

BANKING WITH A CHATBOT – A STUDY ON TECHNOLOGY ACCEPTANCE

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Abstract. The implementation of chatbot technology is evolving rapidly in the banking industry, yet customer acceptance is behind. The aim of the present paper is to identify the factors that influence consumers' intention to use chatbot technology applied in the banking industry. The measurement development and hypotheses were based on the technology acceptance model extended with compatibility, customers' perceived privacy risk and awareness of the service. The sample contains 287 respondents, out of whom 24% have previously used a banking chatbot. The measure items were validated by a measurement model and hypotheses were tested using Partial Least Squares-Structural Equation Modeling (PLS-SEM). The findings highlight the importance of perceived compatibility and perceived usefulness in the adoption of banking chatbot technology. Awareness of the service has an effect on perceived ease of use, perceived privacy risk, and it indirectly affects usage intention of banking chatbots through perceived usefulness. Also, perceived ease of use influences perceived usefulness, and perceived compatibility has an effect on both perceived ease of use and perceived usefulness. Perceived ease of use and perceived privacy risk show no effect on usage intention.

Keywords: Technology acceptance model, Artificial Intelligence, Chatbot, Self-service, Banking, Partial Least Squares-Structural Equation Modeling (PLS-SEM)

JEL classification: M31, O33.

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1. Introduction

Recent technological developments have transformed the way consumers and financial institutions interact with each other (Shaikh and Karjaluoto, 2015). Moreover, the COVID-19 pandemic has led to rapid shift to digital technologies and banks have transitioned to remote sales and provision at a fast pace (McKinsey, 2020). The rise of artificial intelligence (AI) based technology is contributing extensively to this transformation as more and more banks have begun to implement AI-based applications with the aim of deepening customer relationships, providing more personalized offers, detecting and preventing fraud, improving processes for anti-money laundering, and cost saving (Business Insider, 2021). One very popular and impactful form of technological development in the financial sector is the implementation of the AI-based chatbot technology (Richad et al., 2019).

Chatbot technology is a system based on AI that communicates with users and performs basic tasks through chat or speech interfaces (Nguyen and Sidorova, 2017). According to forecast, the chatbot market size is projected to reach 102.29 billion USD by 2025 (Mordor Intelligence, 2019), and the success rate of bot interactions (queries completed without the interference of a human operator) in the banking sector is expected to be over 90% by 2022 (Juniper Research, 2020). Yet, in order for both banks and consumers to exploit from the advantages of the banking chatbot technology, it is important to examine the drivers of consumers' willingness to adopt this technology.

The adoption of innovations applied in the banking industry, such as i-banking and m-banking, is widely studied in the literature. Although the above mentioned studies provide essential contribution to technology adoption in the context of the banking industry, there is limited knowledge on the acceptance of banking chatbots. There are already a few studies that highlighted the importance of studying chatbot acceptance in the context of the banking industry, but only one has conducted a research related to the technology acceptance model (Richad et al., 2019), and one is related to the customer experience for consumers who are banking with chatbot technology (Trivedi, 2019). In order to extend the knowledge regarding chatbot acceptance in banking, the present study aims to investigate the determinants of chatbot adoption in the banking industry, based on technology adoption literature in the banking industry.

The aim of the current study is to identify those factors that have an influence on consumers' intention to use chatbot technology applied in the banking industry. A special adoption model was developed for banking chatbots, extending the TAM model. Data is collected through an online, self-administrated questionnaire and the conceptual model is examined using the PLS-SEM method.

The structure of the paper is as follows. First, in the Literature review section, earlier research findings on banking technology adoption (e.g. i-banking and m-banking) are presented, and the chatbot technology and research on its adoption in the banking industry are described. Next, in the Conceptual framework development section, the research model is conceptualized and hypotheses are formulated. In the Research method section, the sample and measures are described. Thereafter, in the Data analysis section, the data and methods used in this study are presented.

