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Users' Acceptance of Artificial Intelligence-Based Chatbots:
An Empirical Study

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ABSTRACT

This research examines the effects of factors such as perceived ease of use, perceived usefulness, perceived enjoyment, innovativeness, perceived information quality, and perceived customisation on behavioural intention to use Chatbots. The research model designed is empirically validated using structural equation modelling with the aid of AMOS software. A five-point Likert scale-based structured questionnaire was used to collect data from 378 Chatbot users in an online method. The results indicated that the perceived ease of use, perceived usefulness, innovativeness, perceived information quality, and perceived customisation have positive effects on intention to use Chatbots, whereas perceived enjoyment is found to exert no effect. The research further discussed implications and future directions of research.

KEYWORDS

Artificial Intelligence, Chatbots, Technology Acceptance Model

1. INTRODUCTION

'Artificial Intelligence' (AI) denotes conception of intelligent machines that can imitate humans (Stoeffler et al., 2019; Casillo et al., 2020). Simply put, AI extends innovation of machine(s) that can perform like humans (Zheng et al., 2019). Intelligent machines are categorised as weak and strong. The former can address specific situations as weak AI machines cannot think and act independently (Tran and Luong, 2020). In contrast, the latter are look-alike version of humans. The strong AI machines can actually replace humans as they think and act as good as a human brain does (Cuayáhuitl et al., 2019). Majorly, AI machines are designed to minimise fatalities like wars, accidents and natural calamities (Peng et al., 2019). Some real-life examples of AI include self-driven vehicles, google maps and Chatbots (Cameron et al., 2017; Lee et al., 2017; Huang et al., 2018). Undoubtedly, the

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rise of AI based applications opened the gateway of opportunities to the business firms to offer enriched customer experience (Cheung et al., 2003; Tran and Luong, 2020). Amongst all, 'Chatbots' are drawing human attention immensely (Tran and Luong, 2020). The reason is that Chatbots allow interactions between human and services like a real time human to human experience (Peng et al., 2019). This virtual assistant is used by top brands for virtual interaction with the customers for a better service (Ren et al., 2019).

Shawar and Atwell (2007) define Chatbots as 'computer programs that interact with humans through natural language'. The available literature confirms different types of Chatbots depending upon their usage. The foremost is dialogic Chatbots, which are expected to understand user and their expectations. In this, the Chatbots are provided with oral inputs, further analysed with desired language processing tools that produces suitable responses (Peng et al., 2019). The second type is rational Chatbots (Yang and Evans 2019). These Chatbots use existing external knowledge base and common sense to answer and solve human queries (Cuayáhuitl et al., 2019). Generally, they provide user specific content information (Tran and Luong, 2020). The third category is embodied Chatbots. These are the earliest Chatbots and are generally preferred by ordinary users who are not machine savvy (Cummings and Kunzelman, 2015). The present stage of Chatbots is reasonably advance (Ni et al., 2017; Oh et al., 2017). Contemporarily, the companies are adopting Chatbots due to three main reasons. Firstly, Chatbots are capable of answering customer service requests (Gu et al., 2019). Moreover, Ren et al. (2019) argues that after few rounds of training/coaching, Chatbots genuinely ensure improved results (Yang and Evans 2019). Secondly, Chatbots provide a convenient experience to exchange information through text messages. It is as good as natural way of interaction (Cummings and Kunzelman, 2015). Thirdly, Chatbots enable companies to understand the aspects of digital customer service experiences (Blythe and Buie, 2014; Przegalinska et al., 2019). The anticipation of required customer services by Chatbots is really providing benefits to companies (Cuayáhuitl et al., 2019). Companies implement Chatbots services for varied reasons like cost savings, product recommendation, 24X7 access, brand awareness and promotion (Patel, 2019). Major firms using Chatbots in India include HDFC, Fify, Meru cabs, Yatra, Gaana, Niki, Funds tiger and Yes tag (Maharshi, 2017). Despite the potential Chatbots offer, very limited research has been conducted to examine the motives that influence users to choose Chatbots (Blythe and Buie, 2014). This research attempts to study the factors influencing individuals' intention to adopt Chatbots. The current study is founded on the technology acceptance model and studies users' behavioural intention to use Chatbots for customer service support during online purchase.

The rest of the paper is organised as follows. The next section details the literature review followed by section three on hypotheses development and section four on research design. The fifth section comprises data analysis. The final sections presents the discussion, unique contributions and conclusion drawn from empirical study.

