Perception and Adoption of Customer Service Chatbots among Millennials: An Empirical Validation in the Indian Context

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Abstract: The last decade is witness to several successful automation efforts like customers service chatbots. Besides reducing costs for companies, chatbots saves time, effort, and enhances customer experience. Millennials being aspirational, educated and technology savvy find chatbots suited to the way they seek information. While there are several studies on technology adoption, work on chatbot adoption among millennials is scanty. The purpose of this study is to examine the factors which influence user intention, adoption and satisfaction related to chatbots. Hence, the objective is to develop a conceptual model through the extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of chatbot adoption. A mixed method approach was employed characterized by qualitative data collection through five personal interviews followed by a quantitative web-based survey. The data was collected from 60 users of chatbot applications. The proposed model depicting 13 hypothesized relationships was estimated using the partial least squares-structural equation modelling (PLS-SEM) approach. The results show that performance expectancy and social influence significantly influence behavioural intention. Trust and facilitating conditions were found to impact satisfaction significantly. With respect to adoption, facilitating conditions, satisfaction and behavioural intention were found to have a positive but insignificant impact.

1 INTRODUCTION

The last decade is witness to the increasing popularity of chatbots due to advancements in technology innovations like artificial intelligence and natural language processing. Gone are the days when organizations used to route their consumer concerns or complaints directly to their call centers executives. Chatbots have emerged as an intermediary layer between the user and the customer care executives which filters and redirects the concerns depending on its intelligence. A chatbot also known as conversational agents is a software program that simulates and mimics human conversations through a website or an application and helps users in finding relevant answers to their concerns. These programs continuously learn, evolve, and adapt to user requirements and offer high degree of personalized experience which makes it appear as highly personal, smart, useful, and responsive. As per BusinessInsider (2019), the chatbot market size is projected to grow at a CAGR of 29.7% from USD 2.6 billion in 2019 to USD 9.4 billion by 2024.

Due to the advantages associated with chatbots, it is emerging as a preferred medium in the customer service domain. Factors like technology advancements, demand for self-service and the convenience of 24/7 assistance are fuelling the growth of chatbots. According to the Chatbots Magazine (2018) State of Chatbots Report 2018, the most common frustrations reported by consumers included hard to navigate websites (34%), inability to get answers to simple questions (31%), and difficulty in finding essential details about a business (28%).

Due to the inherent benefits, numerous customer service chatbot applications have come up catering to various industries like banking, insurance, food delivery, online retail, hospitality, education, healthcare, ticket bookings to name a few. However, there are various factors which restrict the growth of this market. These include lack of awareness about chatbot applications, low technology skillset, access

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to affordable internet, fear about data privacy and confidentiality etc. According to a US study by EMarketer (2018), the challenges of using chatbot included too many unhelpful responses, redirect to self-serve FAQs, bad suggestions, pop-up chatbot prompts, unnecessary pleasantries, too long to respond and lack of personalization. As per Chatbots Magazine (2019), according to Spiceworks, respondents reported the following about chatbots: chatbots often misunderstood the nuances of human communication (59 percent), chatbots performed commands inaccurately (30 percent), chatbots had difficulties in understanding accents (20 percent). According to Mantra Labs (2019), both businesses and consumers in India consider telephone and email as most preferred channels even though average time-to-resolution through email was 2 hours and 17 minutes. The survey also found that majority (59 percent) of them prefer to talk to an actual person for customer service needs.

The paper is structured as follows. In the next section, a brief overview of relevant literature is provided before detailing the conceptual model and research hypotheses development, research objectives and the methodology. Then, the analysis of data and findings are presented. Conclusion discussing the managerial and academic implications are discussed next. The last section presents the limitations and future research directions.

2 LITERATURE REVIEW

There are various theories and models which explain the acceptance and adoption of new technologies.

2.1 TAM

The Technology Acceptance Model (TAM) is one of the most discussed and cited models of technology adoption which explains why users accept and use a technology. The model has two key constructs - perceived ease of use (PEOU) and perceived usefulness (PU) which explains user attitude, intention, and actual usage. PEOU is defined this as "the degree to which a prospective user believes that using a particular system would be free from effort" while PU is defined as "the degree to which a prospective user believes that using a particular system would enhance his or her job performance" (Davis et al., 1989). Prior research work (Autry et al., 2010; Gangwar et al., 2014) have consistently shown that PEOU and PU explain 40% of the variance in individuals' intention to use and subsequent adoption of a technology. Despite its frequent use by researchers, TAM is often criticized for diverting researchers' attention away from other important research issues and creating an illusion of progress in knowledge accumulation (Benbasat and Barki, 2007).

