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An investigation on the acceptance of technology through the use of banking chabot

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Abstract: The purpose of this research is to investigate the variables impact customers' propensity to utilise banking chatbots. Customer knowledge of the service, their perception of the privacy risk, and the technological acceptance model were the pillars upon which the measurement framework & hypotheses were built. There are 287 people in the sample, and 24 percent of them have used a chatbot for banking at some point. After a measurement model verified that the measure's items were accurate, PLS-SEM was used to evaluate the hypotheses. Research indicates that compatibility & perceived usefulness are the two most critical aspects of banking chatbot adoption. Knowing about the service influences how easy it is to utilise, how worried people are about their privacy, and how likely they are to use banking chatbots because of how valuable they think they are. Not only that, but one's impression of the product's utility affects their impression of how easy it is to use, and vice versa for compatibility. Neither the perceived privacy risk nor the perceived ease of use influences the propensity to utilise.

Keywords: Banking, Technology, Chatbot, Consumers, PLS-SEM

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INTRODUCTION

With the rise of digital technologies, the banking sector has experienced a dramatic upheaval. Of these, AI and ML have been the most revolutionary, changing the way conventional banks do business. Due to AI and ML, automation is now second nature, decision-making is better, and interactions with customers are better than before. Banks are now able to analyse massive databases, identify fraudulent activities, provide individualised financial advice, and simplify risk management procedures thanks to these technological advancements.

By eliminating the need for human agents and offering real-time assistance, chatbots and virtual assistants powered by AI have improved customer service. Banks are able to make data-driven judgements with the use of Machine Learning algorithms for credit scoring, loan approvals, or risk assessment. Furthermore, fraud detection systems powered by AI examine transaction patterns in order to spot irregularities and forestall financial crimes.

Regulatory compliance, ethical considerations, data privacy, and other issues arise when AI & ML are used in banking, despite these improvements. Responsible AI deployment is essential for financial organisations to keep their customers' trust.

Chatbots powered by artificial intelligence have become increasingly popular as a way for customers to connect with and receive assistance from digital banking services. Chatbots in the banking industry help clients with questions, transactions, and financial advice by using algorithms from Machine Learning and Natural Language Processing (NLP). Their capacity to offer personalised services and instant responses has completely transformed customer service in the banking industry.

Nevertheless, factors including trustworthiness, perceived utility, usability, and data security worries determine the extent to which users embrace banking chatbots. A minority of consumers are wary of chatbot-assisted banking because of concerns about privacy & impersonal nature of the service they receive. However, the majority of users do not mind the service's efficiency and convenience.

The primary objective of this research is to catalogue the elements that influence customers' propensity to utilise banking chatbots. A separate adoption model for chatbots in banking was developed, following the TAM approach. We use a self-administered online survey to collect data and put the conceptual model through its paces using the PLS-SEM statistical method.

LITERATURE REVIEW

C. Nagadeepa et al. (2024) The use of chatbots in banking and finance is on the rise. This research intends to learn how factors including task-technology fit (TTF), system compatibility, perceived utility, social impact, and satisfaction affect chatbot users' intentions to stick with the service. In all, 250 people in India filled out a structured questionnaire that was distributed over social media. A structural equation model (SEM) was used to test the hypothesis, and the measurement model that was proposed was based on the SUS or TTF model with other constructs. The study's results demonstrated the connection between Chabot's use in banking and the following constructs: task technology fit, system usability, perceived usefulness, social impact, and continuation intention, with satisfaction serving as a moderator. Through the adoption of a rigorous research methodology and analysis of the collected results, this investigation sheds light on the factors that influence users' intention to continue using chatbots: TTF, system compatibility, perceived utility, social influence, and satisfaction as a mediator.