2. LITERATURE REVIEW

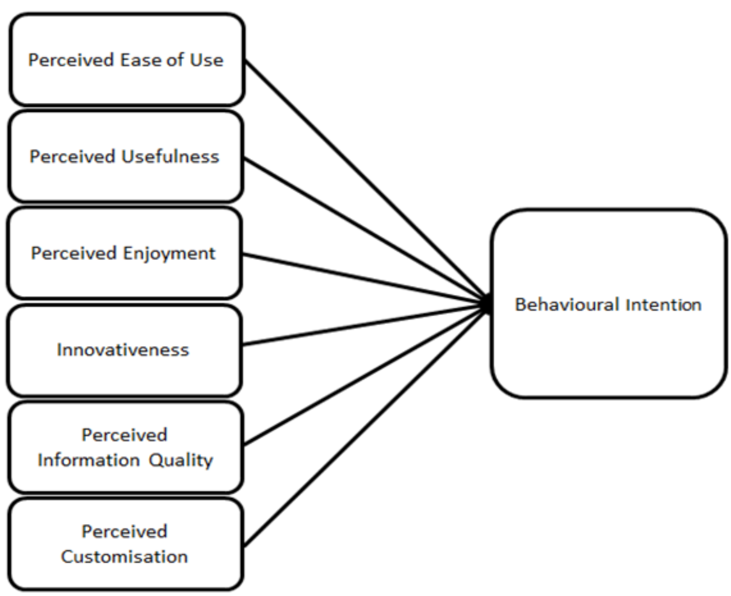
2.2 Underpinning Theoretical Framework

In the current digital era, it is imperative for business firms to adopt digital innovations in order to provide hassle-free and superior services to their customers (Cummings and Kunzelman, 2015). Online customer service is the need of the hour to meet the ever-demanding customer needs (Cameron et al., 2017). Recent developments like artificial intelligence (AI) and natural language processing (NLP) creating a great impact on digital customer service (Yang and Evans 2019). A Chatbot is a text or voice-based customer assistant uses artificial intelligence and natural language processing for human interaction (Shawar and Atwell, 2007, Zhang et al., 2017). Chatbots enable a dialogue system between human and computer along with natural language (Ni et al., 2017). The Chatbots are widely used by customers in Facebook messenger, WhatsApp and WeChat installed on mobile phones and other digitally enables screens for easy access and interaction (Cuayáhuitl et al., 2019). Almost, 93 percent of Indian decision-makers assume that companies must adopt Chatbots for effective customer service to be alive in the competition (PTI, 2019), as Chatbots facilitates operational efficiency opportunities to improvise customer involvement and satisfaction with low expenditures (Gu et al., 2019). The conceptualization of Chatbots is not recent. In fact, the first trace of Chatbots was confirmed long ago in the year 1950, when Alan Turing questioned 'if machines can think' (Zumstein and Hundertmark, 2017; Cuayáhuitl et al., 2019; Gu et al., 2019). Chatbots are widely used across diverse industries such as education, healthcare and retail for customer interface (Forbes, 2017a, 2017b). India stands second among the top five Chatbots user-based countries globally (Milenkovic, 2020).

Technology acceptance model (TAM) posited by Davis (1989) is used as foundation of this research study. According to Davis (1989), perceived ease of use and perceived usefulness are the two major antecedents of users' intention to adopt innovative information systems. A user-friendly technology draws individual attention towards its usage. Perceived usefulness is conceptualised as the extent to which 'a person believes that using the system will enhance his or her performance'; whereas perceived ease of use refers to 'the degree to which a person believes that using the system will be free of mental effort' (Davis, 1989; Sahu et al., 2016, Sahu et al., 2018a, 2018b; Sahu et al., 2020).

Over the years TAM (Davis, 1989), extension of TAM:TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008) have been extensively used and validated in various contexts to study user behaviour in information systems towards tablet applications (Kim, 2016), self-service technologies (Kim and Qu, 2014) and internet banking (Wang et al., 2003). The extensive review of consulted studies enabled research team to propose a research model while considering perceived ease of use, perceived usefulness, perceived enjoyment, innovativeness, perceived information quality, perceived customisation and behavioural intention as constructs towards Chatbots usage. The research model is displayed in figure 1. The research study is based on variables derived from TAM 2, TAM 3, UTAUT 2 and Delone and McLean (2003) models.

Figure 1. Conceptual framework



3. HYPOTHESES DEVELOPMENT

3.1 Perceived Ease of Use

Perceived ease of use is one of the major antecedents of usage behaviour of information systems (Pillai and Mukherjee, 2011; Suki, 2011). Perceived ease of use is a persons' effort towards the usage of a specific technology. Davis (1989) defined perceived ease of use as the degree to which an individual believes that the usage of a technology is free from mental effort. In the context of mobile networking applications, it's the usefulness (socializing) of the mobile network applications to achieve desired results. A technology tends to be more useful if it is easier to use (Davis et al., 1989). Previous research has studied the relationship of how perceived ease of use influences perceived usefulness and behavioural intention in case of online communities (Chung et al., 2010), social networking sites (Ruiz-Mafe et al., 2014; Lemay et al., 2017) and Chatbots (McLean and Osei-Frimpong, 2019). Therefore, we hypothesize:

H1: Perceived ease of use positively affects the intention to use Chatbots.

