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The Impact of Frustration and Anthropomorphism in Chatbots and Digital Assistants' Adoption

Mariana Ferreira Nunes

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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THE IMPACT OF FRUSTRATION AND ANTHROPOMORPHISM IN CHATBOTS AND DIGITAL ASSISTANTS' ADOPTION

by

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

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DEDICATION

To my parents, for fostering in me the taste for knowledge and discovery and for always giving me the necessary conditions to explore them.

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ABSTRACT

This study brings an innovative approach to chatbots' adoption studies by analysing the impact of loss emotions, in this case frustration, and anthropomorphism in user's intention and use behaviour to adopt a chatbot. The innovative theoretical model tested using PLS/SEM, based on a sample of 365 respondents, shows that anthropomorphism and habit positively influence behavioural intention and use behaviour. Frustration negatively influences behavioural intention to adopt chatbots and digital assistants. The presence of anthropomorphic characteristics in the technology decreases frustration and moderates the relation between habit and use behaviour. Behavioural intention is a mediator of all constructs that explain use behaviour. The impacts of anthropomorphism and frustration in this technology adoption not only create an innovative basis for further refinement of individual models of adoption, but also allow practitioners to align functionalities with real costumer needs and implement chatbots and digital assistants with high consumer adoption.

KEYWORDS

Chatbots; Digital assistants; Adoption; Frustration; Anthropomorphism

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1. INTRODUCTION

Nowadays artificial intelligence is revolutionizing the world in the sense that humans are not only working together with machines, but they are also embedding machines with human intelligence alike by creating "thinking machines" (Buchanan, 2005). Today it is estimated that 1.4 billion people use chatbots and digital assistants on a regular basis (Jovic, 2020). Chatbots and digital assistants embrace a variety of areas such as: learning and practice of a language, as an information retrieval tool in e-commerce, business and other domains (Atwell & Shawar, 2007). Although chatbots exist for more than 50 years (Atwell & Shawar, 2007), it was only in the second decade of the 21st century that most of its developments started to be noted and its use became more pronounced (Guzmán & Pathania, 2016). The growth in chatbots and digital assistants usage was mainly due to developments in artificial intelligence associated with neural networks, machine learning and data storing (Intelligence, 2020) together with the growth of messaging services and chatting applications (Io & Lee, 2018). Chatbots market is projected to grow from $2.6 billion in 2019 to $9.4 billion by 2024 at a rate of 29,7% (Nguyen, 2020), confirming their importance. The area is also expected to save businesses more than $8 billion per year by 2022 (Smith, 2017).

Considering the education environment chatbots have applications such as: supporting e-learning environments, help in administrative issues as enrolling in a course, help students with their exam schedules, grades, and other study related details (Adamopoulou & Moussiades, 2020). In customer service chatbots are present in supporting customers with their queries and helping deciding which products are suitable for them (Adamopoulou & Moussiades, 2020). Considering the health sector, chatbots are being used to offer diagnosis, suggest treatments, take care of users' emotional health and remind patients to take their medicine. Chatbots also handle administrative tasks such as arranging appointments, finding hospitals and delivering prescriptions (Adamopoulou & Moussiades, 2020). The banking sector also benefits from chatbot applications able to provide customers with information about account balances, facilitate payments, suggest ways to save resources, help activate cards and collect feedback from customers (Adamopoulou & Moussiades, 2020). With the outbreak of COVID-19 and the remote working imposed by lock-down, companies are very dependent on chatbots to reduce the burden of customer queries due to the minimal availability of employees. Chatbots were also responsible for providing to millions of people important and reliable information concerning COVID-19 daily (Intelligence, 2020).

This study brings several contributions for research, considering the advancements of knowledge through the exploration and discussion of direct implications for any entities that use chatbots or digital assistants as a business or operational tool. This papers' contribution is threefold. Firstly, this study is innovative as it models chatbots and digital assistants' adoption factors by evaluating the impact of anthropomorphism and frustration together with the constructs that explain use from UTAUT2 (Unified Theory of Acceptance and Use of Technology). Therefore the suggestion to extend UTAUT2 model in different countries, age groups and technologies is followed (Venkatesh, Thong, & Xu, 2012). Secondly, there is a need to better study chatbots and digital assistants' adoption factors as, although some users are already willing to use and understand chatbots' advantages in transactional services, several others still show some resistance in using them for services that require more long-term or impactful decisions (Bothun, Lieberman, & Rao, 2017). Moreover the understanding of the adoption factors is considered of extreme importance in order to design, refine and implement a technology to achieve higher consumer adoption (Baptista & Oliveira, 2017). Especially in an economy of instant gratification (Equity, 2019) chatbots and digital assistants play a major role in providing answers and solutions to users' problems without making them spend much time or entry in complex customer assistant systems with many intervening. Thirdly, the impact of frustration and anthropomorphism in the adoption of chatbots and digital assistants is of extreme importance, and they have not yet been sufficiently explored in literature. During utilization many users experience frustration caused by the technology inability to answer their queries or to fulfil their interaction expectations (Perez, 2016). Also, frustration is considered a loss emotion and emotions are very important drivers of behaviours, as the emotions experienced early and during the technology utilization are directly related to its adoption (Beaudry & Pinsonneault, 2010). Nowadays, more than just asking some information or executing a certain activity, users give a great importance to the style, tone and attitude of the chatbot, therefore anthropomorphism is necessary for a complete satisfying user experience (O'Brion, 2017). By including cognitive and emotional constructs, as anthropomorphism and frustration, as influencers of adoption, we are following the recommendation to get a wider understanding of the psychological determinants of commercial chatbots effectiveness (Zarouali, Van Den Broeck, Walrave, & Poels, 2018). Also, it is the first time, to our knowledge, that UTAUT2 constructs influencing behavioural use are combined with anthropomorphism and frustration to explain chatbots and digital assistants' adoption.