Deepti Singh et al. (2024) For the purpose of building an intelligent system, chatbots employ AI and NLP algorithms. Chatbots mimic people and function as digital assistants by mimicking human interactions in the most useful way imaginable. They are great at interacting with clients and fulfilling their needs. These chatbots, or conversation agents, are the next big thing in today's technological world. The ability to cut customer service costs and handle several customers at once has led to chatbots' current surge in popularity in the business field. Many methods exist for incorporating such bright minds into routine operations. In order to ascertain the feasibility of the various approaches, a thorough evaluation of the methodologies is required. In addition to following the development of this innovation, this article elaborates on how chatbots have affected many different types of companies. In addition, a comprehensive overview of the numerous chatbot approaches proposed by different scholars is included. In addition to the survey, an e-commerce customer care chatbot is developed to efficiently and accurately respond to any question using the dataset of commonly requested questions. Because of its efficiency and ability to manage numerous clients simultaneously, this chatbot can cut down on customer care expenses.

Natalia Palomino-Navarro et al. (2022) As chatbots can be hosted on social networks like WhatsApp & Facebook Messenger, it's no surprise that brands have chosen to incorporate them into their digital customer care channels in recent years. Despite their increasing popularity, people still view them as unreliable and inefficient. The idea of designing a chatbot's personality came about as a way for the company to engage with customers in a more personal way, demonstrating its values and creating a pleasant experience. Furthermore, by 2022, the anticipated business value of chatbots for brands is projected to climb to $3.9 trillion. This is why, in a rapidly developing market, it's crucial to understand how companies may depend on chatbots' personalities to positively impact their users. This study aims to shed light on how chatbot personalities impact the way consumers feel about a company. With Lima's young adults as subjects, this exploratory study used a phenomenological design's qualitative methodology. It was then coded descriptively for analysis. Research has shown that the chatbot's social dynamics, social role, and physical appearance are the factors that most affect the user's perception of the brand and the degree to which they identify with it.

Suresh et al. (2020) The primary goal of implementing AI in the banking industry is to better understand client preferences, guarantee consumer satisfaction with bank services, and align customer expectations with bank performance. Both consumers and financial institutions stand to benefit from the widespread adoption of artificial intelligence (AI) in the banking sector, as this study has shown. Customer service, historical contacts, anti-money laundering patterns, voice-assisted banking, underwriting, management decision-making, & fraud reduction are some of the developing trends in AI technology in the banking industry, according to the report. One hundred people participated in the study, and statistical methods like factor and regression analysis were utilised. There is no significant correlation between educational attainment and the reduction of fraud, according to the study's last finding. New trends in artificial intelligence (AI) in banking are based on two aspects identified by factor analysis: individual characteristics and societal context.

DEVELOPING A THEORETICAL FRAMEWORK

This research aims to explore the factors that influence customers' tendency to use banking chatbots. For this reason, the proposed method of study is based on financial services-related technical acceptability measures (Davis' TAM, Venkatesh's UTAUT). Our goal in developing this basic conceptual model was to capture all of the features that were shown to be significant in the acceptance of different banking technology. According to Richad et al. (2019), the usefulness (performance expectancy) & simplicity of use (effort expectancy) of monetary technology, such as banking chatbots, are the two primary variables that decide its acceptability. We will add compatibility as a new driver and privacy risk as a new barrier to the fundamental TAM model. Banks typically notify their clients as part of a communication campaign when they introduce new services. Customers' familiarity with the new technology is, thus, a crucial precondition for its adoption. Within the framework of insurance firms, the knowledge regarding chatbot technology was investigated (Cardona et al., 2019). The suggested research model is shown in Figure 1.