3.2 Perceived Usefulness

Perceived usefulness is the extent to which an individual believes that using a particular technology would improve his or her performance (Davis, 1989). It's the individual's belief that usage of Chatbots offers user the benefits of information systems. Previous studies have confirmed a significant influence of perceived usefulness on users' intention and behaviour towards the use of a technology in various contexts. For instance, the use of collaborative technologies (Cheung and Vogel, 2013); online learning (Albayrak, 2015) and social networking (Suki, 2011) are indicated by literature. Perceived usefulness is a major determinant of behavioural intention towards the use of targeted technology (Venkatest and Davis, 2000). Research studies proved that perceived usefulness has a positive influence on individual's intention to use information systems. It is noticed in varied contexts such as smartphone credit card (Ooi and Tan, 2016), online learning (Albayrak and Yildirim, 2015), social networking (Nedra et al., 2019) and Chatbots (McLean and Osei-Frimpong, 2019). Hence, we hypothesize:

H2: Perceived usefulness positively affects the intention to use Chatbots.

3.3 Perceived Enjoyment

Perceived enjoyment is the intrinsic drive of an individual that relates how users perceives something enjoyable and pleasurable regardless of the consequences (Davis et al., 1992). It is the objective pleasure of an individual while performing a certain activity or a specific behaviour (Moon and Kim, 2001). Previous researchers have investigated the relationship between perceived enjoyment and intention to use an information system and proved that perceived enjoyment is a hedonic determinant of intention to use a specific system or technology. The previous literature suggests that perceived enjoyment and intention to use a specific system are positively related. Oghazi (2012) pointed that perceived enjoyment and intention to use self-service technology are associated. Park et al. (2014) demonstrated that perceived enjoyment is the predictor of intention to use online mobile games. In the context of online services, Lin and Lu (2011), Agrifoglio et al. (2012) and Mouakket (2015) reported that perceived enjoyment has a significant positive relationship with intention to use social media sites and Chatbots (Melián-González et al., 2019). Thus, we hypothesize:

H3: Perceived enjoyment positively affects the intention to use Chatbots.

3.4 Perceived Innovativeness

Innovativeness is the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system (Rogers, 2003). In the context of technology acceptance, innovativeness is conceptualised as the degree to which an individual is responsive to new ideas and adopts innovative decisions freely and earlier than others (Agarwal and Prasad, 1998). Individuals derive intrinsic value by using innovative and novel technologies and get benefited (Venkatesh et al., 2012). Previous researchers indicate a signification relationship between individuals' perceived innovation and adoption of new technologies. In case of mobile internet usage, users' perceived innovativeness positively affect the intention to use Chatbots (Das, 2011; Wang et al., 2017; Melián-González et al., 2019). Therefore, we hypothesize:

H4: Perceived innovativeness positively affects the intention to use Chatbots.

3.5 Perceived Information Quality

Individuals' behaviour is highly influenced by his or her perception towards the information quality. Information quality is defined as the quality of outputs the information system produces (DeLone and McLean, 2003). Information quality is a four-dimensional construct: accuracy, completeness, consistency and currency (Huh et al., 1990). Accuracy is in accordance with the real-world information. Completeness is the information relevancy. Consistency is the extent to which two data-sets provide different information. Currency is to provide latest and updated information. Previous researchers show relationship between information quality and use of Chatbots (Liu et al., 2008; McLean and Osei-Frimpong, 2019). Hence, we hypothesize:

H5: Perceived information quality positively affects the intention to use Chatbots.

3.6 Perceived Customisation

Customisation is one of the critical aspects for superior customer service experience (Zeithaml et al., 2000). It enables the users to access the desired information quickly by eliminating excessive information (Srinivasan et al., 2002). Customised products or services draw users' attention (Ansari and Mela, 2003) and their intention to visit the online platform (Fan and Tsai, 2010). Previous research indicated a positive relationship between users' perceived customisation and behavioural intention (Fan and Tsai, 2010; McLean and Osei-Frimpong, 2019). Thus, we hypothesize:

H6: Perceived customisation positively affects the intention to use Chatbots.