2.2 UTAUT

The unified theory of acceptance and use of technology (UTAUT) is another well cited model to explain user intention and behaviour associated with a technology adoption. Proposed by Venkatesh et al. (2003) it comprises of four constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). EE of the UTAUT model can be considered as PEOU of the TAM model as both focus on the ease-of-use aspect. Similarly, PE is similar PU as both focus on improving business performance. The UTAUT model is a result of the synthesis of eight different theories of technology acceptance: innovation diffusion theory (IDT), theory of reasoned action (TRA), theory of planned behaviour (TPB), the social cognitive theory (SCT), the motivational model (MM), the model of perceived credibility (PC) utilisation, technology acceptance models (TAM) and a hybrid model combining constructs from TPB and TAM (C-TPB-TAM). A meta-analysis of 74 empirical studies on UTAUT from 2003 to 2013 revealed how parsimonious, accurate, and robust UTAUT is at predicting acceptance and use of technology (Khechine and Lakhal, 2016) with behavioural intention emerging as the most often measured dependent variable operationalized as a proxy for system use.

2.3 Cognitive Model of Satisfaction

Oliver (1980) proposed this model which expresses consumer satisfaction as a function of expectation and expectancy disconfirmation. In other words, satisfaction can be viewed as the difference between user expectations and perceived performance. According to Liao et al. (2009) system characteristics of an information system create outcome expectations which results in positive or negative feelings and in turn determines user acceptance. The pre- and post-usage experience results in satisfaction or dissatisfaction, which is believed to influence attitude change and purchase intention.

The two primary constructs of TAM and UTAUT, that is, PEOU/EE and PU/PE can be viewed as characteristics associated with a chatbot platform which determines the acceptance, adoption and subsequent satisfaction. In the present study, the UTAUT model along with trust and security has been used.

Table 1: Summary of Recent Studies on Application of Chatbots.

Author/ Model	PEOU /EE	PU/ PE	SI	FC	TR	PR
Araujo and Casais (2020)/TAM	✓	✓				
Pillai and Sivathanu (2020)/TAM	✓	✓			✓	
Chatterjee and Bhattacharjee (2020)/UTAUT	✓	✓		✓		✓
Kasilingam (2020)/UTAUT2	✓	✓			✓	✓
Gansser and Reich (2021)/UTAUT2	✓	✓	✓			

Notes: PEOU/EE: Perceived Ease of Use/Effort Expectancy, PU/PE: Perceived Usefulness/Performance Expectancy, SI: Social Influence, FC: Facilitating Conditions, TR: Trust, PR: Perceived Risk

3 RESEARCH HYPOTHESES AND CONCEPTUAL MODEL

To explain the intention and adoption of chatbots among millennials in India, the UTAUT model is used as the theoretical basis. The following sub-sections discussed the development of the hypotheses to explain user intention, adoption, and satisfaction with chatbots.

3.1 Effort Expectancy (EE)

Effort Expectancy can be defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Araujo and Casais (2020) conducted a study involving Portuguese respondents and used the TAM model to determine customer acceptance of shopping-assistant chatbots. They found that PEOU use significantly influences attitude toward chatbots which further has a positive influence on behavioural intention. The factor PEOU is identical to effort expectancy which is defined as the expected effort required in doing using a chatbot. As per prior research, PEOU/EE has been reported to play an important factor in influencing the behavioural intention for chatbot adoption in hospitality and tourism (Pillai and Sivathanu, 2020); higher education (Chatterjee and Bhattacharjee, 2020); online shopping (Kasilingam, 2020). More recent studies (Nguyen et al.., 2021; Seo and Lee, 2021) have used a similar construct - system quality, which focuses on the reliability, ease of use, response time, and availability of chatbot systems. Based on the literature, the following hypothesis is proposed:

H1: Effort expectancy has a positive influence on the behavioural intention to use chatbots

3.2 Performance Expectancy (PE)

Performance expectancy is defined as "the degree to which the user expects that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). When users perceive chatbot services to be helpful (seeking information, online transactions, prompt responses, practical solutions) it creates a perception of improved experience resulting in continuance intention (Nguyen et al., 2021). Gansser and Reich (2021) employed the constructs of UTAUT2 model and conducted a study involving three segments of German chatbot users (mobility, household and health). They found that performance expectancy played a significant role in explaining behavioural intention and use behaviour towards artificial intelligence products.