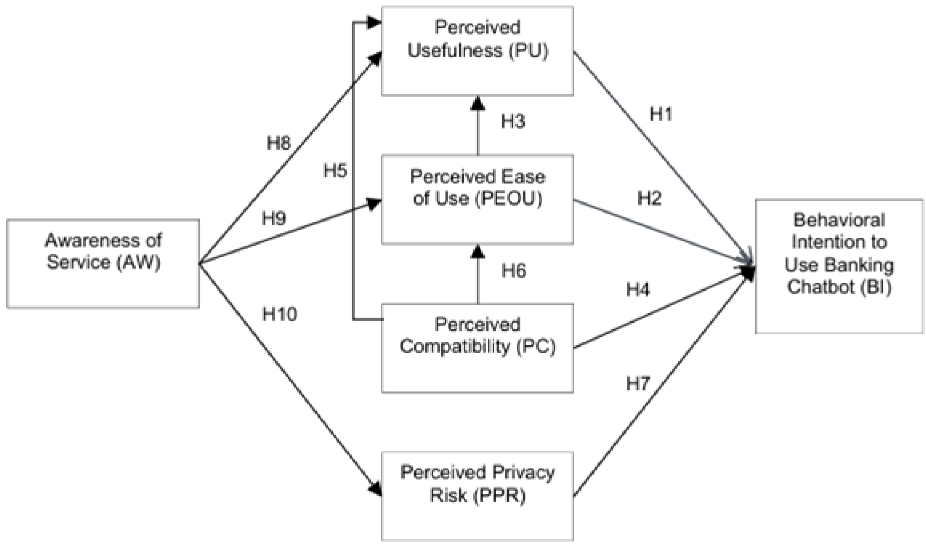

Figure 1: Model for studying the potential adoption of banking chatbots

Preference for Using a Banking Chatbot (BI)

A person's behavioural intention strongly correlates with their actual usage behaviour, according to research by Venkatesh et al. (2003). Based on research conducted by Fishbein and Ajzen in 1975, BI was characterised as "the strength of one's intention to execute a specified behaviour". Since banking chatbots are still in their early stages of adoption, it would be challenging to gauge their real system utilisation. Customers' intent to utilise banking chatbots is the focus of this research. Research on the adoption of technology in banking has shown that factors such as the perceived utility, compatibility, simple utilise, privacy risk, & awareness of the service are important in determining whether or not people will actually utilise the technology.

Perceived Usefulness (PU)

An item's perceived utility can be described as "the degree to which a person believes that utilising a particular system could improve his or her job performance" (Davis, 1989). According to the UTAUT model, PU is similar to performance expectation. This component was utilised & demonstrated to be a robust indicator of intention to use in many studies on the adoption of financial technologies, such as m-banking, i-banking, & m-payment. Multiple research topic of m-banking adoption (Koenig-Lewis et al., 2010; Safeena et al., 2012) and i-banking adoption (Martins et al., 2014; Alalwan et al., 2018) have exposed that PU directly influences the intention to do so. Additionally, the perceived utility of the banking chatbot significantly impacted the intention to behave, according to Richad et al. (2019). Hence, we put forth the first hypothesis:

Hypothesis 1: Customers' intention to utilise a banking chatbot is significantly and positively impacted by perceived usefulness.

Perceived ease of utilize (PEOU)

According to Davis (1989), "the degree to which a person believes that utilising a particular system would be free from effort" makes up perceived ease of use. According to Li and Kishore (2006), PEOU is designed to mimic the expected effort construct seen in the UTAUT model. Research into the spread of various banking technologies has shown that it is a potent indicator of future use. This includes m-banking, i-banking, & m-payment. Many studies have shown that users' PEOU have a direct impact on their intention to embrace electronic banking services (Farah 2018; Giovanis 2019). Furthermore, research shows that i-banking & m-banking both have increased adoption rates when users perceive less effort required (Akturan & Tezcan, 2012; Martins et al., 2014). Richad et al. (2019) also found that the banking chatbot's perceived ease of use significantly affected behavioural intention. Hence, we put up the following two hypotheses:

Hypothesis 2: Customers' inclination to utilise a banking chatbot is significantly and positively impacted by perceived ease of use.

Hypothesis 3: The perceived usefulness is positively and significantly impacted by the perceived simplicity of using.

Perceived compatibility (PC)

The rate of adoption is higher for innovations that fit in with people's daily routines. A concept known as "perceived compatibility" refers to how well an invention fits in with people's preexisting beliefs, experiences, and requirements. Perceived compatibility positively affects the willingness to utilise a specific technology, according to reviews on mobile banking (Koenig-Lewis 2010; Giovanis 2019) and online banking. Users' impressions of compatibility affect their views of usefulness and convenience of utilise, respectively, according to studies on the adoption of internet banking (A. N. Giovanis et al., 2012) or mobile banking (Koenig Lewis et al., 2010). Therefore, we existing the following hypothesis:

Hypothesis 4: Customers' intention to utilise banking chatbot is suggestively and positively impacted by perceived compatibility.

