go & Sundar, 2019). Human visual signs of chatbots can be highly indicative (J. Kim, 2010). Visual cues, which are human-like, are anticipated to generate humanness heuristics (Shyam Sundar, 2008).

Likeability plays a significant role in using technology rather than familiarity with technology (Bartneck et al., 2007). Though familiarizing with technology is essential for its usage, users may not like all the machines they are familiar with.

Social presence is defined simply as “the feeling of being with another” (Biocca et al., 2003). Social presence affects the expectations of users.

For example, richer modality signals activate the supposed "heuristic realism," prompting consumers of face-to-face contact that positively impacts the reliability of information by offering an impression of actual natural communication in contrast to a loud and possibly misleading communication message over textual modality (Y. Kim & Sundar, 2012).

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RESEARCH MODEL AND HYPOTHESIS

The suggested research framework grounded on UTAUT2 and BDI is shown in Figure 1. It theorizes the key role of effort expectancy, performance expectancy, hedonic motivation, social influence, and habit integrated with humanness attributes of anthropomorphism, likeability, and social presence in chatbots.
The *belief* variables encapsulate the factors which the users expect to get from AI technologies for their adoption. However, the user's beliefs may amend in the future based on the user's *desires*. For example, all the user beliefs in the current era about smartphones such as effective and efficient payment, navigation, and entertainment systems being in the palm of the user were desires which users fancied a couple of decades ago (Lundquist et al., 2014). Thus, a user *desires* to move beyond the *beliefs* to encase variables that may represent the objectives that are not currently available, and the consumers aspire for.

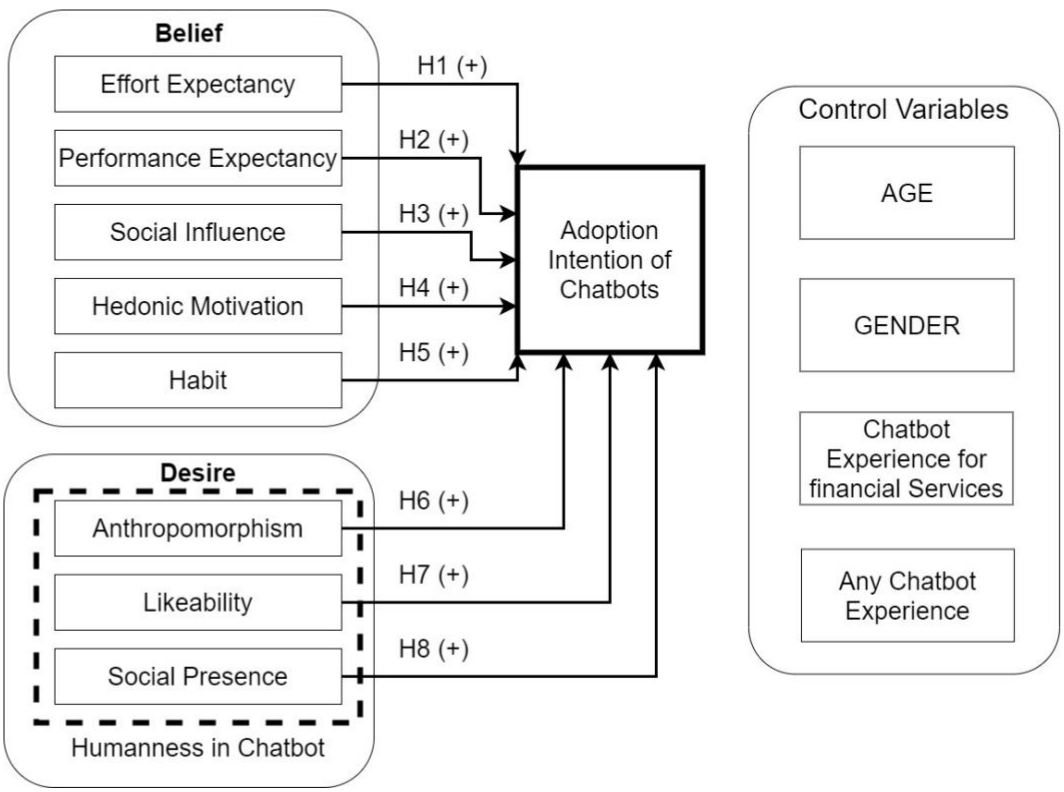

Figure 1: Research Model

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Beliefs

<u>*Effort Expectancy*</u>

Consistent with the conceptualization of effort expectancy in prior information systems research (Davis et al., 1989; Venkatesh et al., 2003), effort expectancy is defined as the extent to which technology provides easy service to its users (Raman & Don, 2013). Effort expectancy has been studied in various technological contexts such as Internet banking (Arenas-Gaitán & Ramón-Jerónimo, 2015) and mobile payments (Tak & Panwar, 2017). In the context of chatbots, effort expectancy encompasses the notion of the customers that the chatbot software is intuitive enough to provide information to its customers without much effort from them. For instance, if a consumer wishes to enquire about a product on a banking portal and can get all the product related queries with ease using an embedded chatbot without seeking help from a human chat agent, s/he tends to believe that the chatbots are easy to use and provide the required information effortlessly. Consequently, he will be willing to use chatbots for future services as well.