Further, if the users feel that the chatbot system is too complex and requires extensive mental effort, the effort in learning to use the system may outweigh the relative benefits associated with it. In other words, effort expectancy determines the extent to which the chatbot system would enable the user to better perform the job and enhance the performance. This savings in terms of time and effort can be used by the user for some other job-related activity and enhance productivity. Davis (1989) provides the justification and the linkage between PEOU and PU.

Based on the above justification, we propose the following two hypotheses:

H2: Performance expectancy has a positive influence on the behavioural intention to use chatbots

H5: Effort expectancy has a positive influence on the Performance Expectancy to use chatbots

3.3 Social Influence (SI)

Social Influence can be defined as “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003). As per the theory of reasoned action (TRA), the behavioural intention is influenced by an individual positive or negative feeling which are developed because of the influence of other individuals known to the subject (Fishbein and Ajzen, 1975). In technology adoption, this is referred to as subjective norm which is the degree to which a user believes that his/her peer group (friends, superiors) influences the use and adoption behaviour (Taylor and Todd, 1995). Subjective norms or social influence can be viewed as informal agreed norms between the user and social influencers where the user is expected to comply with the same. It is believed that stronger is the social influence from the peer group, the stronger would be the behavioural intention.

Therefore, this reasoning leads to hypothesize the following:

H3: Social Influence has a positive influence on the behavioural intention to use chatbots

3.4 Facilitating Conditions (SI)

Facilitating conditions can be defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system. It comprises of external factors in the environment that make an act easy to accomplish (Thompson et al., 1991) and that exerts an influence over a person desire to perform a task (Teo et al., 2007). According to Kasilingam (2020), consumers are more likely to adopt smartphone chatbots if the technical infrastructure for it already exists. In information technology context, it consists of organizational and technical infrastructure to support use of the system (Agarwal et al., 2009). Prior researchers (Lin, 2011; Shaw, 2014) have reported that facilitating conditions like individual skillset, availability of affordable internet, smartphones, legal institutions etc. can influence the intentions of users in adopting chatbots. According to Chatterjee and Bhattacharjee (2020), the existence of good quality technical infrastructure and availability of requisite user training can facilitate the intention to adopt a new technology. Based on these arguments we propose the following hypotheses:

H4: Facilitating Conditions has a positive influence on the behavioural intention to use chatbots

H6: Facilitating Conditions has a positive influence on the chatbot adoption

H7: Facilitating Conditions has a positive influence on the satisfaction with chatbots

3.5 Perceived Risk (PR)

Perceived risk (PR) is commonly thought of as an uncertainty regarding possible negative consequences of using a product or service. It can be defined as the potential for loss in the pursuit of a desired outcome of using an online service.

Chatbots being a relatively new technology and users having limited exposure to it may often result into it being perceived as risky. Since chatbots simulate conversations with humans over the Internet, it can be used by hackers to use social engineering techniques to impersonate themselves and capture confidential, private and sensitive data. In areas where there is a need for limited interactivity in terms of predefined well-structured queries and responses, a chatbot creates good engagement. However, in situation where the communication is unstructured, complex and uncertain, discrepancies in responses may create confusion in the minds of the user. Hence, the degree of perceived risk towards chatbot can influence the trust and the intention to adopt it. It is logical to believe that a greater perceived risk would negatively influence the trust and intention towards chatbots. Thus, we propose that:

H8: Perceived risk has a negative influence on the behavioural intention to use chatbots

H9: Perceived risk has a negative influence on the trust associated with chatbots

3.6 Trust (TR)

Baier (1986) considers trust as "the belief that others will, so far as they can, look after our interests, that they will not take advantage or harm us”. Trust in technology can be defined as “a belief that a specific technology has the attributes necessary to perform as expected in a given situation”. (McKnight et al., 2011). It can also be defined as the degree to which users are confident in the reliability and quality of the chatbot systems (Caceres and Paparoidamis, 2007). According to Komiak (2003), trust comprises of two dimensions: cognitive and emotional. While cognitive trust expects that a chatbot service provider will have the necessary competence, benevolence and integrity while emotional trust is the feeling of security and comfort with the service provider.