Hypothesis 5: The perceived usefulness is positively & significantly impacted by the perceived compatibility.

Hypothesis 6: The perceived simplicity of use is positively and significantly impacted by the perceived compatibility.

Perceived Privacy Risk (PPR)

The privacy and security of customers' financial data while they shop online is a common worry. In addition, customers worry that banks may sell their private information to third parties (Kolodinsky et al., 2004). When people worry that others may use their personal information without their knowledge or consent, for example, this is known as a perceived privacy risk (Akturan 2012). Customers' concerns about privacy and credibility were identified as barriers to i-banking adoption in various research. According to other research on mobile banking, people's attitudes and intentions towards the technology were negatively impacted by their perceptions of privacy risks. As a result, we offer the following hypothesis:

Hypothesis 7: Customers' intention to utilise a banking chatbot is directly and negatively affected by perceived privacy risk.

Awareness of service (AW)

A key component in the adoption of innovative technologies is the level of awareness surrounding a new product or service. One of the most important factors impacting the uptake of online banking is the level of client knowledge about the subject (Pikkarainen et al., 2004). However, a major factor preventing consumers from utilising online banking technology is a lack of knowledge about it. Researchers Al-somali et al. (2009) discovered that people's perceptions of the usefulness and simplicity of using online banking were significantly impacted by their awareness of the benefits of online banking. Additionally, all components of perceived risk were reduced when i-banking was made known (Hanafizadeh and Khedmatgozar, 2012). Hence, we put up the following hypotheses:

Hypothesis 8: Being aware of the service significantly and positively affects how valuable something is regarded to be.

Hypothesis 9: Perceived ease of use is positively and significantly affected by service awareness.

Hypothesis 10: The perceived privacy risk is significantly and negatively affected by awareness of the service.

METHODOLOGY

This study employs a quantitative research design to investigate the acceptance of banking chatbots. A survey-based approach is utilized to collect empirical data, allowing for a systematic analysis of user perceptions and behaviors. The study is guided by the Technology Acceptance Model (TAM) to assess key factors influencing chatbot adoption.

Procedure

To validate the study model, a survey was administered to a representative sample of Indians. Data from an Indian country would broaden the existing literature since most prior research has concentrated on Asian countries. So far, banking chatbots have been adopted by five out of India's thirty-two banks (Curs BNR, 2020). Information was gathered in 2020 from April to May. First, it has to be said that COVID-19 caused a pandemic in India during this time. To that purpose, it was advised that all services make use of digital channels. The Facebook network was used for the online distribution of the questionnaire. We received 307 surveys. Utilising a Mahalanobis Distance Test, we checked for multivariate outliers in the data (Tabachnick 2007). After removing twenty multivariate outliers, the final sample consists of 287 surveys. This work employs a two-pronged strategy for data analysis, the first of which is to evaluate measurement and structural models through the use of PLS-SEM.

Measurement items

The items utilized for assessment in this research were either developed from the ground up with the research review as a basis or were tailored versions of measurements that have already demonstrated clinical efficacy. The English version of the questionnaire was translated into Indian using a forward backward procedure. All comments were evaluated using a 5-point Likert scale, with 1 being completely disagree and 5 being completely agree. Five individuals at random were used to conduct a pilot test of the measures. The results of the pilot study informed the revisions made to the questionnaire wording. For each component, the final questionnaire items are shown in Table 2.