Hence we hypothesize,

> *H1: Effort expectancy is positively related to the intention to adopt chatbots for financial services.*

<u>*Performance Expectancy*</u>

In line with Venkatesh et al. (2003) conceptualization of performance expectancy, we define performance expectancy as the user's beliefs about the benefits of using the technology for specific tasks. The critical role of performance expectancy is shaping user intentions to use new technology that has been witnessed in prior studies (El-gayar et al., 2004; Yousafzai, 2012). In the context of chatbots, performance expectancy revolves around the consumer's impression that the chatbot is useful in the execution of their financial tasks. They believe that chatbots help them in increasing their productivity by accomplishing the required tasks efficiently. For instance, if the bank customer acknowledges that the chatbot is offering a useful suggestion for the purchase of a product based on his/her profile and interest, then the customers will develop the confidence to use chatbots for their future banking services as well.

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Hence we hypothesize,

> *H2: Performance expectancy is positively related to the intention to adopt chatbots for financial services.*

Social Influence

Drawing on Venkatesh et al. (2003), we define social influence as the extent to which an individual feels the importance that the others believe s/he should use the new system. The knowledge and encouragement provided by people related to the customer may play an active role in contributing to customer awareness and technological purposes (Alalwan et al., 2016). Social influence has emerged as an essential variable for the adoption and use of several new technologies such as online gaming (X. Xu, 2014), mobile applications (Tak & Panwar, 2017), and mobile payments (Morosan & DeFranco, 2016). Similar to other contexts, we propose the critical role of social influence in the adoption of chatbots for financial services. The role of social influence for financial services is even more pronounced as people are wary to reveal their personal information to chatbots. They need assurance from their friends and acquaintances whose opinion they value to develop the confidence in using chatbots for efficient and secured service. Hence we hypothesize,

> *H3: Social influence is positively related to the intention to adopt chatbots for financial services.*

Hedonic Motivation

Drawing from prior works in information systems literature, we define hedonic motivation in the context of chatbots as the extent to which a consumer enjoys using the new technology to realize financial services (Brown & Venkatesh, 2005; Holbrook & Hirschman, 1982). In particular, hedonic motivation is expected to provide user gratification, which may influence consumers to adopt and use the new technology (Van Der Heijden, 2004). For instance, in the context of financial services, though customers would interact with chatbots to get information around some serious financial matters, if the interaction is fun and enjoyable for them then begin to draw engaging experiences from its use (Owusu Kwateng et al., 2019).

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Such engaging experiences will motivate the users to adopt the chatbots for their future financial services as well. Hence we hypothesize,

> *H4: Hedonic Motivation is positively related to the intention to adopt chatbots for financial services.*

Habit

In line with Limayem et al. (2007), the conceptualization of habit, we define the habit of technology as its repetitive use due to the behavior of automation from early learning. Prior research has shown a key role of prior use habit in the adoption intention and use of a technology (S. S. Kim & Malhotra, 2005; Limayem et al., 2007). Past research has shown that people are resistant to change their habits with growing age and experience as their information processing capabilities decrease (Owusu Kwateng et al., 2019). The habit is an essential predictor for the adoption of new technologies such as social networking sites (Herrero et al., 2017), NFC mobile payments (Morosan & DeFranco, 2016), and online games (X. Xu, 2014). In the context of chatbots, we believe that the customers who are habituated to using chatbots will find it natural to use chatbots for fulfilling their financial needs as well.

Hence we hypothesize,

> *H5: Habit is positively related to the intention to adopt chatbots for financial services.*

There are two additional constructs that the UTAUT2 model considers: price value and facilitating conditions. The factors were excluded because chatbot use requires no assistance of any kind. It is simply about adding value or talking. The price value factor means customers will have to pay for the use of the commodity. Since commercial chatbots are not the case, this has not been considered. Information Technology (IT) devices are to be funded (e.g., mobile, handheld devices, consumer electronics) when the consumers want to consume a chatbot but the expense is made for the equipment and not for the chatbots' use (Melián-González et al., 2019). Next, we hypothesize the relationship of the desire variables of the customers (studied through the three humanness variables described as anthropomorphism, likeability, and social presence) in the chatbot design to develop the willingness to adopt chatbots.

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Desires

Anthropomorphism

Anthropomorphism is the basic human desire when interacting with machines (Wagner et al., 2019). In the context of chatbots, anthropomorphism can be defined as the degree to which users perceive the human attributes in an artificial machine by instilling such non-human actors with human characteristics, behaviors, motives, and emotions (Epley et al., 2007; Wagner et al., 2019). Anthropomorphism is of particular importance in an artificially driven chatbot as the chatbot interactions serve to replace the need for real human agents for customer services (Y. Kim & Sundar, 2012). Chatbots are beginning to serve as a key source for customers to obtain all the required information and services. The similarity of a chatbot to human behavior is likely to influence the customer's use of chatbots. For example, when a customer interacts with a chatbot for financial services and experiences minimum dissonance in the behaviors and mannerisms of the chatbot as compared to a human agent, customers will consider the services offered by the chatbot to be similar to interacting with the real customer service agent and are more likely to use it (Wagner et al., 2019). Hence we hypothesize,

> *H6: Anthropomorphism is positively related to the intention to adopt chatbots for financial services.*

Likeability

In line with Osgood and Tannenbaum’s dissonance theory (Osgood & Tannenbaum, 1955), we define likeability to be a user’s perception of positive attitudes of friendliness, kindness, and pleasantness demonstrated by the artificial machines so that users begin to like the machines. This conceptualization aligns with the similarity attraction theory which suggests that people tend to be drawn to others when they see and experience some level of similarity in terms of attitudes (Bernier et al., 2010). In the context of financial chatbots, when customers experience positive attitudes such as friendliness and intention to help being demonstrated by such chatbots, they are drawn towards them and develop intentions to use them frequently for all financial queries and information (Wagner et al., 2019). Hence we hypothesize,

H7: Likeability is positively related to the intention to adopt chatbots for financial services.