In this study, we have examined consumer rationality for examining trust by including statements which capture the competence, benevolence, and integrity with chatbots. Eren (2020) in a study involving bank chatbots users from Turkey found perceived trust in chatbots to significantly influence customer satisfaction. While trust in the context of online customer centric services like online banking, mobile banking, social media etc. has been extensively researched, its inclusion in chatbot adoption studies is scanty. The present study combines trust and perceived risk with the UTAUT model and hypothesizes it to be one of the key antecedents of user satisfaction. Hence, the following hypothesis is formulated with respect to trust and satisfaction:

H10: Trust has a positive influence on the satisfaction with chatbots

3.7 Satisfaction (ST)

According to Nguyen et al. (2021), if users' expectations from chatbot services are fulfilled and they feel satisfied after experiencing the same, those experiences will not only shape their intention but will push them to continue using chatbots in the future. Eren (2020) found that if customer expectations from chatbots are met, it results in a positive and significant impact on customer satisfaction. In another study involving using chatbot services for luxury brand, it was found that perceived communication accuracy, credibility and competence positively influences satisfaction (Chung et al., 2020). Based on the above discission, the following hypotheses are proposed:

H11: Satisfaction has a positive influence on the behavioural intention to use chatbots

H12: Satisfaction has a positive influence on the chatbots adoption

3.8 Behavioural Intention (BI)

Behavioural intention (BI) is defined as "a person's subjective probability that he will perform intention some behaviour" (Fishbein and Azjen, 1975). If there is a strong intention, then the likelihood of that converting or resulting in an action or behaviour is very high. In other words, the existence of BI is critical in shaping a technology usage behaviour. Prior studies have provided considerable evidence of the significant effect of BI on actual usage or adoption in technology acceptance studies (Venkatesh et al., 2003; Tarhini et al., 2015)>

H13: Behavioural intention has a positive influence on the chatbot adoption

3.9 Adoption (AD)

The actual system usage or the adoption is the final stage where a user starts using a technology. It can also be defined as a user's initial acceptance of a technology.

Based on the review of literature various hypotheses were derived. Figure 1 shows the proposed conceptual model and the related research hypotheses. The model comprises of six factors of the UTAUT model (performance expectancy, effort expectancy, social influence, behavioural intention, and adoption). An extension of the model has been proposed by the inclusion of three additional factors in the chatbot context (perceived risk, trust and satisfaction). The conceptual model depicts the relationships between various antecedents of behavioural intention, adoption and satisfaction.

Insights from the five personal interviews also strengthened our conceptual model development.

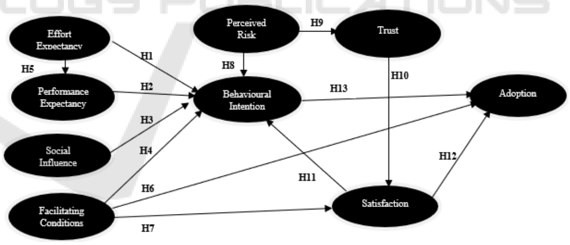

Figure 1: Conceptual Model and Hypotheses.

4 OBJECTIVES OF THE STUDY

The objectives of the study are: 1) To carry out a systematic review of literature on chatbot adoption and examine the underlying models 2) To identify the most frequently discussed constructs by previous studies and supplement the same with the findings of the qualitative analysis 3) To propose a conceptual model and validate the hypothesized relationships using a quantitative survey carried out among a sample of Indian chatbot users.

5 METHODOLOGY

To fulfil the research objectives of the study, a three-step process was employed. In the first step, an exploratory study was carried out by reviewing the existing literature on Chatbot adoption. An extensive search was carried out in bibliographic databases using relevant keywords like “chatbot adoption”, “chatbot intention and satisfaction”, “factors influencing chatbot adoption”, “antecedents to chatbot adoption”, “Unified Theory of Acceptance and Use of Technology”, “UTAUT” etc. The obtained results were examined for their recency, appropriateness, and popularity in terms of citations. After obtaining the list of studies on chatbots, a cross-table was prepared with authors arranged along the rows and constructs along the columns. The underlying model used in the studies was also documented. Based on the mapping between the two (see Table 1), the constructs were clustered to determine the most frequently used constructs.