Table 1: An overview of the measuring instruments

Component		Measurements	References
Perceived usefulness (PU)	PE1 PE2 PE3 PE4	Everyday living is made easier with the banking chatbot. By interacting with the financial chatbot, I improve my odds of accomplishing my goals. With the financial chatbot, I can get more done in less time. My productivity is enhanced when I use the banking chatbot.	(Davis, 1989) (Venkatesh et al., 2003, 2012)
Perceived ease of use (PEOU)	EE1 EE2 EE3 EE4	I have no trouble picking up the skills necessary to operate the banking chatbot. The financial chatbot is easy to comprehend and interact with. The banking chatbot is simple and straightforward. I was able to master the banking chatbot with ease.	(Davis, 1989) (Venkatesh et al., 2003 ., 2012)
Perceived compatibility (PC)	PC1 PC2 PC3	The banking chatbot works great for my schedule. The financial chatbot works nicely with my preferred method of interacting with businesses. If the banking chatbot could replace other customer service options, I would greatly welcome it..	(Moore 1991) (Schierz et al., 2010) (Yang et al., 2012)
Perceived privacy risk (PPR)	PPR1 PPR2 PPR3	There is a risk that the banking chatbot may abuse, share or sell your personal information. The banking chatbot poses the risk of data interception or access. The banking chatbot has the potential to gather, monitor, and analyse personal information.	(Yang et al., 2015)

SECTION TITLE 5

The demographics of the people who filled out the survey were depicted using descriptive statistics. You can see the breakdown of the respondents by gender, age, education level, profession, area of study, and place of living in Table 3.

Table 2: Profile of the survey's demographic participants

Category	Subcategory	Frequency (n)	Percentage (%)
Gender	Male	98	34.15
	Female	152	52.96
	Total	250	87.11
Age	24 and younger	140	48.78
	25-44	90	31.36
	45 and older	20	6.97
	Total	250	87.11
Education	High school	85	29.62
	Superior studies	165	57.49
	Total	250	87.11
Occupation	Employed (including business owner, freelancer)	144	57.60
	Student	101	40.40
	Other (unemployed, retired)	5	2.00
	Total	250	100.00
Field of work	Business (e.g. Accounting, Finance, HR)	109	43.60
	Computer Science & Engineering (e.g. CS, IT)	32	12.80
	Hospitality and other service-related activities are examples.	88	35.20

	Others	21	8.40
	Total	250	100.00
Residence	County seat	92	36.80
	City	113	45.20
	Village	45	18.00
	Total	250	100.00
Satisfaction with financial situation	(1) Very dissatisfied	3	1.20
	(2) Dissatisfied	16	6.40
	(3) Neutral	120	48.00
	(4) Satisfied	90	36.00
	(5) Very satisfied	21	8.40
	Total	250	100.00

Among the 287 respondents, a total of 250 individuals provided their gender information. Out of these, 98 respondents (34.15%) identified as male, while 152 respondents (52.96%) identified as female. The total percentage of responses received regarding gender was 87.11%, indicating that some individuals did not disclose their gender. The respondents' age distribution shows that the majority, 140 individuals (48.78%), were 24 years old or younger. The second-largest group, 90 respondents (31.36%), were aged between 25 and 44 years, while the smallest category consisted of 20 respondents (6.97%) who were 45 years old or older. In total, 87.11% of respondents provided their age information. Regarding education, 85 respondents (29.62%) had completed high school, while the majority, 165 respondents (57.49%), had pursued higher education (superior studies). Overall, 87.11% of respondents provided details about their education level. Among the 250 respondents who provided occupational data, 144 individuals (57.60%) reported being employed, which includes business owners and freelancers. Meanwhile, 101 respondents (40.40%) were students, and only 5 individuals (2.00%) identified as unemployed or retired. The total response rate for occupation was 100%. Regarding professional fields, the most common sector was Business (Accounting, Finance, HR, etc.), with 109 respondents (43.60%) employed in these industries. The Engineering &

Computer Science field (including IT) was represented by 32 respondents (12.80%). The Services sector (such as Hospitality) accounted for 88 individuals (35.20%), while 21 respondents (8.40%) fell into other professional categories. This section also had a 100% response rate. In terms of residency, 92 respondents (36.80%) lived in a county seat, 113 respondents (45.20%) resided in a city, and 45 respondents (18.00%) were from a village. The response rate for this category was 100%. When asked about financial satisfaction, the majority, 120 respondents (48.00%), remained neutral about their financial situation. Meanwhile, 90 individuals (36.00%) reported being satisfied, and 21 respondents (8.40%) were very satisfied. A small proportion of respondents expressed dissatisfaction, with 16 respondents (6.40%) feeling dissatisfied, and only 3 respondents (1.20%) reporting being very dissatisfied. This category also had a 100% response rate.