2. THEORETICAL BACKGROUND

2.1. CONCEPT AND CHARACTERISTICS OF CHATBOTS AND DIGITAL ASSISTANTS

Chatbots are computer programs that engage in a conversation by generating natural language as output (Atwell & Shawar, 2007), through written or voice platforms (Guzmán & Pathania, 2016). There are two types of chatbots according to their intelligence and communication skills: transactional chatbots that are only capable of providing users' a fixed set of choices and conversational chatbots that can maintain a conversation in a natural human-like manner (Rindell, 2019). A digital assistant is considered an advanced chatbot because it uses advanced artificial intelligence techniques providing answers to more complex queries (Oracle, 2021). Digital assistants can learn from a user's history, what embeds them the capability to provide a more personalized conversational experience. Digital assistants can also access various sources to provide an answer making them able to provide recommendations, make predictions and initiate conversations. For this research a chatbot is considered as a technology able to interact with its users through writing, voice or both interfaces. The ones embedded with artificial intelligence that can capture and answer users' interactions using natural language processing are considered as a digital assistant if they are able to answer complex queries, initiate conversations and make predictions and/ or recommendations.

Frustration is defined as a duality of cause and effect, the cause is associated with an external event that triggers an emotional reaction and the effect is the emotional response directed towards the environment (Lazar, Jones, Bessiere, Ceaparu, & Shneiderman, 2012). Frustration characterizes the experience of some users when using chatbots and digital assistants as described by different authors (Gnewuch, Morana, Adam, & Maedche, 2018; Io & Lee, 2019; Jenkins, Churchill, Cox, & Smith, 2007; Temple & Elie, 2019; Wünderlich & Paluch, 2018). This frustrating experiences arise due to things that occur during correct states of the system that annoy users and decrease their adoption interest (Lazar, Allen, Kleinman, & Malarkey, 2007). Anthropomorphism is the act of attributing to the behaviour of a non-human agent human like characteristics, motivations, intentions and emotions (Wang, 2017). Anthropomorphism is an important characteristic of chatbots as it provides the machine the characteristics it needs to be socially engaging, facilitate interaction and triggering acceptance (Duffy, 2003).

2.2. PRIOR RESEARCH ON CHATBOTS AND DIGITAL ASSISTANTS

Although chatbots exist since 1966 with the creation of ELIZA (Io & Lee, 2019), its continuous utilization and application to different areas of society has been more present and stronger since 2012 (Bothun et al., 2017). Chatbots and digital assistants allow customers real-time self-service, availability anytime and across any channel, device or platform (Reddy, 2017). 37% of people use customer service chatbots to get a quick answer in an emergency and 64% state that the best feature of chatbots in customer service is the 24-hour service (Jovic, 2020). Chatbots and digital assistants are expected to provide personalized recommendations (Bothun et al., 2017), potentiating personalised customer offerings and new product creations (Verweij & Rao, 2017). For companies they will create consumption side effects as increased consumption and customer loyalty (Verweij & Rao, 2017). Another advantage is the improvement in labour productivity, considering that employees do not have to assist customers in all customer service tasks, giving them time to focus on higher value-adding work (Bothun et al., 2017), potentiating a cut up to 30% in operational costs (Bhutani & Wadhwani, 2019).

Chatbots allow companies to save resources, as the marginal cost for a chatbot to handle more conversations and taking more time with customers is almost zero (Guzmán & Pathania, 2016).

In the last years we witnessed a growth of chatbots and digital assistants related studies, nevertheless research is still scarce and very fragmented (Io & Lee, 2018). Also, research in this area is mainly related to computer science and engineering, with the major focus in the technical part of the technology (Io & Lee, 2018). Only a few studies published in top tier journals have analysed the adoption of chatbots and digital assistants in the last years (Hill, Randolph Ford, & Farreras, 2015; Jang, Jung, & Kim, 2021; Laumer, Maier, & Gubler, 2019). Hill et al., (2015) analysed how users' communication patterns change when people communicate with an intelligent agent as opposed to another human. Jang et al., (2021) used social representation theory with core periphery analysis to report what was the opinion of the Korean financial sector managers of chatbots. Three pillars of challenges were found regarding chatbots adoption: technological factors, organizational and managerial factors. Laumer et al., (2019) studied the factors that influenced individuals to adopt conversational agents for disease diagnosis by using UTAUT2 (Unified Theory of Acceptance and Use of Technology) factors together with privacy risk expectancy, trust in provider, system compatibility, experience in e-diagnosis and access to health system.

The need to study chatbots and digital assistants' acceptance arises as consumer resistance is a determinant factor in the failure of innovative services (Ram & Sheth, 1989), therefore in order to guarantee the success in the adoption of a technology, sufficient user acceptance is necessary (Wu & Wang, 2005). As such, this study introduces innovation to earlier chatbots and digital assistants' studies, as it presents an innovative model that combines UTAUT2 constructs influencing use behaviour together with frustration and anthropomorphism. The model does not consider the UTAUT2 constructs that influence behavioural intention as this phenomenon was previously already studied in many contexts and with many technologies, and because the main focus is to study the impact over the use behaviour.

3. RESEARCH MODEL AND HYPOTHESIS

Bearing in mind that, in IT, emotions have the role of bridging the gap in the moments where users' routines are interrupted, they play a major role in technology adoption (Beaudry & Pinsonneault, 2010), therefore frustration is expected to have a negative impact in explaining adoption. Nowadays users consider chatbots and digital assistants as participants in the social circle, therefore their perception of its human capabilities is crucial and potentiates its adoption (Duffy, 2003). Although chatbot over emphasized anthropomorphic characteristics can be a source of negative emotions (Gnewuch et al., 2018; Knijnenburg & Willemsen, 2016) it is expected that anthropomorphism positively influences use behaviour. To date, there are no chatbots or digital assistants' studies that capture the impact of these psychological determinants in technology adoption. Therefore, the combination of the UTAUT2 model constructs that explain use behaviour (facilitating conditions, habit and behavioural intention), with frustration and anthropomorphism will expectably provide a stronger significance and predictability of the results. The model also accounts for the exploration of the moderation role of anthropomorphism, as well as the behavioural intention mediation effects between the chosen set of constructs and the chatbot and digital assistants' use behaviour. Figure 1 presents the research model.