In the second step, five personal interviews were conducted with chatbot users labelled as R1 to R5. A screening question was used to gauge whether the chatbots users were aware of the application. Six questions were framed some of which were incorrect and those respondents who correctly answered all the questions were shortlisted for personal interview. An interview template was prepared which included open-ended questions related to frequently used chatbot applications; reasons for using chatbots; positives and negatives about chatbot applications; factors which influence the chatbot adoption behaviour; experience using chatbots; and satisfaction. Each interview was recorded and transcribed verbatim. Content analysis was performed on the qualitative data and broad themes along with statements justifying the same were extracted. The content analysis resulted in the generation of few statements which were added to the established constructs as given in the review of literature.

In the final step, the hypothesized relationships were represented in the form of conceptual model and a survey instrument was designed. The questionnaire comprised of three sections. Section one comprised of questions on frequency of chatbot usage and frequently used chatbot applications. Section two comprised of perception-based questions on factors influencing behavioural intention, satisfaction and adoption measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The last section captured the user demographic details. Due to pandemic restrictions, only online surveys were used for data collection. A convenience sample along with purposive sample was considered as most appropriate in the study. Convenience sampling was deemed appropriate as the authors personally knew the respondents. Purposive sampling was utilised to select respondents who extensively used the internet and chatbots. The idea behind using these sampling techniques was to get a representative sample. A total of 250 respondents were mailed the online survey out of which 70 respondents filled the survey. Ten responses were omitted as there were no standard deviation found in their responses pertaining to the Likert scale questions. 60 responses were finally considered for subsequent data analysis indicating a response rate of 24 percent. The minimum sample size for a PLS model should be at least ten times the largest number of inner model paths which in our case is six. Thus, the study meets the minimum sample requirement of 60 (Hair et al., 2017).

The sample comprised of more males (35, 58.3%) than females (25, 41.7%). The minimum and maximum age of the respondents was 26 and 40 respectively with 31.5 as the median age.

The distribution of all statements in the instrument was checked for normality distribution. The kurtosis range was found to be -1.487 to 2.974 and skewness range was found to be -1.288 and 0.498. Thus, for majority of statements (35 out of 48) the skewness and kurtosis values lie between −1 and +1 acceptable interval. The results show that there was no major deviation from normal distribution (Hair et al., 2017).

To examine and validate the efficacy of the conceptual model in explaining user intention, the current study used the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique. This technique employs a two-stage process starting with the assessment of the measurement model (reliability and validity) and the estimation of the structural model (testing the hypothesized relationships).

6 ANALYSIS AND FINDINGS

Smart-PLS 3.0 was used to estimate the measurement and the structural model.

6.1 Estimation of the Measurement Model

The measurement model was assessed using discriminant validity and convergent validity. The internal consistency was examined using Cronbach Alpha. As evident from Table 2, the Cronbach’s alpha value for all constructs was found to exceed 0.70, which indicate that the measurement is reliable (Lin and Huang, 2008). Convergent validity refers to how closely the statements of a multi-item construct are related to each other. In other words it is the extent to which a measure relates to other measures of the same phenomenon (Hair et al., 2017). For convergent validity, the values of composite reliability (CR) should be at least 0.7 and the average variance extracted (AVE) must be greater than the threshold value of 0.5. As evident from Table 2, the composite reliability for all constructs was found to be greater than 0.7 and the AVE was greater than 0.50 thereby fulfilling the conditions of convergent validity.

Table 2: Cronbach's Alpha (CA), Composite Reliability (CR) and Average Variance Extracted (AVE).

Constructs	CA	CR	AVE
EE	0.718	0.843	0.649
PE	0.868	0.904	0.655
SI	0.875	0.914	0.726
FC	0.731	0.831	0.552
PR	0.920	0.936	0.675
TR	0.887	0.915	0.644
BI	0.855	0.892	0.580
ST	0.913	0.928	0.591
AD	0.668	0.798	0.500

Discriminant validity of the constructs was assessed using three methods a) cross-loadings b) Fornell and Larcker criterion, and c) Heterotrait-Monotrait Ratios (HTMT). For the first method, the indicator loading on its own construct should be higher than the loading on any other construct (Chin, 1998). This condition was found to be satisfied. The discriminant validity is satisfied if the square root of the AVE for each construct is higher than the correlation coefficient with other constructs (Fornell and Larcker, 1981). In our case, all the diagonal elements which are the square root of the AVE are more than the inter-item correlations reported below the diagonal for the corresponding constructs (refer Table 3). Further, it is seen that the HTMT value is below 0.9 (range 0.156 and 0.895) between any two reflective constructs. Since all the three conditions are satisfied, discriminating validity is established.