4. RESEARCH METHODOLOGY

4.1 Materials

The research team designed questionnaire after an extant review of literature and consultation with the academicians and domain experts. A pre-test has been performed with 65 respondents to assess the content validity of the instrument based on five-point likert scale (ranging from strongly disagree to strongly agree). Cronbach's alpha of the instrument is found to be more than 0.70 (Hair et al., 2010) which ensures the reliability of the instrument. Data were obtained from respondents aged between 14 and above 50 years of age. Out of 650 respondents contacted, 378 responses are received with a response rate of 58.1 percent. Respondents are mainly those who contacted Chatbots during their online purchase for any information.

4.2 Measures

Measurement items of the constructs were drawn from well-established and validated research studies. These items were customised to suit the current research context. In all, 27 items were taken to measure perceived ease of use (4 items) from Davis (1989); perceived usefulness (4 items) from Davis (1989); perceived enjoyment (3 items) from Venkatesh et al. (2002); innovativeness (4 items) from Karaiskos et al. (2007) and Aldás-Manzano et al. (2009); perceived information quality (6 items) from Huh et al. (1990), Doll et al. (1994), Wang and Strong (1996), Kahn et al. (2002) and Nelson et al. (2005); perceived customisation (3 items) from Gazley et al. (2015); and Behavioural intention (3 items) from Bhattacherjee (2001). A non-probabilistic convenience sampling method is adopted to choose the respondents. The sample size is large enough (Hair et al., 2008) and the measures are well-established and validated across various contexts over the years (Davis, 1989; Doll et al., 1994; Bhattacherjee, 2001; Venkatesh et al., 2002; Nelson et al., 2005; Karaiskos et al. 2009; Aldás-Manzano et al., 2009; Gazley et al., 2015). The demographic profile of respondents is presented in table 1.

Table 1. Respondents demographic profile

Category	Group	Frequency	Percentage
Gender	Male	211	55.82
	Female	167	44.17
Age (years)	14-20	95	25.13
	21-30	129	34.12
	31-40	87	23.01
	41-50	51	13.49
	Above 50	16	4.23
Education	High School	39	10.31
	Diploma	85	22.48
	UG	146	38.62
	PG	97	25.66
	Ph.D.	11	2.91
Occupation	Student	165	43.65
	Working Professionals	92	24.33
	Business	78	20.63
	Retired	15	3.96
	Homemaker	28	7.4
Family Income (monthly)	<20,000	25	6.61
	20,000-30,000	47	12.43
	30,001-40,000	78	20.63
	40,001-50,000	96	25.39
	>50,001	132	34.92
	Total	**378**	**100**

Source: Authors' Compilation

From the total Chatbots users it is found that 59.25 percent of the users under the age of 30 years. Major percentage (71.41 percent) of the users are found to have undergraduate level qualification (refer to Table 1).

4.3 Reliability

Exploratory factor analysis is performed to identify the factors and their structure. Cronbach's alpha of items is 0.895. Reliability of the data is assessed by using Cronbach's alpha. The Cronbach's alpha more than 0.70 is assures internal consistency of the data (Hair et al., 2010). From table 2, it is inferred that the Cronbach's alpha is above cut-off value of 0.70 that confirms the reliability of the data. The focus of the paper is narrow as it consists of technology acceptance dimensions (ease

Table 2. Factor loadings, construct reliability and convergent validity

Factor	Code	Factor Loading	Cronbach's Alpha	CR	AVE
Perceived Ease of Use (PEOU)	PEOU1	0.799	0.841	0.811	0.589
	PEOU2	0.759			
	PEOU3	0.755			
	PEOU4	0.751			
Perceived Usefulness (PU)	PU1	0.885	0.926	0.925	0.758
	PU2	0.865			
	PU3	0.838			
	PU4	0.801			
Perceived Enjoyment (PE)	PE1	0.840	0.888	0.891	0.732
	PE2	0.823			
	PE3	0.812			
Innovativeness (IN)	IN1	0.862	0.906	0.905	0.705
	IN2	0.852			
	IN3	0.834			
	IN4	0.814			
Perceived Information Quality (PIQ)	PIQ1	0.893	0.896	0.897	0.602
	PIQ2	0.880			
	PIQ3	0.828			
	PIQ4	0.809			
	PIQ5	0.705			
	PIQ6	0.670			
Perceived Customisation (PC)	PC1	0.873	0.813	0.824	0.614
	PC2	0.841			
	PC3	0.706			
Behavioural Intention (BI)	BI1	0.926	0.894	0.897	0.745
	BI2	0.906			
	BI3	0.855			

Source: Authors' Compilation

of use and usefulness), perceived enjoyment, innovativeness, information quality and customisation from information perspective.