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Social Presence

Consistent with the conceptualization in prior information systems research (e.g. Biocca et al., 2003; Srivastava & Chandra, 2018), social presence is defined as ‘the feeling of being with another’. It is the extent to which the human characteristics infused in the chatbot provides its customers with a feeling of emotional closeness and/or social connectivity (Bente et al., 2008). Kim & Sundar (2012) emphasized social presence when interacting on e-commerce portals. In the context of financial chatbots, social presence encompasses the notion of the presence of a customer service agent for meeting the customer information or service needs by imbibing human-like attributes and behaviors (Moon, 2000; Sundar et al., 2015). For instance, a customer could use a financial chatbot to get information about his/her eligibility for a bank loan. In this case, the chatbot should be interactive enough to gather all the required customer information such as his/her salary details and other investments to assist the customer. When the chatbot fails to demonstrate its presence to the customer, s/he may be hesitant to share the personal details with the chatbot and request for the human service agent. This is consistent with the work that has identified social presence to be an essential aspect of human desire and can affect an individual’s use of an innovation or new service such as chatbot service agents (Go & Sundar, 2019).

Hence we hypothesize,

> *H8: Social presence is positively related to the intention to adopt chatbots for financial services.*

RESEARCH METHOD, DATA AND ANALYSES

We used a survey methodology for this research. A survey instrument was first developed with elements on a five-point Likert scale to examine the model which is represented in Figure 1, with ranges from strongly disagree to strongly agree. The scales used for the survey are presented in Appendix A. The sampling frame comprised individuals who had prior experience with chatbots as well as individuals who had never used chatbots. For individuals who had used chatbots, there was a subcategory to identify consumers who had previously used a chatbot for financial services. This sample was considered appropriate for the research objective. Based on prior sample group selection conducted by (Melián-González et al., 2019), it was noted that a sizeable number of older users had never used, or even seen, a chat agent. Hence the sample group considered for this research consisted primarily of younger individuals.

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The participants were required to complete a survey through an online survey link developed using google forms. The survey was distributed to more than 350 participants, and the correspondents were primarily from Singapore, India, and the USA. There were 284 responses recorded for the survey, out of which 250 were usable with a response rate of 88%; Incomplete questionnaires were excluded from the responses.

The sample scope was validated established on G*Power taking into account the statistical technique employed (Erdfelder et al., 2009). In accordance, with a statistical power of 0.95, examining the suggested model mandated a minimum sample size of 178 individuals. Consequently, it can be determined that the used sample size (250) was satisfactory for the current research. Appropriate control variables were incorporated into the research framework (Figure 1) in addition to the focal research attributes. The control variables are characteristics of possible adopters that could affect a consumer's chatbots acceptance. Control variables that were used in this research were gender, age, and experience (Venkatesh et al., 2012). As the responses were obtained from different demographics and experiences, it was imperative to avoid any possible misapprehension or variance in the results by controlling these variables.

Partial least squares (PLS), a latent structural equation modeling (SEM) technique carried out in SmartPLS 3.0, is used for data analysis, using a component-based path modeling framework (S. y Becker, 2017). PLS allows minimum sample size, calculating sizes, and residual distributions demand relative to supplementary SEM techniques (e.g. EQS, LISREL, or AMOS) (Chandra et al., 2010, 2012). Different research studies engaged PLS and established it to be an important analytical technique (Chandra et al., 2010; Hsieh & Tseng, 2018; Liang et al., 2007). A 95% confidence interval across 5000 bootstrap resamples was achieved in this study.

RESULTS

Demographics

The demographic brief of the survey responders is available in Table 1.

The majority of respondents were in the age range of 26 to 35 at 39% followed by the younger population of 18 to 25 at 35% and the age group of 36 to 45 contributed to 21% of the survey population. The age category of 36 to 45 had 9 respondents corresponding to 3.6% and only one respondent above 61 years of age resulting in 0.4%. The majority of the respondents were male corresponding to 65.2% and female respondents were at 34.8%. The experience category was further subdivided into 2 variables – People with any chatbot experience and people with chatbot experience in financial services.

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There were 64% of respondents who have experienced chatbots and 36% who never experienced chatbots, while only 48% of respondents experienced chatbots for financial services, 52% of the respondents had no experience of chatbots for financial services. We added the demographic variables of consumers' age, gender, and chatbot experience as control variables in the model as past research has found that chatbot usage depends heavily on the consumer's dispositional factors (Lortie & Guitton, 2011).