Since the conditions for both convergent and discriminant validity were met, the measurement model was considered satisfactory.

Table 3: Discriminant Validity.

	AD	BI	EE	FC	PE	PR	ST	SI	TR
AD	.71								
BI	.57	.76							
EE	.64	.61	.81						
FC	.53	.58	.59	.74					
PE	.62	.75	.76	.54	.81				
PR	.08	.27	.29	.29	.19	.82			
ST	.55	.68	.60	.58	.70	.22	.77		
SI	.59	.67	.68	.52	.71	.13	.69	.85	
TR	.31	.53	.44	.51	.53	.45	.64	.50	.80

AD: Adoption; BI: Behavioural Intention; EE: Effort Expectancy; PE: Performance Expectancy; SI: Social Influence: FC: Facilitating Conditions; PR: Perceived Risk; TR: Trust: ST: Satisfaction. Diagonal values are squared roots of AVE; off-diagonal values are the estimates of the inter-correlation between the latent constructs

6.2 Assessment of the Structural Model

To examine the problem of multi-collinearity of the inner model, the VIF (Variance Inflation Factor) was computed for the five endogenous constructs. It was found that VIF varied from 1.15 to 3.25, 1.68 to 2.08 and 1.35, 1 and 1 for intention, adoption, satisfaction, performance expectancy and trust respectively. These values are below the threshold value 3.33 (Diamantopoulos and Siguaw, 2006). Therefore, no evidence of multicollinearity was found in the present research.

Since the respondents were asked to answer questions pertaining to both independent and dependent variables, common method bias could be a concern. To check for the presence of common Method Bias, Harman's single factor test was conducted which involves examining the unrotated factor solution to determine if a single factor accounts for more than 50 percent of the variance (Podsakoff et al. 2003). The results indicate that eleven different factors accounted for 78.59 percent of the variance. The single largest factor accounted for 35.65 percent, which is below the threshold, common method bias doesn't seem to a problem.

The structural model was estimated by applying bootstrapping technique, which is a resampling technique that draws many subsamples, say 5000 from the original data (Vinzi et al., 2010). The standardized path coefficients (refer Table 4) indicate the estimates and significance of the hypothesized relationships between the constructs. Hypothesis H1 which examines the influence of EE on BI was found be insignificant with an opposite sign (β = - 0.109, p =0.427). One of the plausible reasons could be that the respondents have not explored the full capabilities of chatbots or have not been able to interpret the question correctly. Hypothesis H2 relating to performance expectancy to intention was found to have a strongest and significant relationship with respect to intention (β= 0.479, p=0.000). As expected and consistent with prior research on chatbots (Eren, 2020; Chatterjee and Bhattacharjee, 2020; Kasilingam, 2020; Melián-González et al, 2021; Gansser and Reich, 2021), the results show that performance expectancy is the main predictor of intention.

Hypotheses H3 (β= 0.195, p=0.068) and H4 (β= 0.163, p=0.195). pertaining to social influence and facilitating conditions, respectively, with intention were found to be in the hypothesized direction. However, only social influence was found to have a significant influence at 10 percent level of significance. Hypothesis H5 (β= 0.764, p=0.000), which examines the influence of effort expectancy on performance expectancy was found to be strongest and significant in the entire conceptual model. Thus, greater is the degree of ease associated with a chatbot system, greater are the perceived improvements in personal and professional activities. Hypothesis H6 (β= 0.245, p=0.167), H12 (β= 0.213, p=0.213). and H13 (β= 0.278, p=0.114) depicting the influence of facilitating conditions, satisfaction and intention on adoption were found to be positive but insignificant indicating that the existence of facilitating conditions, satisfaction with chatbots and intention influence adoption although not significantly.

Hypotheses H7 (β= 0.348, p=0.001) and H10 (β= 0.458, p=0.000). which examine the influence of facilitating condition and trust on satisfaction found that both the constructs were significant in explaining satisfaction with chatbots. With respect to hypotheses H8 (β= -0.107, p=0.219) and H11 (β= 0.160, p=0.333) which looks at the relationship between perceived risk and satisfaction on intention it is evident that higher is the risk, lower is the intention, and higher the satisfaction higher is the intention. While both hypotheses are in the right direction, the influence on intention is insignificant. Further, H9 (β= -0.450, p=0.000) explaining the influence of perceived risk on trust is found to be significant. In other words, higher the risk lower would be the trust with chatbots.