4.4 Validity

Measurement model is tested by using convergent validity and discriminant validity. Convergent validity refers to the degree to which multiple methods of measuring a variable provide the same results (O'Leary-Kelland and Vokurka, 1998). It is established if the construct relaibility (CR) values for each construct is more than 0.70 and average variance extracted (AVE) is above 0.50 (Fornell and Larcker, 1981). From table 2, the AVE values of each measure are more than 0.50 that ensures convergent validity.

Discriminant validity is the degree to which the measures of different latent variables are unique (O'Leary-Kelly and Vokurka, 1998). It is assessed based on AVE values (Fornell and Larcker, 1981). To ensure discriminant validity of the model, the square root of a construct's AVE, should be more than the correlations between the construct and other constructs. From table 3, it is noted that the AVE values are more than the correlations of those constructs. It confirms discriminant validity.

5. DATA ANALYSIS AND FINDINGS

Initially, all the measurement items were checked for reliability. It is 0.895 that is well beyond the suggested value (Hair et al., 2010). Later, the research team pursued with exploratory factor analysis by using SPSS. All the items were well loaded with the respective factors. The received KMO value of 0.861 is well above the threshold value of 0.70 (Hair et al., 2010). Bartlett's Test of Sphericity is significant to proceed with further analysis. Finally, model fit is assessed by using structural equation modelling. Measurement model fit is assessed based on model fit indices. CMIN/DF value <3 good, <5 acceptable (Hair et al., 2010); GFI cut-off value 0.9 good, 0.8 acceptable (Hair et al., 2010); AGFI 0.8 good (Hair et al., 2010); CFI value 0.9 good, 0.8 acceptable (Barrett, 2007; Greenspoon and Saklofske, 1998); RMSEA threshold value <0.05 is good, <0.08 acceptable (Bryne, 2010; Hooper et al.,2008, Hu and Bentler, 1998). As noted in table 4, the fit indices of the measurement model indicate a good fit of the measurement model. From table 4, the fit indices values denote a good structural model fit.

6. DISCUSSION

Contemporarily, online purchase of various products and services constitutes one of the prominent activities for individuals. The ease of services contributed by online retailers has brought a

Table 3. Correlations matrix

	PC	PEOU	PU	IN	PE	BI	PIQ
PC	**0.783854**						
PEOU	0.428	**0.757774**					
PU	0.429	0.523	**0.871099**				
IN	0.230	0.392	0.310	**0.83981**			
PE	0.353	0.493	0.445	0.488	**0.855824**		
BI	0.138	0.165	0.158	0.131	0.132	**0.863604**	
PIQ	0.090	0.143	0.154	0.341	0.289	0.072	**0.776178**

Source: Authors' Compilation; Perceived Customisation (PC), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Innovativeness (IN), Perceived Enjoyment (PE), Behavioural Intention (BI), Perceived Information Quality (PIQ)

Table 4. Model fit indices

Fitness Index	Accepted Value	Measurement Model	Structural Model
CMIN/DF	<3 good, <5 acceptable	2.047	3.298
GFI	0.9 good, 0.8 acceptable	0.892	0.805
AGFI	0.8 good	0.866	0.801
CFI	0.9 good, 0.8 acceptable	0.953	0.891
RMSEA	<0.05 is good,<0.08 acceptable	0.053	0.078

Source: Authors' Compilation

revolutionary change in the lifestyle of people. However, lack of in person interaction to receive information related to any particular product or service poses big hindrances and challenges for the customers, hence leaving them only with two options i.e. either to refrain themselves to buy product or service; or to regret if the received product or service is not appropriate. This situation emphasises the technology where users can expect personal attention to their queries during online shopping. The virtual existence of assistance received by the users provides them a real time experience that eases the process of purchase for the customers. This facility motivates the users to pursue online shopping confidently with minimum investment of resources. Given above discussion, the purpose of this study is to highlight various factors affecting behavioural intention of customers to use artificial intelligence based Chatbots while pursuing online purchase. Results of the study show a significant positive influence of perceived ease of use on behavioural intention to use Chatbots which corroborates with the findings of Lemay et al. (2017) in case of online communities and McLean and Osei-Frimpong (2019) for live chat. Respondents feel that ease of using a specific technology is the key factor for usage intention. Findings reveal that users perceived usefulness has a strong positive influence on intention to use information systems (Venkatesh and Davis, 2000; Nedra et al., 2019; McLean and Osei-Frimpong, 2019). Further, perceived usefulness has a positive influence on behavioural intention to use Chatbots. The results of the current study are also aligned with the studies of Agrifoglio et al. (2012) and Mouakket (2015), where perceived enjoyment positively affects the intention to use Chatbots. Previous researches indicate significant relationship between individuals' perceived innovation and adoption of new technologies (Wang et al., 2017; Melián-González et al., 2019). However, the current study confirms insignificant results as a) it included different age categories b) Chatbots is in nascent stage and a relatively new technology to adopt. This study is in congruent with those of McLean and Osei-Frimpong (2019) and Liu et al., (2008) who found a positive relationship between perceived information quality and intention to use a particular technology. The present findings are aligned with the studies conducted by Fan and Tsai (2010) and McLean and Osei-Frimpong (2019) who proved the significant positive relationship between perceived customisation and intention to use technology.