Table 3: An Overview of the Chatbots Used by Evaluation Participants

Respondents	**Frequency**	**Percentage (%)**
Employ of banking technology(n=250)		
I-banking	130	52.0
M-banking	78	31.2
M-payment technology	30	12.0
Other	10	4.0
None	2	0.8
Total	250	100.0
Are familiar with banking chatbots (n=250)		
Yes	50	20.0
No	200	80.0
Total	250	100.0

Implementation of chatbots for various banking services (n=50)		
Personal account	38	76.0
Business account	4	8.0
Both	8	16.0
Total	50	100.0
Financing chatbot's initial deployment (n=50)		
Present month	5	10.0
A month ago,	9	18.0
6 months ago,	13	26.0
A year ago,	12	24.0
More than 1 year ago	11	22.0
Total	50	100.0
Awareness of chatbot developed for banking (n=210)		
Yes	150	71.4
No	45	21.4
Don't know	15	7.1
Total	210	100.0

The measuring scale's validation

To determine whether the measurement items were reliable and valid, the data was analysed using a two-stage procedure including PLS-SEM. Analysis of the measurement model was the first stage, and testing of structural links between latent components was the second. The measurement model was examined by estimating the following validity measures: convergent validity, discriminant validity, composite reliability, internal consistency reliability, or indicators (Ringle et al., 2015).

The reliability was determined utilising Cronbach's Alpha and composite reliability (CR), while the validity was evaluated utilising Average Variance Extracted (AVE) and factor loadings (outer loadings). The results demonstrated that the questions' construct reliability was within reasonable bounds, and that the measures' convergent validity for the latent variables was excellent. CR factor loadings (outer loadings), and Cronbach's Alpha (the reliability measure) were all greater than the necessary threshold values of 0.8 & 0.6, respectively, as shown in Table 4.

Table 4: Constructs' psychometric characteristics

Construct	Indicator	Outer weights	Outer Loadings	Cronbach's	CR	AVE
AW	AW 1	0.298	0.913	0.902	0.907	0.932
	AW 2	0.306	0.820			
	AW 3	0.287	0.920			
	AW 4	0.243	0.859			
PU	PE 1	0.27	0.88	0.928	0.929	0.949
	PE 2	0.284	0.902			
	PE 3	0.274	0.906			
	PE 4	0.287	0.932			
PEOU	EE 1	0.258	0.902	0.933	0.934	0.952
	EE 2	0.288	0.922			
	EE 3	0.275	0.928			
	EE 4	0.274	0.8			
PC	PC 1	0.392	0.889	0.871	0.876	0.921
	PC 2	0.386	0.917			
	PC 3	0.343	0.872			
	PPR 1	0.287	0.857			

PPR	PPR 2	0.243	0.897	0.894	0.935	0.926
	PPR 3	0.231	0.815			
	PPR 4	0.378	0.913			
BI	BI 1	0.302	0.915	0.926	0.928	0.947
	BI 2	0.265	0.907			
	BI 3	0.268	0.893			
	BI 4	0.273	0.902			

A relevant measure for measuring discriminant validity has been identified as the "Heterotrait-Monotrait ratio (HTMT)" (Henseler et al., 2015). Since no item's HTMT ratio was higher than the minimum acceptable value of 0.85, all items were considered to have strong discriminant validity (Table 5). The verification of the measurement model allows for the evaluation of the structural model to proceed. We have built a measurement model with six constructs to validate and confirm the measuring equipment and establish the relationships between the observed and unseen variables. The results demonstrated that the measurement model that was fitted gave a respectable match; the NFI value of 0.874 was higher than the good model threshold of 0.8 (Forza 1998), & SRMR value was 0.049.