Table 1 – Demographic Profile of Survey Respondents

Demographic Variable	Category	Frequency [N=250]	Percentage
Age	18 to 25	89	35.6%
	26 to 35	98	39.2%
	36 to 45	53	21.2%
	46 to 60	9	3.6%
	61 or older	1	0.4%
Gender	Male	163	65.2%
	Female	87	34.8%
Experience - Any chatbot Experience	Yes	160	64.0%
	No	90	36.0%
Experience - Financial Services Chatbot Experience	Yes	121	48.4%
	No	129	51.6%

Measurement Model

Based on the recommendations by Anderson et al. (1988), a two-staged analytical structure was followed. The first phase involved the confirmatory factor method which was used to study the robustness of the measurement model, then followed by a structural relation analysis to determine the association among the factors.
There were three types of validity examinations conducted to examine the robustness of the measurement model content strength, convergent validity, and discriminant validity. The trustworthiness of the gauging elements with prevailing research works was investigated, along with pilot validation of the instruments for content validity (Bock et al., 2005; Chandra et al., 2010). A convergent validity test was conducted to analyze the point to which various substances used to quantify the hypothesized theories are gauging the same notion (Srivastava, SC ., & Teo et al., 2007).

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Composite reliability and average variance extracted(AVE) were observed to carry out convergent validity, where AVE being the ratio of construct variance to the total variance among indicators (Hair, J. F., Black, W. C., Babin, B. J., Anderson, 1998). Previous studies using PLS for the research considered 0.5 for the CR threshold as an indicator; the recommended reliable measurement limit is, however, 0.7 or above as per (Chin, 1998). The CR range is between 0.89 and 0.96 as noticed in Table 2. Likewise suggested AVE threshold is 0.5 (Fornell & Larcker, 1981). From the values highlighted in Table 2, it can be observed that AVE ranges from 0.67 to 0.88 which are above the limit.

Based on the recommendation by Fornell & Larcker (1981), the discriminant rationality of the independent variables was tested by computing the square root of AVE. Results displayed in Table 3 confirm the discriminant validity. The measurements of AVE square root seen in Table 3 diagonal are all higher than that of the inter-construct correlations (measurements in Table's off-diagonal cell entries) demonstrating acceptable convergent and discriminant validity. Additionally, the heterotrait-monotrait ratio of correlations (HTMT) represented in Table 4 suggests discriminant validity when the stricter standard of $HTMT_{.85}$ is considered as recommended by Henseler et al. (2014). We note that the correlations between the independent and control variables are not above 0.80 in Table 3. We determine, therefore, no severe multicollinearity issues disturb the outcomes (Gujarati, 2009). Further, the multi-collinearity among the independent variable was examined by the variation inflation factor (VIF). The range of 1.35 and 2.6 was observed for the resultant VIF values which were under the moderate threshold of 5 (Allison, 2012; Chandra et al., 2010).

Table 2 – Descriptives - CR, AVE, CA, VIF.

	CR	AVE	CA	Mean	SD	VIF
Adoption Intention	0.94	0.83	0.90	3.44	1.07	
Anthropomorphism	0.89	0.67	0.84	3.88	1.06	1.36
Effort Expectancy	0.89	0.74	0.83	4.00	0.92	1.72
Habit	0.93	0.77	0.90	2.74	1.26	2.33
Hedonic Motivation	0.96	0.88	0.93	3.62	1.09	2.20
Likeability	0.95	0.79	0.93	3.78	0.86	1.45
Performance Expectancy	0.92	0.73	0.88	3.60	1.04	2.32
Social Influence	0.95	0.87	0.93	3.27	1.10	2.32
Social Presence	0.96	0.81	0.94	3.22	1.16	2.41
Key: CA – Cronbach's Alpha; AVE – Average Variance Extracted; CR – Composite Reliability; SD – Standard Deviation.						

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Table 3 – Fornell-Larcker Criterion

	AI	AM	EE	HA	HM	LA	PE	SI	SP
Adoption Intention	**0.91**								
Anthropomorphism	0.25	**0.82**							
Effort Expectancy	0.38	0.38	**0.86**						
Habit	0.65	0.21	0.30	**0.88**					
Hedonic Motivation	0.58	0.25	0.50	0.55	**0.94**				
Likeability	0.40	0.44	0.32	0.30	0.39	**0.89**			
Perf Exp	0.60	0.23	0.55	0.54	0.63	0.35	**0.85**		
Social Influence	0.63	0.18	0.41	0.69	0.59	0.28	0.65	**0.93**	
Social Presence	0.75	0.21	0.29	0.67	0.61	0.38	0.56	0.66	**0.90**

Key: AI: Adoption Intention; AM – Anthropomorphism; EE – Effort Expectancy; HA – Habit; HM – Hedonic Motivation; LA – Likeability; PE – Performance Expectancy; SI – Social Influence; SP – Social Presence

Table 4 - Heterotrait-Monotrait ratio of correlations

	AI	AM	EE	HA	HM	LA	PE	SI	SP
Adoption Intention									
Anthropomorphism	0.29								
Effort Expectancy	0.42	0.48							
Habit	0.72	0.23	0.33						
Hedonic Motivation	0.63	0.28	0.57	0.59					
Likeability	0.43	0.50	0.37	0.32	0.42				
Perf Expectancy	0.67	0.26	0.63	0.61	0.69	0.38			
Social Influence	0.68	0.21	0.44	0.76	0.63	0.30	0.71		
Social Presence	0.81	0.24	0.31	0.72	0.65	0.40	0.61	0.70	

Key: AI: Adoption Intention; AM – Anthropomorphism; EE – Effort Expectancy; HA – Habit; HM – Hedonic Motivation; LA – Likeability; PE – Performance Expectancy; SI – Social Influence; SP – Social Presence

Common Method Bias

Since the information was self–reported on all variables for this study and obtained with a cross-sectional research design through the same questionnaire over the same period, confirmation for any probability of common method bias is essential. Variance resulting from the gauging method can lead to systematic computing error and prejudice to the true association between the hypothetical constructs (Chandra et al., 2012).