Finally, the results are discussed, including the implications for theory and practice, limitations of the study and further possible research directions are outlined, and conclusions are drawn.

2. Literature review

2.1 Banking technologies' adoption by customers

The banking industry has been profoundly influenced by technological evolution in recent decades and consumer adoption of banking technologies is a widely researched topic in the literature. Thus, a more in-depth look into the processes behind the adoption of banking chatbots can be gained through the review of the existing literature on the adoption of other technologies applied in the banking sector, such as i-banking and m-banking.

Several theories have been implemented in order to analyze the adoption of different IT systems. According to Hanafizadeh and Khedmatgozar (2012), the most influential theoretical models applied in i-banking adoption studies, are the Diffusion of innovation theory (DIT), the Technology acceptance model (TAM), the Decomposed theory of planned behavior (DTPB), the Extended technology acceptance model (TAM2) and the Unified theory of user acceptance of technology (UTAUT), the latter becoming dominant in the literature in recent years. Shaikh and Karjaluoto (2015) analyzed and synthesized existing studies of m-banking adoption and concluded that the most frequently used adoption models were TAM, followed by DIT and UTAUT, while several studies applied a combination of different technology acceptance models (e.g. TAM and DIT). Several of the above mentioned models are composed of intention to use or actual usage as the dependent variables. Consequently, the key dependent variables in the i-banking adoption literature (Yousafzai, 2012) are behavioral intention to use and actual usage of the technology, while in m-banking adoption, besides the two earlier mentioned dependents, attitude is also adopted in order to analyze technology acceptance (Shaikh and Karjaluoto, 2015).

Based on the literature review, it could be concluded that usefulness and ease of use are fundamental variables in studying technology acceptance in the banking sector. It should also be highlighted that compatibility was found as a key determinant for m-banking (Koenig-Lewis et al., 2010; Shankar and Kumari, 2016; Giovanis et al., 2019) and i-banking (Giovanis et al., 2012) adoption. Therefore, it is expected that compatibility will influence banking chatbot adoption as well. However, technology acceptance could be inhibited directly or indirectly (Moldovan and Săplăcan, 2018) by several factors, such as different types of risk factors. In some cases, perceived privacy risk was found to be a barrier for m-banking (Arif et al., 2016; Shankar and Kumari, 2016) and i-banking (A. N. Giovanis et al., 2012) adoption. Supposedly, perceived privacy risk will be a barrier in adopting banking chatbot as well.

2.2. Chatbot technology: description and previous research

A chatbot application is a computer program that mimics human conversations in its natural format, including text or spoken language, using artificial intelligence techniques, such as Natural Language Processing (NLP), image and video processing and audio analysis (Bala et al., 2017).

Chatbot applications offer benefits for both companies and consumers. First, chatbots enable consumers to get in touch with companies anytime from anywhere using their own mobile devices, thus they can get quick and relevant responses to their questions. Second, the implementation of these applications allows companies to target consumers in a more direct and personal way, and companies can save on personnel costs in the area of customer services. In addition to the benefits of the technology, the usage of chatbots may also involve several risk factors, including issues regarding data security and financial risks (Vieira and Sehgal, 2017; Richad et al., 2019).

Recently published scientific papers analyzed the adoption of chatbot technology in the tourism industry (Melián-González et al., 2021), in the health care industry (Laumer et al., 2020), and in the field of higher education (Almahri et al., 2020). Regarding the adoption of chatbots applied in the financial industry, only a few studies examined the acceptance of these applications in the context of the insurance sector (Cardona et al., 2019) and the banking sector (Gupta and Sharma, 2019; Quah and Chua, 2019; Trivedi, 2019; Richad et al., 2019; Sarbabidya and Saha, 2020). Although several studies have examined the factors influencing the acceptance of chatbots, the findings carried out in different fields may not be transferable for financial services (Cardona et al., 2019). Specific research is required in case of banking.