Table 5: HTMT for discriminant validity of constructs

	PEOU	**AW**	**BI**	**PC**	**PPR**	**PU**
PEOU						
AW	0.403					
BI	0.479	0.331				
PC	0.546	0.33	0.74			
PPR	0.17	0.19	0.172	0.109		
PU	0.546	0.41	0.623	0.782	0.109	

Analysis the research hypotheses

Evaluating the structural model involved looking at the beta weight (β) & coefficient of determination (R2), which are path coefficients. The level of correlation between the dependent & independent variables is shown by the β value, while the R2 value, to determine the extent to which the independent variables contribute to the overall variation, which might be seen as the model's predictive power. The results of the research hypothesis evaluation are shown in Table 7, and the statistical investigation of the research model is shown in Figure 2. There is statistical support for seven variables, according to the results. The first thing to notice is that being aware of the service has a strong positive correlation with how beneficial it is and how easy it is to use, as well as a negative correlation with how much of a threat it poses to privacy. The PEOU are also highly connected to one another (β = 0.168; p≈ 0.001). The PU (β = 0.581; p 0.001) & PEOU (} = 0.421; p < 0.001) are both positively and significantly affected by PC. PC (β = 0.484; p=: 0.001) and considerably positive PU (β = 0.176; p 0.05) are the last factors influencing the intention to utilise. There is no correlation between PE & PEOU, and neither does simplicity of use, according to the research. Thus, the empirical evidence supported H1, H3, H4, H5, H6, H8, H9, and H10, but rejected H2 and H7.

Table 6: Structural model evaluation

No.	Hypothesis path	Path Coefficient	STDEV	t-Value	P-value	Support
H1	PU →BI	0.176	0.068	2.601	0.010*	yes
H2	PEOU → BI	0.104	0.055	1.909	0.057^{ns}	no
H3	PEOU → PU	0.168	0.052	3.23	0.001*	yes
H4	PC → BI	0.484	0.06	8.116	0.000**	yes
H5	PC → PU	0.581	0.047	12.451	0.000**	yes
H6	PC → PEOU	0.421	0.054	7.807	0.000**	yes
H7	PPR → BI	-0.082	0.045	1.81	0.071ns	no
H8	AW → PU	0.143	0.038	3.763	0.000**	yes
H9	AW → PEOU	0.25	0.051	4.896	0.000**	yes
H10	AW → PPR	-0.173	0.066	2.63	0.009*	yes

*Note: *Significance at p<0.05); **(p<0.001); ^{ns} Not significant*

Perceived suitability, simplicity of utilise, and service knowledge account for 55% of the variation in perceived usefulness, according to the research. Perceived compatibility and service awareness account for 30.3% of the variation in perceived ease of utilisation. Perceived privacy risk is also 3% dependent on service awareness. Lastly, 48.5% of the variation in behavioural intention may be explained by the combined effects of perceived utility and perceived compatibility.