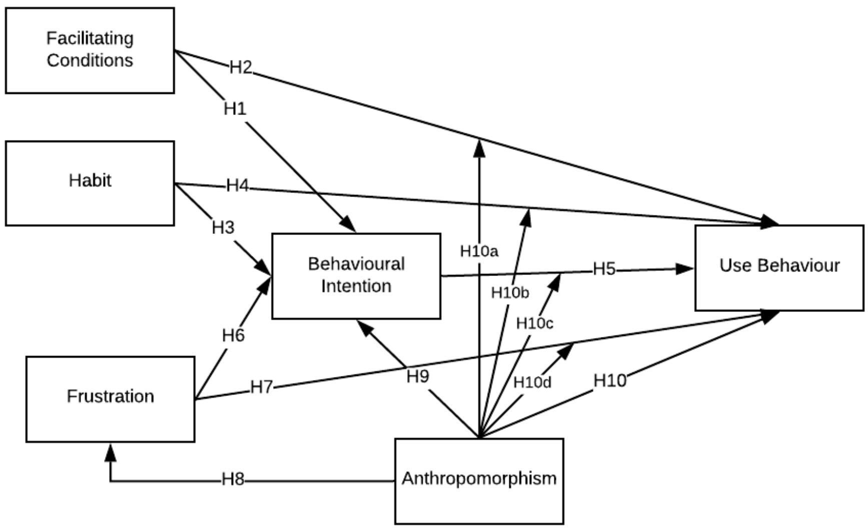

Figure 1 - Research model

3.1. FACILITATING CONDITIONS, HABIT AND BEHAVIOURAL INTENTION

Facilitating conditions are defined as the degree to which the user believes that a technical infrastructure to support the use of the system exists (Venkatesh, Morris, Davis, & Davis, 2003)(Venkatesh et al., 2003). Facilitating conditions are an important driver of technology adoption as they act as perceived behavioural control (Venkatesh et al., 2012). The presence of facilitating conditions increases users' expectancy of success, what will also raise their perceived self-efficacy with the usage of the technology. This will create in the users a sense of perceived behavioural control which will increase their effort in using the technology and, consequently, succeed in its usage (Ajzen, 1991). Moreover, the presence of a support infrastructure increases users' awareness of the technology ease of use, what potentiates their intention and use behaviour (Venkatesh et al., 2003). With chatbots and digital assistants, facilitating conditions are access to tutorials of utilization, service description, Q&A sections as well as chatbots' demos. Therefore, it is expected that the presence of an infrastructure that supports the use of chatbots and digital assistants will positively influence the user's intention and use behaviour.

H1. The influence of facilitating conditions on behavioural intention to adopt a chatbot or digital assistants will be positive.

H2. The influence of facilitating conditions on chatbot or digital assistants' use behaviour will be positive.

Habit is associated with the repetition of prior experiences over time, therefore it also has a link with automaticity and can be defined as the extent to which individuals perform behaviours in an automatic manner because of learning (Venkatesh et al., 2012). On the one hand, the repetition of a particular behaviour can establish attitudes and intentions in the user that are triggered by environmental cues. Moreover, every time the user recognizes an environment where the use of a particular technology was useful and positive, he/she will develop the conscious belief that that technology is useful and will use it in that environment (Kim, Malhotra, & Narasimhan, 2005). On the other hand, the same situation can also trigger an unconscious response in the user that is independent of any attitudes, beliefs, subjective norms and intentions (Ajzen, 1991). In this scenario, the repetition of a particular past behaviour produces habituation behaviours that are triggered by environment cues, however the users response is unconscious and automatic (Venkatesh et al., 2012). Either ways, habit reflects the result of prior experiences and is a predictor of future behaviour, as the frequency of past behaviour is one of the principal determinants of present behaviour (Ajzen, 1991). Therefore, it is expected that users' prior experience with chatbots will have a positive impact on their intention and use behaviour.

H3. The influence of habit on behavioural intention to adopt a chatbot or digital assistant will be positive.

H4. The influence of habit on chatbot or digital assistants' use behaviour will be positive.

Behavioural Intention is the extent to which one is willing to try and execute while performing a behaviour (Leong, Hew, Tan, & Ooi, 2013). Behavioural intention is influenced by individual intention which gives an indication of how hard people are willing to try and how much effort they are planning to apply in order to execute a particular behaviour (Ajzen, 1991). Moreover, when behaviours do not present serious problems of control they can accurately be predicted from intentions (Ajzen, 1991), what makes behavioural intention to have a significant positive influence on technology adoption (Venkatesh et al., 2003). Also, consumers with high intention to adopt a new technology are more willing to become adopters (Leong et al., 2013).

H5. The influence of behavioural intention on chatbot or digital assistants' behavioural use will be positive.

3.2. Frustration and Anthropomorphism

Frustration is an emotional response that arises when individuals live a situational opposition that prevents them from accomplishing their goals (Brown, 1954). Different authors describe frustrating user experiences during the utilization of a chatbot, some point the lack of human communication and behavioural patterns, especially in the inability to provide clear responses and giving the same answers, when the displayed answer is not the desired by the user (Jenkins et al., 2007). The technology inability to fit users' expectations on the sociability, interactivity and degree of personalization is also stated as a cause of frustration (Wünderlich & Paluch, 2018), specifically when the chatbot or digital assistant presents unfitting emotions, empty phrases or ruse statements the user usually tends to become frustrated. Other causes of frustrating experiences are when the technology provides wrong information (Wünderlich & Paluch, 2018), when the chatbot is not able to solve the users' problems in a timely manner (Io & Lee, 2019), or when it provides generic answers to specific questions (Temple & Elie, 2019). Another example is the chatbot released by Facebook in 2016 that allowed users to interact with different businesses (as CNN, Poncho or Spring) in a platform embedded in the messenger application (Constine Josh, 2016). However, the use of this technology was described as "more frustrating and disappointing than using the businesses' websites" (Perez, 2016). Users' apply social rules in their expectations with technologies that use natural language speech or display other human characteristics, therefore, when the technology is not able to fulfil this expectations frustration arises in the user (Gnewuch et al., 2018). This emotion triggers in the users a feeling of impediment to accomplish their goals (Beaudry & Pinsonneault, 2010), what will make them limit the encounters with the stressor (Han, Lerner, & Keltner, 2008). As in this case the stressor is the use of the technology, it is stated that the frustration felt during the use of the chatbot will negatively influence users' intention to adopt and actual use the technology.

H6. The influence of frustration on behavioural intention to adopt a chatbot or digital assistant will be negative.

H7. The influence of frustration on chatbot or digital assistants' use behaviour will be negative.