7. RESEARCH CONTRIBUTION

Customer support through online channels is the effective and low-cost way to customer assistance and enhances customer experience with instant and continuous support of service personnel (McLean and Wilson, 2016). It provides a high-quality customer service (Micu et al., 2019). Various customer self-service technologies include ATMS, interactive voice response systems (IVRS), telephone banking, kiosks in supermarkets and vending machines to name a few (Meuter et al., 2000). Specifically, many online users prefer to use live chat for numerous reasons include search support and decision support (Turel et al., 2013). For example, Watson from IBM offers chat service platform to provide personalised information to consumers (IBM, 2017). Chatbots based on natural language engage in real-life interaction with its users. They provide conversational experience with human-like interaction that makes it unique in comparison to other online platforms (Dale, 2016; Deloitte Digital, 2018). Though the online technologies offer multiple benefits it cannot be realised unless the users adopt these technologies (Lin, 2011). The research contributes by studying the various factors influence the user's acceptance of AI based Chatbots in online shopping. Maximum likelihood approach is used to assess the model robustness and fit. From table 5, it can be seen that all hypothesis from H1-H6 are supported except H3. The results proved that perceived ease of use (β=0.318, $p<0.05$); perceived usefulness (β=0.272, $p<0.05$); innovativeness (β=0.245, $p<0.05$); perceived information quality (β=0.217, $p<0.05$); perceived customisation (β=0.327, $p<0.05$) are highly influential.

8. CONCLUSION

Comprehensively, technology has deeply penetrated into our lives both personally and professionally. Imagining our lives without technology is something similar to a punishment or an offence. The present piece of work is a novel contribution by author(s) towards existing body of knowledge with respect to artificial intelligence and Chatbots. The theme revolves around the customer support required during online shopping, which if realised is a wonderful service for customers. The real time support for any query related to a product in a fraction of second is something beyond imagination. The online shopping is providing a real ease for customers globally. The technology is breaking every barrier in online shopping that used to exist a few years ago, and a great share of this amusement is dedicated to Chatbots. Enjoying human-like services without actual involvement of humans at one click is really a delightful experience. In tune with above said conversation, the research study provides insights to theory and practice. Previous research organised to study the use of live chat usage in varied areas. However, Chatbots usage is less researched in the context of online purchase. This study aimed at studying the various factors affects Chatbots users' intention to seek support during online purchase. Chatbots related factors such as influence of quality of information provided and customisation had an impact on usage behaviour. Chatbots offers enormous potential to the business firms which can be optimised by making Chatbots more user friendly and customised service as it is the key for the success of any service-based technology. The present study focussed on the factors influence users' intention to adopt Chatbots for customer support during online purchase. The dimensions included in the research were perceived ease of use, perceived usefulness, perceived enjoyment, innovativeness, perceived information quality, perceived customisation and intention to use Chatbots. User's intention to use Chatbots is positively influenced by perceived ease of use, perceived usefulness, innovativeness, perceived information quality and perceived customisation. Perceived enjoyment had no effect on users' intention. The study has certain limitations which can be eliminated in the future research. The Chatbots user chosen for the survey is representative of the population as they were self-selected.

Table 5. Hypothesis testing

Hypothesis Path	Estimate	t-statistic	p-value	Results
H1	0.318	0.095	***	Supported
H2	0.272	0.076	***	Supported
H3	0.196	0.082	0.09	Not supported
H4	0.245	0.065	***	Supported
H5	0.217	0.051	***	Supported
H6	0.327	0.087	***	Supported

Source: Authors' Compilation

The data obtained for the study were cross-sectional in nature. Longitudinal studies can better depict the attitudinal changes among the Chatbots users. The research focussed on select factors influencer users' intention to use Chatbots, future studies could consider users' satisfaction, experience and loyalty towards the Chatbots. Further, studies may also be taken up to study the moderating effects of demographic factors such as age and gender. The research model presented in this study can be applied in varied areas of research as healthcare, education and banking for comparative results. Refer to Table 6, Figure 2 and Figure 3.