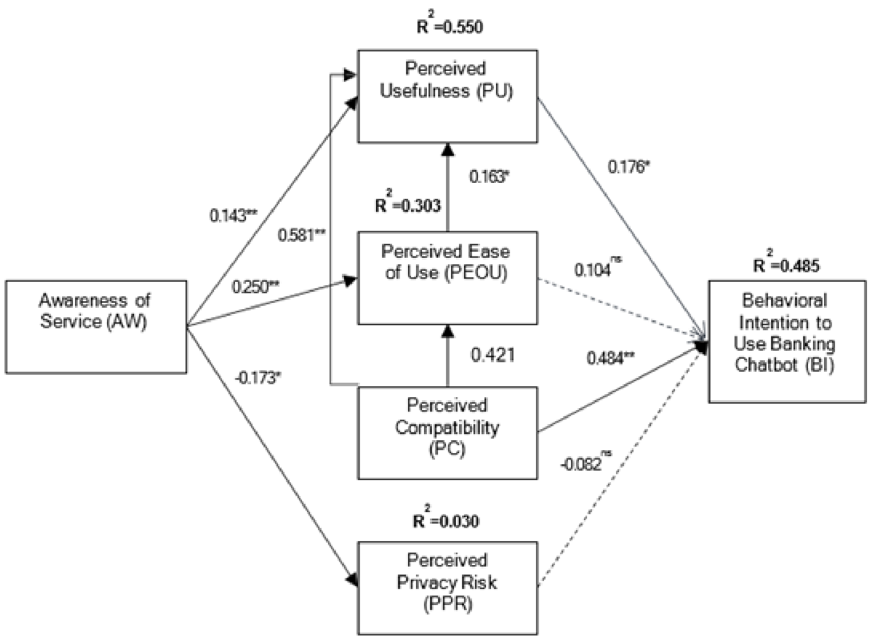

Figure 2. Attitudes towards banking chatbots: a suggested research model

DISCUSSION

When it comes to automating customer care procedures in the financial sector, chatbot applications based on artificial intelligence have become quite popular. These apps are changing the way banks communicate with their customers. Chatbots have been used by numerous banks to enhance service quality while decreasing expenses. So, it's crucial for these businesses to figure out what makes customers want to use this technology. Perceived utility and perceived compatibility were found to be two characteristics that considerably affect customers' propensity to utilise banking chatbots in the Indian banking business, according to the current investigation. Also, unlike multiple studies that used TAM, the suggested research model accounted for 48.5% of the behavioural intention for utilising banking chatbots, which is a higher value (Venkatesh 2000). According to previous study on the adoption of i-banking & m-banking, PEOU banking chatbots is most affected by perceived compatibility, out of the two highlighted variables. Customers are more likely to embrace new technology if they believe it will improve their lives, and this holds true for banking chatbots. It is crucial to ensure that banking chatbots are designed and implemented in a manner that aligns with the consumers' lifestyle and values.

Research on the adoption of technology in banking has shown mixed results regarding the impact of perceived ease of use on behavioural intention. Some studies on i-banking (Alalwan et al., 2018) or m-banking adoptions found that perceived ease of use strongly impacted usage intention, while other studies found no such significant relationship (Pikkarainen et al., 2004; Koenig-Lewis et al., 2010). Pikkarainen et al. (2004) found that PE did not significantly effect usage intention for i-banking, while Koenig-Lewis et al. (2010) found the same for m-banking. These findings are consistent with this study. Furthermore, the results of this study demonstrate that the PEOU of banking chatbots substantially affects behavioural intention to use these tools via perceived utility. According to several studies, technology is more affected by PU than PE. This is because perceived usefulness increases technological adoption through perceived ease of use.

In contrast to expectations, PEOU banking chatbots was unaffected by PPR. Despite previous research on i-banking acceptance (Giovanis et al., 2012) and m-banking adoption having similarly found no significant association between perceived privacy risk and intention to use, this study failed to achieve the same conclusion. Perceptions of privacy issues did not substantially affect users' intentions to utilise the service, according to research on mobile banking uptake by Akturan (2012). There are two possible reasons for the paucity of evidence about this issue. First, according to research on the adoption of i-banking, there are six categories of perceived risk factors: time, money, performance, society, security, and privacy (Hanafizadeh 2012). Not every aspect of risk is pertinent when discussing online banking services, as stated by Aldás-Manzano et al. (2009). This study's findings suggest that one risk dimension that is irrelevant to the adoption of banking chatbots is perceived privacy risk. Secondly, most of the participants in this study were young adults (those with a bachelor's degree or less) who were full-time students. People in this age and education bracket often have extensive background with internet-related activities, such as mobile phone use, online banking, and more. Therefore, the age of the participants in this study explains the lack of a substantial relationship between perceived privacy risk and behavioural intention.

CONCLUSION

There is a lot of research on the prevalence of technology adoption in the banking sector. There has been little focus, however, on chatbot technology, which is becoming increasingly popular and used in the banking industry. In light of this knowledge vacuum, the current study set out to determine what variables most strongly impact consumers' propensity to avail themselves of banking chatbot services. Taking cues from the TAM model, the suggested research model adds compatibility, customers' perceptions of privacy risk, and service awareness as its extensions. The data used in this investigation came from 287 customers who filled out an online survey on their own. The results lent credence to the theoretical hypothesis as they could account for 48.5% of the variation in the behavioural intention. Customer propensity to utilise the banking chatbot was strongly predicted by perceived compatibility and perceived utility. Perceptions of the service's usefulness, privacy danger, and convenience of use were all influenced by users' level of awareness of the service. Perceived compatibility affected both perceived utility and perceived ease of use, while perceived usefulness impacted perceived ease of use.

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