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Harman's one-factor test (Podsakoff & Organ, 1986) was conducted where considered variables under examination were fitted into exploratory factor analysis and analyzed the factor solution to assess the range of attributes vital to justify the variance in the factors (Podsakoff et al., 2003). As seen in Table 5, a total of 5 factors contribute to about 70% of the variance and since there was no single factor that emerged and a single common factor did not contribute towards much of the variance, the aforementioned can be concluded that the common method bias is not a substantial issue about the data under consideration (Podsakoff et al., 2003).

Table 5 - Harman's One Factor Test

Factor	Initial Eigenvalues			Extraction Sums of Squared	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	14.3	42.14	42.14	**13.8**	**40.59**
2	3.99	11.73	53.87		
3	2.44	7.17	61.04		
4	1.6	4.7	65.74		
5	1.32	3.87	69.61		
6	1.1	3.23	72.84		
7	0.97	2.85	75.69		
8	0.86	2.53	78.22		
9	0.76	2.25	80.47		
10	0.64	1.88	82.35		
11	0.54	1.6	83.95		
12	0.5	1.48	85.43		
13	0.44	1.3	86.73		
14	0.42	1.24	87.97		
15	0.35	1.02	88.99		
16	0.34	1	89.99		
17	0.32	0.95	90.94		
18	0.31	0.9	91.84		
19	0.27	0.78	92.62		
20	0.25	0.75	93.37		
21	0.24	0.71	94.08		
22	0.23	0.69	94.77		
23	0.21	0.63	95.4		
24	0.2	0.58	95.98		
25	0.19	0.57	96.55		
26	0.17	0.51	97.06		

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27	0.17	0.5	97.56		
28	0.15	0.43	97.99		
29	0.14	0.42	98.41		
30	0.13	0.38	98.79		
31	0.12	0.35	99.15		
32	0.11	0.32	99.47		
33	0.1	0.29	99.76		
34	0.8	0.24	100		

Structural Model

The suggested theories were examined using Partial Least Squares (PLS) after the validity of the measurement model had been established. The analysis results are captured in Figure 2. The model's variance of 65 percent illustrates the validity of the proposed chatbot acceptance model. After evaluating the antecedents, which were framed as a result of extending the UTAUT2 framework, the first variable, effort expectancy's relationship with adoption intention is not significant (β=0.014, t= 0.244, p>0.05) which is contradictory to the findings of (Venkatesh et al., 2003) and many prior studies (Cheung & Vogel, 2017). This principle has, however, been checked with technologies that are bound to have an assured learning curve. It is not the case for chatbots which are quite simple to use (Melián-González et al., 2019), thereby not supporting hypothesis H1. The relationship between performance expectancy and adoption intention is significant (β=0.136, t= 1.684, p<0.05), which is in line with the previous research (El-Masri & Tarhini, 2017; Venkatesh et al., 2012). The strong positive association hypothesized at H2 is thus formed. Next, the antecedent social influence associated with the intention of chatbots was demonstrated to be insignificant (β=0.048, t= 0.702, p>0.05) thus rejecting hypothesis H3. Next, the antecedent hedonic motivation relationship was found not to be significant with the acceptance intention of chatbots (β=0.034, t= 0.55, p>0.05) therefore rejecting hypothesis H4. The antecedent habit was found to have a strong association with the adoption intention of chatbots (β=0.19, t= 3.187, p<0.01), strongly supporting hypothesis H5 as expected which was supporting the observations of earlier research (Lewis et al., 2013; Venkatesh et al., 2012).

The antecedent anthropomorphism association with the adoption intention of chatbots was found to be insignificant (β=0.024, t= 0.473, p>0.05) negating hypothesis H6. This relationship is contrary to the previous findings (Y. Kim & Sundar, 2012; Sheehan, 2017), the conceivable reason for this non-significant relationship could be explained that consumers consider less anthropomorphic visual cues, such as avatar in the adoption of a chatbot for financial services.

This will be discussed further in the following section.

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The next antecedent considered under humanness was likeability which had a substantial (β=0.084, t= 1.671, p<0.05) relationship with the adoption intention of chatbots for financial services supporting hypothesis H7. The final attribute that conceded the test of validity was social presence; its association with the intent to adopt chatbots shows an important relationship (β=0.447, t= 5.393, p<0.01) so instituting the hypothesized relationship in H8. Prior chatbot experience (control variable) for financial services is negatively associated with the adoption intentions of chatbots for financial services (β=-0.097, t= 2.274, p<0.05), understanding such experiences is crucial for providers of chatbots to support chatbot acceptance among target consumers (Følstad & Brandtzaeg, 2020) while the control variables age, gender, and any chatbot experience show an insignificant relationship with the adoption intention of chatbots