Anthropomorphism is defined as the presence of human like characteristics, motivations, intentions and emotions (Epley, Waytz, & Cacioppo, 2007) in non-human agents or the individual tendency to attribute human characteristics to non-animate objects, animals and others with the goal of rationalize them (Duffy, 2003). Examples of chatbots' anthropomorphic characteristics are the presence of dynamic response delays, which increases users' perception of humanness and social presence (Gnewuch et al., 2018), chitchat and emotional behaviour during the conversation (Jenkins et al., 2007) and situations when the chatbot acts like a friend, trainer or helps the user from getting bored (Io & Lee, 2019). More and more users are expecting the chatbots not only to provide knowledge, but also to interact in a natural way (Morrissey & Kirakowski, 2013). According to the simulation theory, humans understand others' minds by simulating another's' situations in order to understand their mental state or emotion (Riek, Rabinowitch, Chakrabarti, & Robinson, 2008). Therefore, the more similar a chatbot is to the user the stronger the empathy, as anthropomorphism will make people neurologically view the robot like themselves (Riek et al., 2008). Building a chatbot or a digital assistant like a human makes the user see the technology more accordingly with their own image, which makes them stop treating it as a mere object and start seeing it as a moral agent worthy of respect and concern (Epley et al., 2007). Therefore, anthropomorphism provides the machine the characteristics it needs to be socially engaging and facilitate interaction, triggering users acceptance (Duffy, 2003).

Users will be more patient with chatbots' flaws, such as providing incorrect or incomplete information (Jenkins et al., 2007), as well as more available to initiate the correction of misunderstandings (Corti & Gillespie, 2016) with anthropomorphised agents. This type of chatbots are also able to decrease or avoid potential frustrating experiences (Chaves & Gerosa, 2020) as they show conversation and social intelligence during the interaction with the user. Social intelligence is the capability of the chatbot to use social conversational protocols. The usage of these protocols will reduce or avoid frustration because the technology will use expected coherent language patters, will have manners, manifest a polite behaviour and will be able to control damage and predict users' satisfaction. Conversational intelligence is the capability of the chatbot in being proactive, conscious and communicative (Chaves & Gerosa, 2020). The chatbot capacity to be conscious reflects in its ability to understand the conversational context and follow its flow. This characteristic also allows the technology to evaluate satisfaction and avoid frustration by using confirmatory messages and seeking clarification. A communicative chatbot is able to teach the user how to interact with it in order to reach all its potential and capabilities, what potentiates a decrease in the appearance of frustrating experiences (Chaves & Gerosa, 2020).

Anthropomorphism impact does not depend only on the characteristics of the technology but is also dependent of the impact those characteristics have on each particular user and how he/she judges them. Moreover, many social responses to computers are created subconsciously (Wang, 2017) and users' perceptual biases have an influence on how the robot is realized (Duffy, 2003). Therefore, there is a threshold of the impact the presence of anthropomorphic characteristics have on users, as there is a point from where the user does not feel affinity anymore (Rietz, Benke, & Maedche, 2019) and may perceive the chatbot as uncanny and weird – concept known as "The Uncanny Valley" (Duffy, 2003). Attempts in embedding chatbots and digital assistants with overly humanized representations emphasize users' expectations about the agents' communication capabilities, especially considering the expectations of social rules that users' apply in technologies that use natural language or display other human characteristics (Gnewuch et al., 2018; Knijnenburg & Willemsen, 2016). Therefore, anthropomorphic characteristics should be applied with balance as these non-fulfilled users' expectations will negatively affect the technology adoption (Wünderlich & Paluch, 2018).
Therefore, it is hypothesized:

H8. The influence of anthropomorphism on frustration will be negative.

H9. The influence of anthropomorphism on behavioural intention to adopt a chatbot or digital assistants will be positive.

H10. The influence of anthropomorphism on chatbot or digital assistants' use behaviour will be positive.

Anthropomorphism approaches the communication and usage of a chatbot with a human agent. Therefore, it is able to provide this particular technology the characteristics it must have in order to fulfil users' expectations and answer its queries in a productive and timely manner: be socially and conversationally intelligent (Chaves & Gerosa, 2020). Furthermore, anthropomorphised agents potentiate technology acceptance and aid in how to use it, due to the potential creation of a social connection. These characteristics also enable a sense of efficacy and usefulness, as users are more likely to cooperate with an anthropomorphised agent due to the created social bond (Epley et al., 2007). It is proposed that the presence of anthropomorphism positively moderates the relation between facilitating conditions, habit and behavioural intention with use behaviour and negatively moderates the relation between frustration with use behaviour.

H10a. Anthropomorphism moderates the relation between facilitating conditions and chatbot or digital assistants' use behaviour.

H10b. Anthropomorphism moderates the relation between habit and chatbot or digital assistants' use behaviour.

H10c. Anthropomorphism moderates the relation between behavioural intention and chatbot or digital assistants' use behaviour.

H10d. Anthropomorphism moderates the relation between frustration and chatbot or digital assistants' use behaviour.

4. METHODS

4.1. MEASUREMENT

To test the theoretical model a survey was developed and conducted. A questionnaire was developed for the survey using items and constructs from the literature, as presented in Appendix. Items measuring the constructs facilitating conditions, habit and behavioural intention were adapted from (Venkatesh et al., 2012), use behaviour was adapted from (Zhou, Lu, & Wang, 2010), frustration was adapted from (De Guinea, Titah, & Léger, 2014) and anthropomorphism items were adapted from (Wang, 2017). The items from (Venkatesh et al., 2012; Wang, 2017; Zhou et al., 2010) were measured on a 7 point range scale from "strongly disagree" (1) to "strongly agree" (7). Items from (De Guinea et al., 2014) ranged from "I Disagree" (1) to "I Agree" (7).

The questionnaire was administered in Portuguese and English and reviewed for content and consistency validity by language experts from a university. The survey was pilot tested among a group of 48 subjects in November 2020. Preliminary analysis confirmed that the scales were reliable and valid. To avoid skewing the results, the data from the pilot test was not used in the second phase of the data collection.

4.2. DATA COLLECTION

Adults with 18 or more years old selected from WhatsApp groups, Facebook groups, Reddit subreddits, and Instagram were used as source to collect the questionnaire answers. Bachelor and master students from Nova Information Management School, registered between 2018 and 2020, were also contacted by email. The respondents needed to have internet access and could only answer the questionnaire once. Previous experience with chatbots and digital assistants was not needed. The questionnaire had an introduction with the definition of a chatbot, some examples of its applications and links to access Facebook chatbots. 692 individuals started, however only 365 completed the survey. The sample is composed by 365 individuals, 40% of which are male and 60% are female. 50% of the respondents have a Master or a Postgraduate degree, 37% have a Bachelor degree, 10% an High school degree and 2% a Doctorate degree. Considering the nationality of the respondents, 83% are European, 5% are Latin American, 4% are from United States, 5% did not answer, and 3% have other nationalities. Considering the age of the respondents, 39% have between 18 and 23 years old, 41% between 24 and 29, 9% between 30 and 35, 4% between 36 and 41, 5% between 42 and 47 and 2% between 48 and 53 years old. The sample is an indicative group to test the instruments because chatbots and digital assistants' users are mostly young (Schrier, 2021) and literate individuals (Green, Vosloo, & Conole, 2018). Common method bias was examined using two different methods: Harman's one-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), confirming that none of factors individually explain the majority of the variance and correlation matrix analysis, with all the variables bellow the maximum correlation threshold ($r < 0.9$) (Bagozzi, Yi, & Philips, 1991). All datasets used in the study are available from authors, on demand.