Table 6. Operationalization of constructs

Construct	Items	Reference
Perceived ease of use	My interaction with Chabot is clear and understandable My interaction with Chatbots does not require any mental effort It is easy to become skilful at using Chatbots Overall, I find Chatbots is easy to use	Davis (1989)
Perceived usefulness	Chatbots app provides useful information and service to me. Chatbots app helps me to find information quickly I think Chatbot enhances the effectiveness of my life in general. Overall, I find Chatbots app is useful to me.	Davis (1989)
Perceived enjoyment	It is fun using Chatbots Chatbot provides me lot of enjoyment. Using Chatbots is unpleasant.	Venkatesh et al. (2002)
Innovativeness	If I know about Chatbots, I would look for ways to experiment with it. Among my friends, I am the first one to experiment with Chatbots I like to experiment with Chatbots I would try Chatbots even my friends have not tried it before.	Karaiskos et al. (2009); Aldás-Manzano et al. (2009)
Perceived information quality	The information provided by Chatbots is accurate The information provided by Chatbots is complete The information provided by Chatbots is concise The information provided by Chatbots is useful The information provided by Chatbots is comparable to other outputs The information provided by Chatbots is easily understood	Doll et al. (1994); Nelson et al. (2005)
Perceived customisation	The message/information provided by Chatbots tailored to my needs. This information/message provided by Chatbots makes me feel that I am a unique customer. I believe that this information/message provided by Chatbots is customised to my needs.	Gazley et al., (2015)
Behavioural intention to use	I expect to use Chatbots for networking I am likely to use Chatbots I would continue to use Chatbots	Bhattacherjee, (2001)