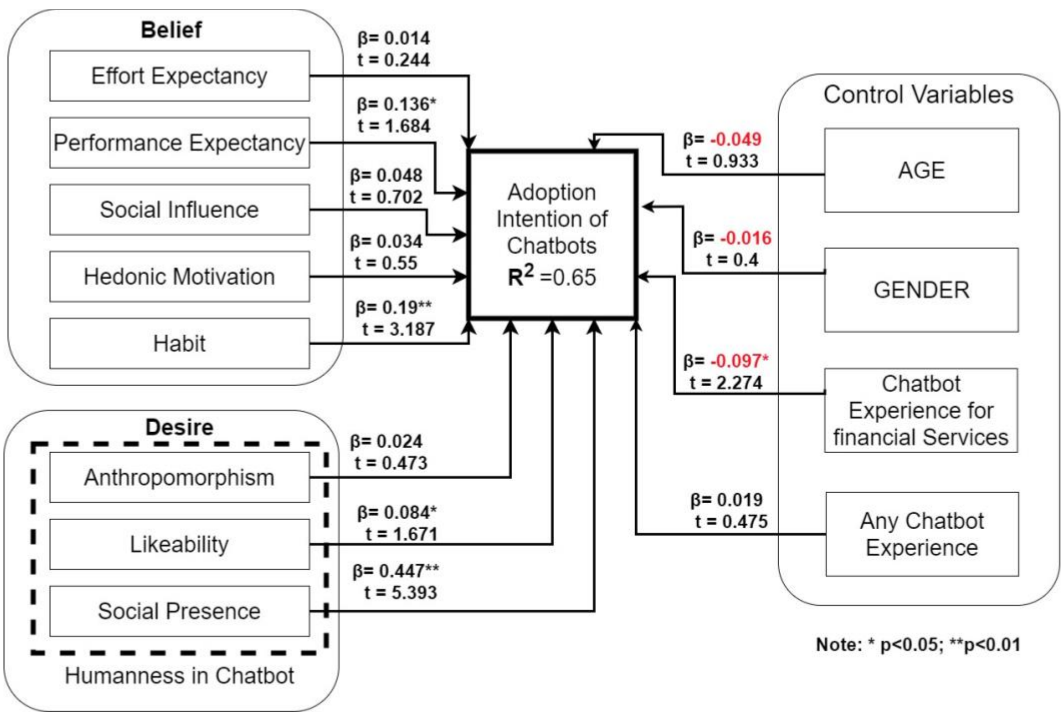

Figure 2: Research Model—Results

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DISCUSSION

Analysis results indicate that the variables performance expectancy, habit, likeability, and social presence are essential variables that influence the purpose of adopting chatbots in financial services, thereby supporting hypotheses H2, H5, H7, and H8. Firstly, the study findings showed that effort expectancy was not a significant factor in the adoption intention of chatbots, this seemed logical as there was no learning curve in using chatbots, and using a chatbot would, in most cases, merely imply opening the chat agent, keying queries, and attempting to converse with the system naturally (Melián-González et al., 2019). Next, the variable performance expectancy has a substantial effect on the intention of adopting chatbots in financial services. Thus, this research study confirms that performance expectancy is crucial for the adoption of chatbots in the financial services sector. The outcomes are in alignment with the previous studies in the context of chatbots (Melián-González et al., 2019) also in other technology adoption models (Alalwan et al., 2017). Chatbots are a way to obtain quick information on the topic user is interested in and the ability to achieve it faster plays an important role in consumers adopting chatbots for financial services. In regards to the role of social influence, the results were noted differently for what was proposed in the current study's conceptual model, consumers, the opinions, and behaviors of their reference groups seem less interested in formulating their intent to adopt chatbots for their financial transaction (Alalwan et al., 2017). The results of this study on social influence were found to be diverse from those of earlier research studies that used UTAUT as a reference model in their research, for example (Yu, 2012); the studies backed the part of social influence in behavioral intent. Other researches in the applicable area, however, have rejected the influence of the social influence considering the example, a research work utilized UTAUT as a framework to forecast the acceptance of customers to adopt online banking by (Riffai et al., 2012) who observed social influence to be the smallest irrelevant attribute (Alalwan et al., 2017). Hedonic motivation variable association with the adoption intention of chatbots was observed to be insignificant, which is in divergence with earlier research studies (Venkatesh et al., 2012) this shows that consumer doesn't observe pleasure and fun while using chat agents for financial services. One of the possible explanations for this is that chatbots for financial services are more seen as task-oriented and customers are not looking for novelty in the program which is harmonious with the studies piloted by (Ain et al., 2016). Habit was observed to exhibit a robust impact on the adoption intention of chatbots. Conversational agents use to become habitual, customers must be able to use them without difficulty and deliberate thought (Wang et al., 2013). Communicating through text has generally developed into an essential method of interaction worldwide, and its acceptance is growing at a rapid rate (Sultan, 2014),

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For some people, texting is the most common way for people to communicate on their social media, above the utilization of face to face messages, electronic mails and telephonic calls (Skierkowski & Wood, 2012). People are used to sending text messages and receiving instant responses for their queries and this habit is one of the important factors for consumers when adopting chatbots whose primary function is to address user queries instantly. Anthropomorphism relationship with chatbot adoption was found to be non-significant, which is indifferent from the previous research studies (Araujo, 2018), this could be since chatbot consumers for financial services were not interested in the anthropomorphic cues, similar studies on anthropomorphic design cues have found that the variable to be not significant (De Cicco et al., 2020). The next variable likeability was observed to establish a substantial relationship with the adoption intention of chatbots, which was in acceptance with the previous research on likeability (Bartneck et al., 2009, 2007). People were more inclined towards adopting chatbots for financial services if they liked the machine they were interacting with. Lastly, the variable social presence was observed to have a strong significant relationship with the adoption intention of chatbots for financial service. Increasing social presence on the website is seen positively by consumers(Gefen & Straub, 2003) by consumers of chatbots for financial services.