The SmartPLS tool computes the coefficient of determination (R square) which represents a measure of predictive power that explains the degree to which the antecedents explain the variance in an endogenous construct in the model. In our model, there are five endogenous constructs namely behavioural intention, adoption, satisfaction, performance expectancy and trust. The R square values of these endogenous constructs are 0.658, 0.403, 0.494, 0.583 and 0.203 in that order. The proposed model can explain 65.8 percent of the variation in behavioural intention, 40.3 percent in adoption, 49.4 percent in satisfaction, 58.3 percent in performance expectancy and 20.3 percent in trust.

The cross-validated predictive relevance of structural model was estimated by calculating Stone Geisser Q^2 value with an omission distance of 7 (Geisser, 1974; Stone, 1974). Higher is the value of Q^2, higher is the predictive accuracy of the model. In our case, the values of Q^2 are found to be 0.370, 0.343, 0.271, 0.162 and 0.125 respectively for the endogenous constructs: performance expectancy, intention, satisfaction, adoption, and trust. Since all Q^2 values are greater than zero for the endogenous constructs, it indicates that the values are well reconstructed, and the model has predictive relevance.

Lastly, the effect size f^2 was computed for each endogenous construct. The f^2 values of 0.02, 0.15, and 0.35 present small, medium, and large effects (Cohen, 1988). For the endogenous construct intention, PE had a medium effect size, FC, SI, ST and PR had a small effect size whereas EE has an insignificant

Table 4: Structural Model Estimates.

Hypothesis	Relationship	Path Coefficient	p- value
H1	EE -> BI (+)	-0.109	0.427
H2	PE -> BI (+)	0.479	0.000*
H3	SI -> BI (+)	0.195	0.068**
H4	FC -> BI (+)	0.163	0.194
H5	EE -> PE (+)	0.764	0.000*
H6	FC -> AD (+)	0.245	0.167
H7	FC -> ST (+)	0.348	0.001*
H8	PR -> BI (-)	-0.107	0.219
H9	PR -> TR (-)	-0.450	0.000*
H10	TR -> ST (+)	0.458	0.000*
H11	ST -> BI (+)	0.160	0.333
H12	ST -> AD (+)	0.213	0.213
H13	BI -> AD (+)	0.278	0.114

** indicates significance at 1 percent ** indicates significance at 10 percent* effect size since the f^2 value was below 0.02. Regarding the endogenous construct, adoption, the exogenous constructs FC, ST and BI had a small effect size as the f^2 values were 0.06, 0.037 and 0.062 respectively. For the endogenous construct, satisfaction, FC and TR were reported to have a medium effect size as the values obtained were 0.177 and 0.307. With respect to trust, PR had a medium effect size of 0.254. Lastly, with respect to performance expectancy, EE had a large effect size as the f^2 value was found to be 1.4 which is greater than 0.35.

7 CONCLUSIONS AND IMPLICATIONS

The results of the structural model indicate that of 17 the proposed 13 hypotheses, six were supported. Further, out of the remaining seven, six were not supported though they had the desired hypothesized direction. In case of H2 (relationship between effort expectancy and intention), a contrary insignificant relationship was found.

Performance expectancy seems to be the most important factor explaining behavioural intention. Thus, unless a user perceives that using a chatbot will result in superior performance and enhanced efficiency and productivity, their intention to use it would be limited. Use of chatbots is in terms of queries, doubts, searches and finding relevant results. Organizations providing chatbot services should keep in mind that users expect instant responses and short answers which are simple to comprehend and can guide users to follow-up questions. These chatbots should be able to train and re-train themselves to evolve into intelligent conversational agents. Another important aspect is the timing of escalating a problem which cannot be resolved by a chatbot. Unnecessary inundating the user with back and forth questions can be irritating. Technology experts can build in these expectations to enhance user ability to derive better performance.

Although performance expectancy emerged as an important determinant, social influence was also perceived by users as significantly influencing chatbot intention. Depending on the context, whether the user is using it in personal capacity or in an organizational context, the social influence would vary. In personal communications or transactions involving chatbots, the influencers could be the friends and family. In an organization, the management or the peer community could influence technology adoption. Since are sample comprise of millennials, companies offering chatbots services can target this group through social media and mobile advertisement to create awareness about chatbot capabilities.