4.3. DATA ANALYSIS AND RESULTS

The PLS-SEM is suitable for this case because: the presented model was never tested in the literature; there are no data assumptions and not all items in our data are normally distributed ($p < 0.01$, based on K-S's test); the model has formative and reflective measurement models and it is considered complex (Chin & Newsted, 1999). To estimate the research model Smart PLS3 was used. Firstly, the measurement model will be analysed, followed by the structural model.

4.4. MEASUREMENT MODEL

The formative measurement model was examined for collinearity issues, significance and relevance of the indicators. Items ANT3 and ANT4 were removed because they had VIF values higher then 3.3 (Kock & Lynn, 2012), what compromised the model for collinearity. The items that remained presented VIF values bellow 3.3. To test the significance and relevance of the items predicting formative indicators the t-value was analysed for loadings and weights, their contribution was statistically significant at least for all loadings, therefore the remaining items from anthropomorphism were kept (Hair, Hult, Ringle, & Sarstedt, 2016).

Constructs	Items	VIF	Loadings	t-value	Weights	t-value
Anthropomorphism	ANT1	1.582	0.323	3.696	-0.146	1.626
	ANT2	2.699	0.395	4.692	0.273	2.329
	ANT5	2.534	0.290	3.405	-0.176	1.449
	ANT6	1.852	0.398	4.718	0.023	0.235
	ANT7	1.651	0.932	31.365	0.708	9.757
	ANT8	1.775	0.713	12.583	0.210	2.346
	ANT9	2.014	0.732	12.450	0.235	2.606

Table 1 - Quality criteria for formative constructs (VIF), factor loadings and weights

The reflective measurement model was examined for internal consistency, indicator reliability, convergent validity and discriminant validity. Internal consistency was tested based on Cronbach Alpha and composite reliability. As shown in Table 2, quality criteria for internal consistency is above 0.7, which confirms that the constructs are reliable (Straub, 1989). The criteria used to evaluate indicator reliability and convergent validity was that loadings should be higher than 0.7, computing an AVE of 5 or more (Hair et al., 2016). UB6 and UB7 were eliminated due low loadings. Considering discriminant validity, as shown in Table 3, loadings are always higher than cross-loadings and the square root of the AVE is higher than the correlation with the remaining constructs (Table 2). HTMT values are below the threshold of 0.9 for all constructs (Table 4). As the three criteria are satisfied there is evidence of the presence of discriminant validity (Hair et al., 2016).

	Mean	Composite Reliability	Cronbach's α	SD	FC	HB	F	ANT	BI	UB
Facilitating Conditions (FC)	5.677	0.880	0.821	1.107	**0.806**					
Habit (HB)	2.295	0.902	0.854	1.442	0.250	**0.835**				
Frustration (F)	2.949	0.959	0.936	1.711	-0.259	-0.244	**0.942**			
Anthropomorphism (ANT)	3.838	NA	NA	1.547	0.201	0.531	-0.317	NA		
Behavioural Intention (BI)	4.189	0.963	0.942	1.677	0.361	0.716	-0.374	0.603	**0.947**	
Use Behaviour (UB)	2.868	0.871	0.821	1.265	0.161	0.666	-0.226	0.510	0.510	**0.757**

Table 2 - Fornell-Lacker Criterion: matrix of correlation constructs and the square root of the AVE (in bold)

Construct	ITEM	FC	HB	F	ANT	BI	UB
Facilitating Conditions (FC)	FC1	**0.820**	0.155	-0.118	0.095	0.237	0.052
	FC2	**0.841**	0.174	-0.136	0.108	0.264	0.053
	FC3	**0.847**	0.219	-0.265	0.150	0.330	0.133
	FC4	**0.706**	0.229	-0.259	0.250	0.298	0.228
Habit (HB)	HB1	0.261	**0.884**	-0.175	0.417	0.657	0.577
	HB2	0.008	**0.717**	-0.077	0.311	0.367	0.538
	HB3	0.192	**0.849**	-0.294	0.534	0.622	0.548
	HB4	0.321	**0.879**	-0.243	0.492	0.697	0.568
Frustration (F)	F1	-0.242	-0.219	**0.949**	-0.289	-0.349	-0.211
	F2	-0.241	-0.207	**0.923**	-0.273	-0.329	-0.185
	F3	-0.248	-0.259	**0.953**	-0.329	-0.375	-0.238
Anthropomorphism (ANT)	ANT1	0.010	0.256	0.023	**0.323**	0.186	0.253
	ANT2	-0.072	0.272	0.024	**0.395**	0.178	0.366
	ANT5	-0.155	0.211	0.075	**0.290**	0.130	0.305
	ANT6	0.001	0.254	0.028	**0.398**	0.248	0.290
	ANT7	0.239	0.475	-0.330	**0.932**	0.572	0.443
	ANT8	0.087	0.426	-0.179	**0.713**	0.446	0.374
	ANT9	0.030	0.428	-0.157	**0.732**	0.430	0.434
Behavioural Intention (BI)	BI1	0.358	0.631	-0.378	0.590	**0.930**	0.569
	BI2	0.328	0.693	-0.336	0.545	**0.945**	0.596
	BI3	0.341	0.709	-0.349	0.580	**0.966**	0.593
Use Behaviour (UB)	UBEH1	0.254	0.592	-0.236	0.419	0.647	**0.756**
	UBHE2	0.225	0.605	-0.293	0.507	0.680	**0.769**
	UBEH3	0.025	0.383	-0.112	0.315	0.288	**0.758**
	UBEH4	0.033	0.402	-0.089	0.333	0.286	**0.777**
	UBEH5	-0.030	0.451	-0.043	0.288	0.270	**0.726**