In summary, the outcomes emphasize the prominence of the factors involved and support the significance of the chatbot acceptance for financial services. Those factors, therefore, need to be taken into account by financial services companies when building a chatbot technology and employing it. Forthcoming research with supplementary variables may however be carried out to advance the precision and fluidity of the suggested model.

IMPLICATIONS

There is a lot of interest in the area of chatbots, most technology firms including Facebook, Google, and Microsoft perceive chat agents as the subsequent promising tech; Satya Nadella, CEO of Microsoft, informed, "Chatbots are the new apps"(Brandtzaeg & Følstad, 2017). Since the initial optimism regarding Facebook and Microsoft launching chatbots, some critics have pointed out that the acceptance of accessible chat agents by users is low on the point of significance than anticipated (Brandtzaeg & Følstad, 2017). Literature in the past suggests that the consumer's belief factors, such as performance expectancy, effort expectancy, social influence, hedonic motivation, habit are important factors for chatbot adoption. However, consumer desire factors, such as social presence and likeability also play an important part in the acceptance of chatbots by the consumer for financial services.

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Not only is it imperative to understand the aspects influencing the chatbots' adoption intentions for financial services, but it is also important to comprehend how a firm can meet the customer's needs, resulting in better consumer engagement and satisfaction. This study is based on these important theoretical and practical issues linked to chatbot adoption. This present research inspects the variables that impact adoption of chatbots in financial services by examining the humanness factors which the consumers desire. The paper also pinpoints some vital suggestions for both practice and research.

Implications for Research

First, the present form of chatbot studies in financial services is scarce. A major user study challenge in this field is the dramatic growth in technological innovations and consumer preferences(Brandtzæg & Heim, 2009). More or less of the chief motivations for using chat agents, however, might be constant over time, as the basic needs are reflected, such as social interaction and productivity (Brandtzaeg & Følstad, 2017). As the chatbot adoption study in the field of financial services is scarce, this research theoretically adds value by laying the groundwork for future study in this area. *Second*, a past study on consumer adoption of technology has been studied using well-established adoption theories, such as the UTAUT2 (Venkatesh et al., 2012) model, this is one of the models which has extended the UTAUT2 model with consumer desire factors of the humanness of chatbots. Though there is existing literature concentrating on the belief components of the consumer for the adoption of chatbots (Alalwan et al., 2017), this research provides insights into the desired facets of the consumers concentrating on the humanness aspect of chatbots and how it influences the adoption of chatbots for financial services. The authenticated model highlighted in Figure 2 could be utilized as a reference for further study to analyze the intention of consumers to adopt the technology. This research suggests the key role of social presence, habit, likeability and performance expectancy extending the literature on chatbot adoption. It will be instrumental in boosting potential researchers' interest towards chatbots application and administration. *Third*, the research illustrates variables that could affect the acceptance of technologies like chatbots. The study extends the literature on various factors as well as the literature on chatbots adoption by providing a theoretical model that delivers a theoretical foundation for gaining insights into the predictors of chatbots' adoption intentions. Future studies can look in depth at some of these character traits to broaden the list. *Fourth*, the study provides a validated research model for the intention to adopt financial services chatbots.

The system could be utilized to research the implementation of similar technologies such as AR, virtual reality for financial services.

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Implications for Practice

Besides highlighting suggestions for research, this study has numerous vital significances for various financial services companies that have implemented or intended to implement chatbots for their organizational needs as well as for their end-users. *First*, the introduction and development of a suitable chat agent involve a great amount of ambiguity for businesses, because chatbots can be configured in various means using a different set of guidelines (Zarouali et al., 2018). Chatbot designers need to identify cases where chatbots are more effective in meeting user productivity needs than is possible through other interaction methods. The popularity of chat agents as personal assistants and health care consultants demonstrates the necessity to build efficiency (Brandtzaeg & Følstad, 2017). This study is predicated on this gap. This paper highlights the importance of chatbots and what variables businesses should consider promoting their business model's easy adoption of this technology. *Second*, the research indisputably points out the factors that are crucial drivers for acceptance of chatbots for financial services and encourages professionals, chatbot retailers, and engineers to take these factors earnestly into consideration for the effective implementation of chatbots to provide better value for customers. While it could be alluring for companies to implement chatbots without prior study, companies need to do field study before the implementation phase as the desire and driving factors for consumers may vary across industries. Past studies have underscored the importance of comfort of usage and supposed usefulness in the adoption of novel technologies by consumers. Nonetheless, this study emphasizes that humanness factors are crucial for chatbots adoption and display various features— the acceptance must be extensively examined in the setting given to recognize the contextual relevance and value creation. *Third*, companies wishing to give consumers a favorable impression should accept the customer's needs and create engaging interactions that enhance the amount of social presence and ultimately the mindset towards the chatbots (De Cicco et al., 2020). The entity's appearance is primarily responsible for its attractiveness(Bartneck et al., 2007), companies ensuring better likeability of chatbots, which focus on performance and provide a user interface, which is likable to the users would enable higher acceptance of the technology among consumers. To sum up, it is vital that financial firms, chatbot vendors, and industry experts proactively consider the context of the humanness of chatbots for better consumer adoption and to be able to stand out in the market.