Facilitating conditions and trust emerged as key determinants which influence user satisfaction. Chatbot providers should create chatbot services which can run on any basic smartphone with decent internet connectivity. Further, the availability of the chatbot to communicate and engage in local language is important. Since a chatbot simulates a human conversation through artificial intelligence, the user expectation is that their queries would result in relevant suggestions which would help in developing trust with the platform. Chatbot providers must ensure that service and information quality is good as poor initial experiences can create doubts resulting in loss of trust. Professional interactions, quality of request and advice, ensuring privacy etc. can help in building trust. Managerial implications for chatbot providers can be drawn from the findings related to perceived risk and trust associated with chatbots. To ensure that user expectation of safe and secure transaction besides privacy and confidentiality of data is in place, awareness sessions to educate users about what user data is collected, how its stored and analysed must be conducted. Rewards in the forms of coupons and cashbacks could be a way to introduce and encourage users to validate the security of the platform. The managerial implication of this research is that chatbot providers must pay attention to perceived usefulness, perceived risk, trust, social influence and facilitating conditions so as to increase the satisfaction, intention and adoption of chatbots.

Besides managerial applications, the research presents an extension of the UTUAT model. The explanatory power for the model to explain intention is good.

8 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Like all studies, this study also has few limitations, which provide directions for future research. First and foremost, is the small sample size. While the study meets the minimum sample size criteria, considering the size and importance of the millennial population, future study can be carried out with a larger sample size. A comparison between the perceptions of the millennial user with Gen Z could add to the existing body of knowledge on chatbots.

Secondly, the study was restricted to four constructs adopted from UTAUT model. Since UTAUT 2 model has additional constructs like hedonic motivation, habit, price value etc. future examinations with these additional constructs could help in improving our understanding of intention and usage of chatbots.

Thirdly, we have considered chatbot application as a broad category. It would be worth exploring how the hypothesized relationships in the structural model besides the predictive power compare with respect to different chatbot applications (for e.g. Online Shopping, banking, healthcare, tourism to name a few).

Lastly, we have collected demographic details like gender, age, income, education etc. Prior researchers have examined the moderating effect of these demographic variables. Future studies may be carried out in this direction.

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APPENDIX

Appendix – 1 Please indicate your agreement or disagreement on the following statements

Performance Expectancy (PE)
(Source: Venkatesh et al., 2012)
Chatbots:

- help me accomplish things more quickly
- are useful in my daily life (N)
- enable me to complete the task efficiently

- enhances my task effectiveness
- give relevant suggestions (N)

Effort Expectancy (EE)
(Source: Gefen et al., 2003; Venkatesh et al, 2012)
Chatbots:

- interaction is clear and understandable.
- are flexible to interact with
- are anticipative and intuitive in nature (N)

Social Influence (SI)
(Source: Venkatesh et al, 2012)

- Peers who influence my behaviour think that I should use chatbots
- Peers important to me think that I should use chatbots
- Organization peers promotes and supports the use of chatbots
- Peers whose opinion I value prefer that I use chatbots

Facilitating Conditions (FC)
(Source: Venkatesh et al, 2012)

- I have the resources needed to use chatbots
- I have the knowledge needed to use chatbots
- Chatbots are compatible with other technologies I use
- I know whom to seek help when I face difficulties in using chatbots

Perceived Risk (PR)
Chatbots:

- makes me vulnerable to potential fraud (N)
- makes me feel unsafe (N)
- appear to be suspicious (N)
- can misuse your personal information (N)
- are risky (N)
- puts my privacy at risk (N)
- exposes me to an overall risk (N)

Trust (TR)
(Source: Gefen et al., 2003)

- I don't think chatbots are harmful
- Chatbots are trustworthy
- I do not doubt the honesty of chatbots
- I feel there are adequate legal provisions for problems with chatbots
- Chatbots do not involve any user monitoring
- Overall, I trust chatbot transactions

Behavioural Intention (BI)
(Source: Venkatesh et al., 2012)

In the next one year

- I intend to use chatbots
- I predict to use chatbots
- I plan to continue using chatbots
- I will use chatbots in my daily life (N)
- I will prefer chatbots over human interaction (N)

Adoption (AD)
I use chatbots to:

- generate product purchase suggestions (N)
- order product online (N)
- make online reservations (N)
- to get the latest news updates (N)

Satisfaction (ST)
Bargas-Avila et al. (2009)
Suggestions made by chatbots are:

- complete
- easy to understand
- personalized (N)
- relevant
- secure (N)
- reliable (N)
- flexible
- integrated (N)
- accessible

Notes: *N means new statements*