Table 3 - Loadings and cross-loadings

	Facilitating Conditions	Frustration	Habit	Behavioural Intention	Use Behaviour
Facilitating Conditions					
Frustration	0.275				
Habit	0.294	0.263			
Behavioural Intention	0.398	0.397	0.783		
Use Behaviour	0.247	0.229	0.769	0.647	

Table 4 - HTMT

4.5. STRUCTURAL MODEL AND HYPOTHESIS TESTING

In order to test the structural model for possible multicollinearity, an issue considered a threat to experimental model design (Donald & Glauber, 1967), the variance inflation factor (VIF) was analysed. As all VIF values were above the threshold of 3.3 the model was considered free of multicollinearity (Hair et al., 2016). To test the hypotheses and construct's relationships we analysed the standardized paths and estimated their significance level using the bootstrap resampling method, with 5.000 iterations (Hair et al., 2016). Figure 2 shows the results of the PLS estimation.

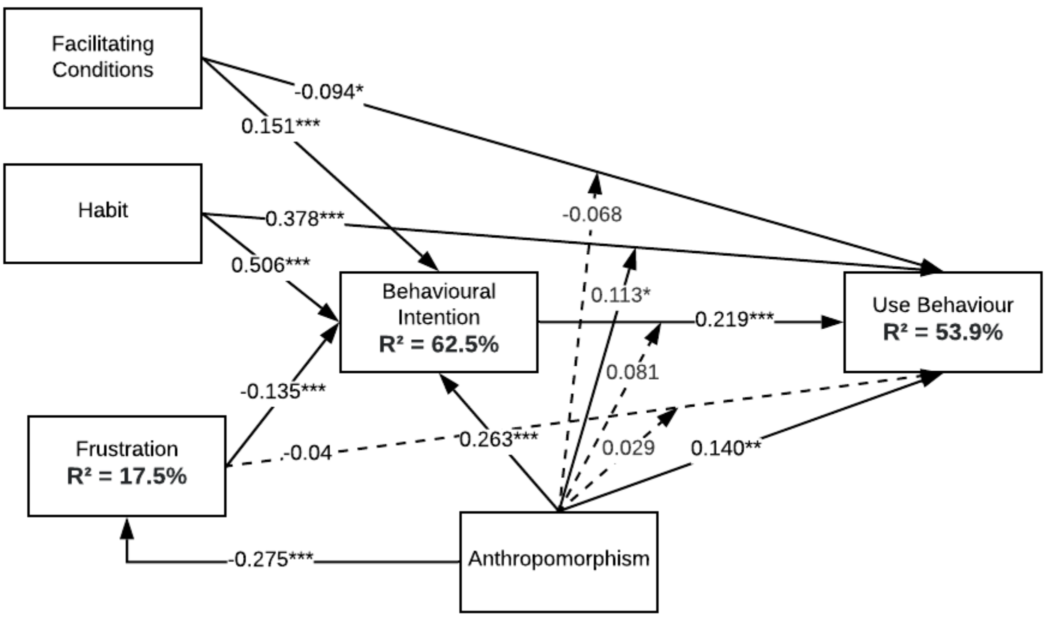

Figure 2 - Research hypothesis and results

The model explains 62.5% of the variation of behavioural intention to adopt a chatbot or digital assistant. Hypotheses related to behavioural intention – H1, H3, H6 and H9 are confirmed. The model explains 53.9% of the variation of chatbots or digital assistants use behaviour. Hypotheses related to use behaviour – H4, H5, H7 and H10 are confirmed and hypothesis H2 and H7 are not. 17.5% of the variation of Frustration is explained by the model and hypothesis H8 is confirmed.

Habit ($\hat{\beta}$=0.506; p<0.000) is the most important construct in explaining behavioural intention, followed by anthropomorphism ($\hat{\beta}$=0.263; p<0.000), facilitating conditions ($\hat{\beta}$=0.151; p<0.000) and frustration ($\hat{\beta}$=-0.135; p<0.000). Considering use behaviour, habit ($\hat{\beta}$=0.378; p<0.000) remains the most important variable in explaining the construct, followed by behavioural intention ($\hat{\beta}$=0.219; p<0.000), anthropomorphism ($\hat{\beta}$=0.140; p<0.006) and facilitating conditions ($\hat{\beta}$= -0.094; p<0.044). Age and gender were used as control variables and did not show a statistically significant effect in explaining the latent variables behavioural intention and use behaviour. However, age is an important and statistically significant construct in explaining frustration ($\hat{\beta}$=0.261. p < 0.001) following anthropomorphism ($\hat{\beta}$=0.275. p < 0.001).

Regarding the Anthropomorphism moderation effects, hypotheses H10b was supported and H10a, H10c and H10d were not supported (Figure 2). Therefore, anthropomorphism influences the relationship between habit and the use of a chatbot or digital assistant. Moreover, the effect of habit on a predictor of the use of a chatbot or digital assistant will be stronger when the technology has high anthropomorphic characteristics (Figure 3). Further research should be addressed to clarify this matter.

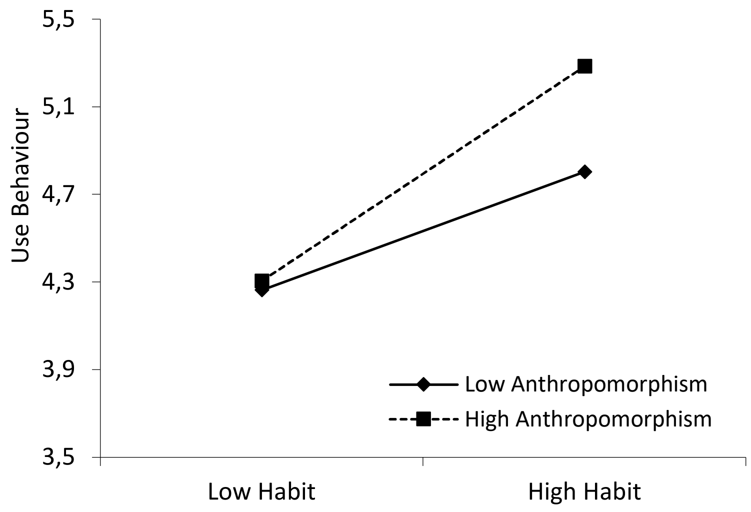

Figure 3 - Structural model (variance-based technique) for use behaviour

Mediating effects were also analysed. Considering the mediating effects of behavioural intention, it is confirmed that the intention to use chatbots and digital assistants mediate the effects of the actual use of this technology. The results reported in Table 5 show the results of two complementary mediation effects, one competitive effect and one indirect-only mediation effect (i.e. full mediation). Both indirect and direct effects of habit and anthropomorphism on use behaviour are significant and point in the same direction, confirming a complementary mediation. Although both effects of facilitating conditions are also significant, they point in opposite directions, therefore confirming a competitive mediation. Concerning the effects of frustration, only the indirect effect is statistically significant therefore this effect is considered indirect-only mediation, meaning it is a full mediation.