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LIMITATIONS OF THE STUDY AND FUTURE SCOPE

While this research contributes substantially to a better understanding of the adoption of chatbots from a humanness point of view, there are some limitations. *First*, the observations and their inferences were based on a set of population samples. Therefore, they are not a broad representation of the entire population. The generalization of the outcomes could thus be observed as a problem. The study shows the important aspects affecting the intention to adopt chatbots in financial services, but even more studies on this subject are needed to identify additional dimensions. *Secondly,* while the study has identified some variables influencing the adoption of the chatbot, future revisions may identify additional factors to enhance the model's capacity. It might be rational to add other humanness factors, such as animacy, perceived intelligence or perceived safety to extend the model (Bartneck et al., 2009). Since most of the respondents of the survey are from the Asian region, a future study could be performed in this area for similar topographies, where the consumer’s mindset and perception may vary. *Thirdly*, at a single point in time, the study measured expectations and intentions. However, there is a great probability of perception varies as time evolves and consumers get to know and experience the technology (Chandra & Kumar, 2018). *Lastly*, variables such as effort expectancy, hedonic motivation, social influence, anthropomorphism though hypothesized were not found to be significant in this study, however, it could be different when considering a different technology and geography, future studies should contemplate including the non-significant suggested factors.

CONCLUSION

This study suggests and also evaluates the technology adoption model of chatbots for financial services, which can serve as an insight into how consumers effectively embrace chatbots. Contrary to earlier research on technology adoption, which focuses on customer belief factors, this study highpoint the important attributes affecting the intention of adopting chatbots from the desired perspective of the consumer, which focuses on the humanness of chatbots along with the factors of belief. The validation of the measuring model sets the robustness of the suggested framework. The conceptualization of attributes affecting the adoption intention provides direction to financial services companies such as banks, insurance firms, chatbot retailers, technology specialists, and scholars to emphasize not only on the belief standpoint but also on the desire attributes of the customer, as acceptance choices are reliant on these qualities. Besides, the Structural Model Analysis authenticated the association between various suggested factors and the objective to adopt chatbots for financial services, emphasizing the urgent requirement to

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develop suitable approaches for the fruitful acceptance and creation of value by leveraging technology.
The outcomes of the structural association could work as a beginning argument for financial organizations to articulate their policies based on the noticeable factors, comprising of performance expectancy, habit, likeability, and social presence. Further to providing empirical authentication of the suggested model based on the UTAUT2 framework, the paper provides researchers with numerous guidance points for further studies on the adoption, applications, and effects of potentially valuable chatbot technology in this focus area.

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Appendix

Effort Expectancy Adapted from (Venkatesh et al., 2012)
1. Learning how to use chatbots is easy for me. 2. It's easy for me to become skilful at using chatbots. 3. I find chatbots easy to use.
Performance Expectancy Adapted from (Venkatesh et al., 2012)
1. I find chatbots would be useful when I perform my financial transaction on a secure website. 2. Using chatbots increases my chance of achieving things that are important to me. 3. Using chatbots would help me to accomplish things more quickly. 4. Using chatbots would increase my productivity.
Social influence Adapted from (Venkatesh et al., 2012)
1. People who are important to me think that I should use chatbots. 2. People who influence my behavior think that I should use chatbots. 3. People whose opinion that I value prefer that I use chatbots.
Hedonic motivation Adapted from (Venkatesh et al., 2012)
1. Using chatbots is fun. 2. Using chatbots is enjoyable. 3. Using chatbots is very entertaining.
Habit Adapted from (Venkatesh et al., 2012)
1. The use of chatbots has become a habit for me. 2. I am addicted to using a chatbot. 3. I must use a chatbot. 4. Using chatbot has become natural to me.
Anthropomorphism Adapted from (Bartneck et al., 2009)
Please rate how you would like the chatbot to be? 1. Fake Vs Natural. 2. Machine like Vs Human-Like. 3. Unconscious Vs Conscious. 4. Artificial Vs Life Like.
Likeability Adapted from (Bartneck et al., 2009)
Based on the chatbot Avatar (Human VS chatbot) please rate your impression for the factor below – 1. Dislike Vs Like. 2. Unfriendly vs Friendly. 3. Unkind vs Kind. 4. Unpleasant vs Pleasant. 5. Awful vs Nice.
Social Presence Adapted from (Gefen & Straub, 2003)

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1. There is a sense of human contact when communicating with chatbots. 2. There is a sense of personalness when communicating with chatbots. 3. There is a sense of sociability when communicating with chatbots. 4. There is a sense of human warmth when communicating with chatbots. 5. There is a sense of human sensitivity when communicating with chatbots.
Adoption Intentions Adapted from (Chandra et al., 2010)
6. Given a chance, I intend to adopt chatbots in the future for financial services. 7. Given a chance, I predict that I will frequently use chatbots in the future for financial services. 8. I will strongly recommend others to use chatbots for financial services.

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