Source: Authors' Compilation

Figure 2. Measurement model

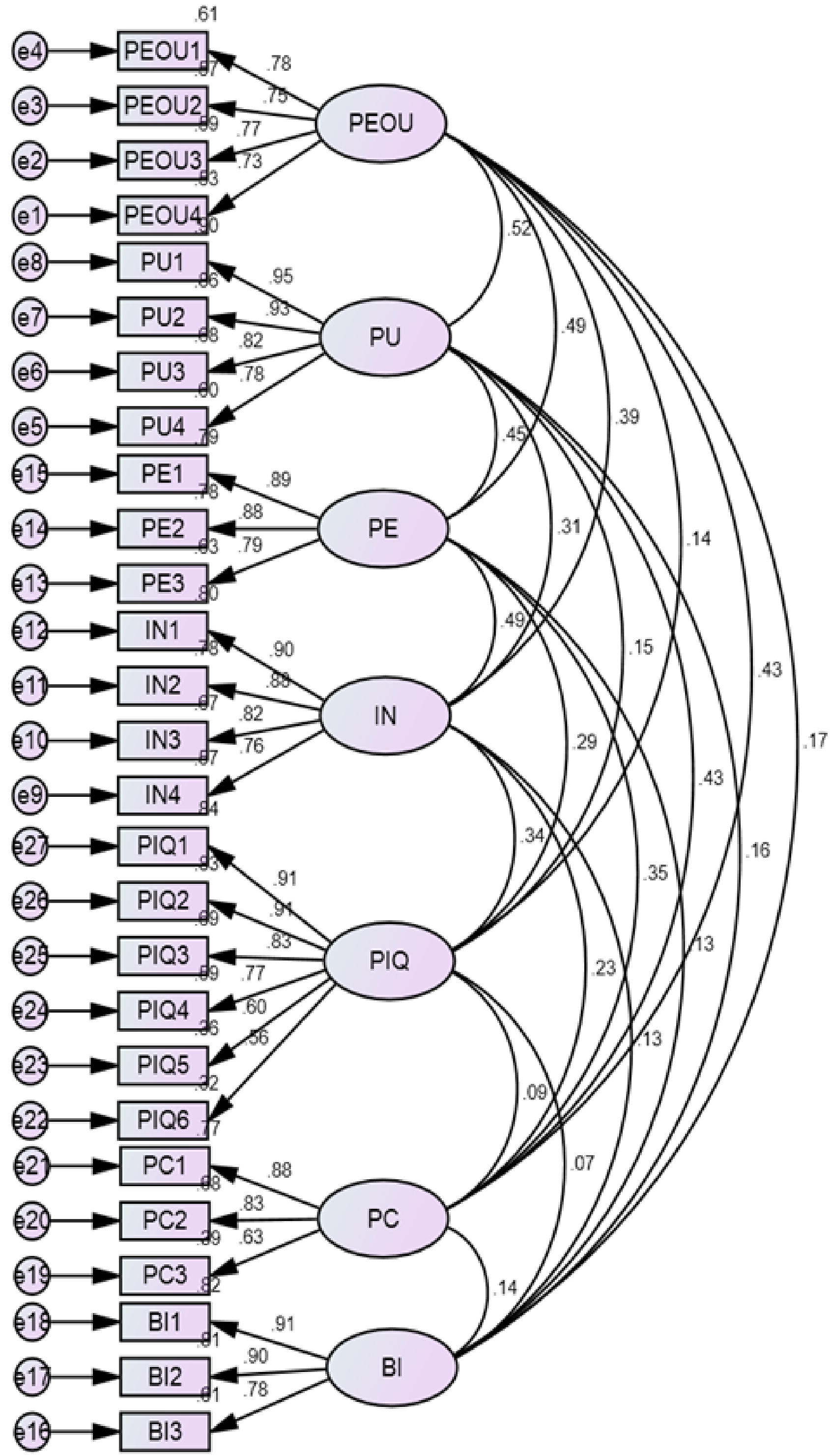
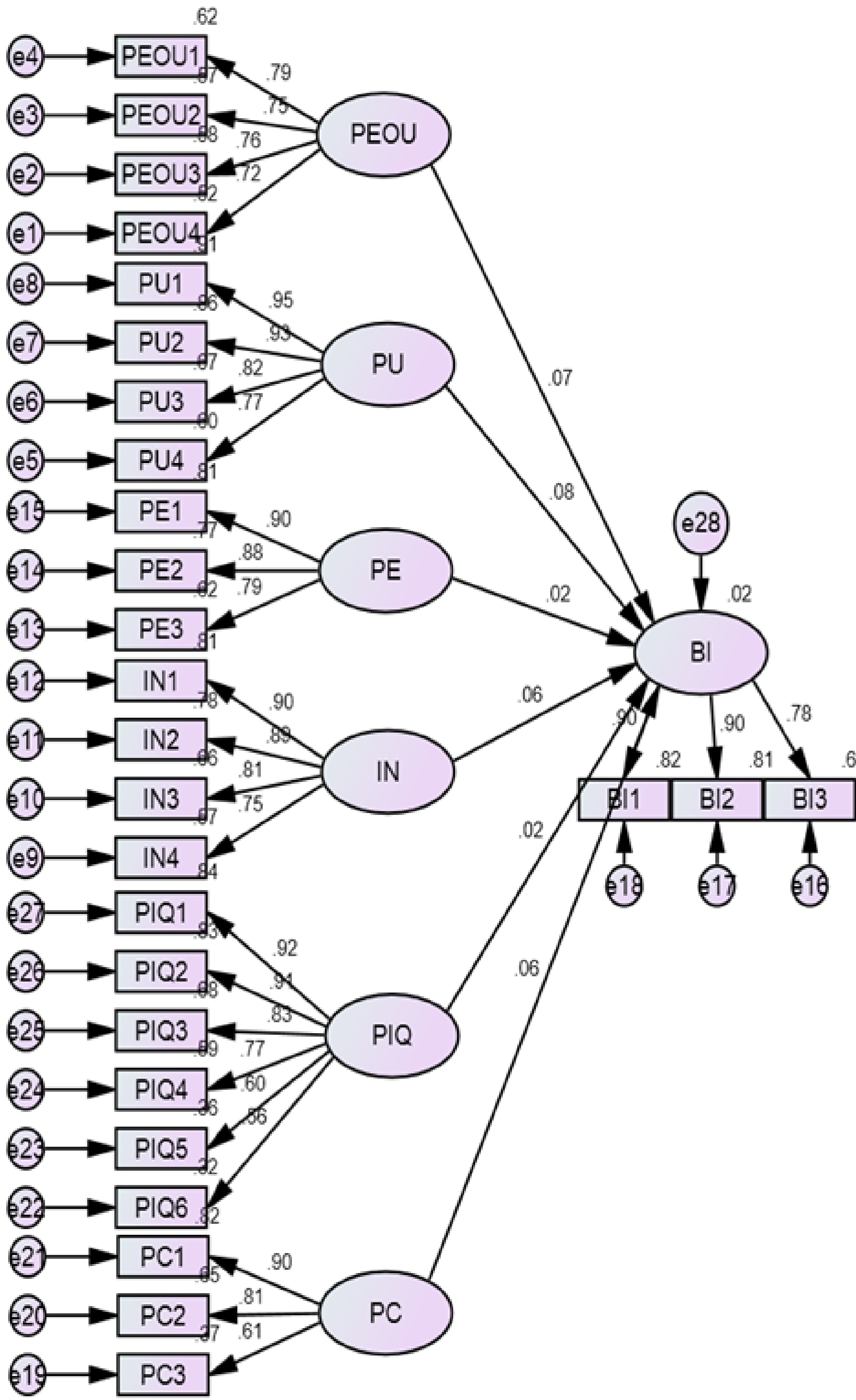


Figure 3. Structural model



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