Note: FC = Facilitating conditions; HB = Habit; F = Frustration; ANT = Anthropomorphism; BI = Behavioural intention; UB = Use behaviour.

Effect of	Indirect effect	p-value	Direct effect	p-values	Sign	Interpretation	Conclusion
FC → BI → UB	0.033	0.005	-0.094	0.044	Negative	Competitive Mediation	Supported
HB → BI → UB	0.111	0.000	0.378	0.000	Positive	Complementary Mediation	Supported
F → BI → UB	-0.029	0.007	-0.04	0.332	n.a	Indirect-only Full Mediation	Supported
ANT → BI → UB	0.058	0.004	0.140	0.006	Positive	Complementary Mediation	Supported

Table 5. Mediation results

5. DISCUSSION

Previous research on chatbots and digital assistants' adoption factors has not been fully explored, mainly those studies related with psychological factors. Our research model is unique as it combines facilitating conditions, habit and behavioural intention with anthropomorphism, frustration, the moderating effects of anthropomorphism and the mediating effect of behavioural intention in use. The research explains 17,5% of the variation in frustration, 62,5% of the variation in behavioural intention and 53,9% of the variation in use behaviour. The impact of facilitating conditions, habit and anthropomorphism were found significant in explaining both behavioural intention and use behaviour of chatbots and digital assistants. In accordance with Venkatesh et al.(Venkatesh et al., 2012), users intention to use a technology is influenced by their belief that a support infrastructure is available, even though chatbots and digital assistants are considered a technology that is easy to use (Brandtzaeg & Følstad, 2017). However, the presence of frustrating experiences during its utilization blocks the users' ability to accomplish a task (Perez, 2016), making him/ her need the help of some form of facilitating conditions. Habit is also significant in explaining behavioural intention and use behaviour, in accordance with Venkatesh et al., (2012), proving that the repeated act of using chatbots or digital assistants to perform a variety of tasks will shape users' behavioural intention and actual use of the technology. As expected, the presence of a frustrating emotion has a negative influence in behavioural intention, as users will tend to limit the encounters with the stressor (Han et al., 2008). On the other hand, users' perceived anthropomorphism has a positive influence over behavioural intention and use behaviour, in accordance with Duffy, (2003) results. It is proved that the presence of anthropomorphic characteristics not only allows the fulfilment of users' social expectations towards the technology (Duffy, 2003) but also triggers empathy in the user (Riek et al., 2008) potentiating behavioural intention and actual use of the technology. Moreover the machine has the capabilities to be socially engaging and facilitates interaction what makes it more likeable for the user to cooperate with it (Duffy, 2003).

The negative impact of anthropomorphism in frustration was also confirmed, in accordance with Chaves & Gerosa, (2020), confirming that an anthropomorphic chatbot is able not only to trigger empathy in the users, but also has enough conversational and social intelligence to avoid or solve potential frustrating experiences during the interaction.

However, and contrary to the expectations of Beaudry & Pinsonneault, (2010), frustration is not a predictor of use behaviour. Therefore, one can conclude that, although frustration shapes users' intentions it is not so important on actual use, if the technology has anthropomorphic characteristics and the user builds the habit to use it. Also, contrary to what was expected (Venkatesh et al., 2012), facilitating conditions show a negative influence on use behaviour, indicating that the presence of support conditions decreases the chance of users' adopting chatbots or digital assistants. This signal may be a specific characteristic of the sample used in this work, or a direct signal that focus should move from facilitating conditions, in earlier stages, to the specific functionalities and use cases of the service in a more advance stage of adoption As expected the impact of behavioural intention on use behaviour is significant and positive, indicating that users are more likely to use chatbots and digital assistants if they have the intention to use it, in accordance with Venkatesh et al., (2012).

The moderation effect of anthropomorphism was only relevant for the relation between habit and use behaviour, so that the impact of habit is higher as anthropomorphism increases. This is a relevant finding, showing that the presence of anthropomorphism boosts the importance of one of the most important variables in explaining chatbots' adoption. Behavioural intention mediates all the relations with use behaviour, being a full mediator between frustration and use behaviour. These findings show the importance of decreasing frustrating experiences during trials and the first usages of the technology, as the negative influence of frustration during these first usages will negatively influence use behaviour and consequently decrease the chances of the user adopting the technology.

5.1. THEORETICAL IMPLICATIONS

Chatbots and digital assistants are an emerging technology, which presence in society is increasing. Therefore, the importance of this study arises, to better comprehend the factors that make users adopt or reject this technology. This research presents a pioneer study in the area, as it analyses the impact of anthropomorphism and loss emotions (in case, frustration) in the adoption of chatbots and digital assistants. It also models the intractability between the two variables, as well as the moderating effect of anthropomorphism in the other variables that predict use. For researchers, this study provides a basis for further refinement of individual models of adoption, especially in what concerns the interrelation between frustration and anthropomorphism, as well as anthropomorphism and other factors that influence intention and adoption. The proposed model also helps to improve the results significance and predictability in explaining behavioural intention and actual use of chatbots and digital assistants. The most important factors in explaining intention to adopt are habit and anthropomorphism, as habit and behavioural intention are in explaining the use of chatbots and digital assistants. Facilitating conditions have a low negative impact in predicting use and frustration's impact is not relevant. However, frustration negatively influences behavioural intention to adopt and, through it, indirectly also influences the use. Anthropomorphism is shown to decrease frustration, because people tend to judge machines based on their outcomes and people based on their intentions (Hidalgo et al., 2021). Therefore, even if a person is not able to fulfil a goal because the chatbot did not allow it, if the robot has social and conversational intelligence (demonstrating manners, have context awareness and realize its errors and tries to solve them) the user will perceive it as anthropomorphic and will approach the judgement to a human. This effect will soften the frustrating experience. The moderating impact of anthropomorphism is only relevant in habit, and not in facilitating conditions and use behaviour, contrary to what was expected.

5.2. MANAGERIAL IMPLICATIONS

For practitioners understanding the key constructs that influence adoption of chatbots and digital assistants is crucial to design, refine and implement applications, systems and services that may achieve a high level of consumer adoption. The present study also allows practitioners the knowledge to align technology functionalities with real customer needs, as well as adapting marketing strategies, service development and service design to effectively reach users. Although chatbots and digital assistants are a technology that is considered easy to use, the presence of facilitating conditions is a requirement during first usages to boost use intention. During this first usages, chatbot developers and customer service should include facilitating conditions such as tutorials or demos and embed them with chatbot interactions that may lead or teach users how to better use the technology. Practitioners should also guarantee that the users use the technology systematically and regularly, by embedding it with anthropomorphic characteristics, evaluating users' satisfaction regularly and ensuring that the presence of artificial intelligence in the technology provide the best possible user experience, adapting to the users' communication patterns and answering their queries effectively. These characteristics are expected to guarantee users' habitual use of the technology that has a tremendous impact not only in use intention but also in adoption. The presence of anthropomorphic characteristics will boost habitual use of the technology, as the interaction will be more pleasant to the user. Frustrating experiences that block the user to attain his/her goal with the technology, must be avoided especially during first usages, as they will negatively influence use intention and, consequently, adoption. Users must perceive the chatbots and the digital assistant as an anthropomorphic agent, therefore these should have conversational and social intelligence by being able to recover the context of a conversation, have speech patterns like humans and be able to adapt to the users' types of emotions. Chatbots and digital assistants should show these characteristics so that users perceive them has having intention, experience emotions, have a personality, being efficient, attractive and powerful. However, chatbots and digital assistants should show a balanced presence of anthropomorphic characteristics, so that they do not become uncanny and do not raise users' expectations to unfulfilling levels, potentiating frustration. The presence of anthropomorphic characteristics and the decrease in frustrating experiences during use also improve channel usability and user experience as they allow to improve chatbots results.

5.3. LIMITATIONS AND FUTURE RESEARCH

There are several limitations in this research that require further examination and additional investigation. Research should be replicated to examine the findings across different environments, individuals and chatbots and digital assistants that serve different purposes. Moreover, the model should be tested in different countries, age groups and technologies. The relation between frustration and anthropomorphism should be deepened, as although anthropomorphism has a negative impact in frustration, research also shows that high levels of anthropomorphism can also be a source of a sense of frustration in the user. The limits of anthropomorphism in chatbots and digital assistants should also be studied, considering the uncanny valley, and its analysis should be made comparing different technologies and application realities. The negative impacts of facilitating conditions on use behaviour should also be deepened in future studies. The use of technological agents, in this case chatbots and digital assistants, triggers in the users emotions belonging to four main groups: achievement, challenge, loss and deterrence (Beaudry & Pinsonneault, 2010). As emotions are a human characteristic, and chatbots and digital assistants are technologies that embed anthropomorphic characteristics, the impact of other emotions on acceptance and use of these technologies should be studied, as well as the impact of anthropomorphism and gamification on them. Further research should also analyse the impact of frustration and anthropomorphism in individual performance with chatbots and digital assistants.

6. CONCLUSIONS

Habit is the most impactful variable in explaining behavioural intention and use behaviour of chatbots and digital assistants. However, as chatbots are considered a social robot, the presence of anthropomorphic characteristics, as intentions, emotions and personality, are also a very important explainer of intention and use behaviour. Therefore, chatbots and digital assistants should embed anthropomorphic characteristics, so that they are able to display social and conversational intelligence when interacting with users. Anthropomorphic characteristics are also able to minimize frustrating experiences, which directly negatively influence users' intention to adopt a chatbot or digital assistant and indirectly (through behavioural intention) influence adoption. Frustrating experiences should be minimized especially during the first usages of the technology. Facilitating conditions influence adoption intention and should be present during first usages. Behaviour intention is a mediator of all variables that influence use behaviour, therefore, by assuring it, the probability that the users will adopt the technology will increase directly and indirectly.

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8. APPENDIX - INSTRUMENT

Constructs	Description	Source
Facilitating conditions	FC1. I have the resources necessary to use chatbots/ digital assistants. FC2. I have the knowledge necessary to use chatbots/ digital assistants. FC3. chatbots/ digital assistants are compatible with other technologies I use. FC4. I can get help from others when I have difficulties chatbots/ digital assistants.	(Venkatesh et al.. 2012)
Habit	HB1. The use of chatbots/ digital assistants has become a habit for me. HB2: I am addicted to using chatbots/ digital assistants. HB3. I must use chatbots/ digital assistants. HB4. Using chatbots/ digital assistants has become natural to me.	(Venkatesh et al.. 2012)
Frustration	While using the system… F1. Trying to get use chatbots/ digital assistants was a very frustrating experience. F2. Being frustrated comes with using chatbots/ digital assistants. F3. Overall. I experience a lot of frustration when using chatbots/ digital assistants.	(De Guinea et al.. 2014)
Anthropomorphism	Please rate your level of agreement to the following anthropomorphic descriptors: My chatbots/ digital assistant has intentions My chatbots/ digital assistant experiences emotions My chatbots/ digital assistant has free will My chatbots/ digital assistant has a mood of its own My chatbots/ digital assistant is conscious My chatbots/ digital assistant has personality My chatbots/ digital assistant is efficient My chatbots/ digital assistant is attractive My chatbots/ digital assistant is powerful	(Wang. 2017)
Behavioural intention	BI1. I intend to continue using chatbots/ digital assistant in the future. BI2. I will always try to use chatbots/ digital assistant in my daily life. BI3. I plan to continue using chatbots/ digital assistant frequently.	(Venkatesh et al.. 2012)
Use behaviour	UB1. I often use chatbots/ digital assistants to obtain assistance or information UB2. I often use chatbots/ digital assistants to save time UB3. I often use chatbots/ digital assistants to kill time	(Zhou et al.. 2010)

	UB4. I often use chatbots/ digital assistants to be entertained
	UB5. I often use chatbots/ digital assistants to strengthen social interactions with other people
	UB6. I often use chatbots/ digital assistants to avoid loneliness or fulfil a desire for socialization
	UB7. I often use chatbots/ digital assistants to explore the limits of their abilities