2.3 Chatbot technology in the banking industry

Chatbots applied in the financial industry can assist customers in managing financial transaction such as reviewing an account, reporting lost cards or making payments, renewing a policy or handling a refund (Tarbal, 2020). In the literature, there are several recently published studies that focused on chatbot technology applied in the financial industry (Cardona et al., 2019; Gupta and Sharma, 2019; Quah and Chua, 2019; Richad et al., 2019; Trivedi, 2019; Sarbabidya and Saha, 2020) (Table 1).

Cardona et al. (2019) studied the adoption and diffusion of chatbots in the context of insurance, concluding that the majority of the participant were familiar with the technology and would prefer to use it at the beginning of the advisory process, while one third of the participants rejected the adoption of chatbots. Gupta and Sharma (2019) examined the customers' attitude towards chatbots in the banking industry and the findings of the study revealed positive correlation between the positive attitude for chatbots and their utility, accessibility and threats. Quah and Chua (2019) explored the effectiveness of the use of chatbot technology in Singapore's banking industry and investigated chatbot functionality to determine if it would meet customer expectations. They found that detailed information provided by the banking chatbot was the most important factor for consumers, followed by fast response, functionality, interactivity, ease of use and data privacy and protection. It was also found that some of the users were not satisfied with the banking chatbot because it didn't provide an immediate answer when needed. Richad et al. (2019) investigated the acceptance factors of chatbot technology in the banking industry in Indonesia in case of Millennials based on TAM, and found that innovativeness, perceived usefulness, perceived ease of use and attitude towards using the chatbot had significant effect on behavioral

intention. Trivedi (2019) examined customer experience of using banking chatbots and its impact on brand love adopting the Information Systems (IS) success model among. The results showed that system quality, information quality and service quality had significant impact on customer experience, system quality being the strongest predictor. Perceived risk reduced the impact of the three quality dimensions on customer experience, and customer experience of using the chatbot led to love for the brand that provided the technology. Sarbabidya and Saha (2020) found that the role of chatbots in customer service of the banking industry was positively affected by advisory services, ease of use and convenient service, cost effective and efficient service, customer-friendly service, customized service, relationship banking services, responsive service, trustworthy service, value-based useful service and maintaining customers security and privacy.

Table 1: Summary of studies regarding banking chatbots

Authors	The aim of the study	Theories/Studied variables	Research method/sample	Data analysis
(Cardona et al., 2019)	Adoption and diffusion of chatbots in the German insurance sector	DOI: relative advantages, compatibility, complexity, trialability, observability TOE: top management support, IS infrastructure, costs, environmental threats, competitive pressure, collaborative networks TAM: perceived usefulness, perceived ease of use, perceived behavioral control	Qualitative, quantitative Semi-Structured Expert Interviews, N=7 Web-based cross sectional survey, N=300 Data collected in Germany in 2018	Descriptive
(Gupta and Sharma, 2019)	Analysis of customers' attitude towards the chatbots in banking industry of India	attitude observed utility (ease of use, ease of process, engagement with customer service) observed accessibility (easy for basic transactions, speedy process, user friendliness) observed threat and awareness (data security and privacy, social awareness, friends and family using it)	Quantitative Data collected via Facebook and WhatsApp, N=72 Data collected in India in 2019	Bivariate analysis
(Quah and Chua, 2019)	Analysis of the effectiveness of the current use of chatbots in Singapore's banking industry	user experience: response rate, functionality and usability satisfaction: interactivity, informative, data privacy and protection	Quantitative, qualitative Interviews Qualitative user tests	Descriptive
(Richad et al., 2019)	Analysis of the factors that influence millennial's technology acceptance of chatbots in the banking industry in Indonesia	TAM attitude towards usage, behavioral intention innovativeness, perceived usefulness, perceived ease of use	Quantitative Simple random sampling technique, N=400 Data collected in Indonesia in 2018	SEM

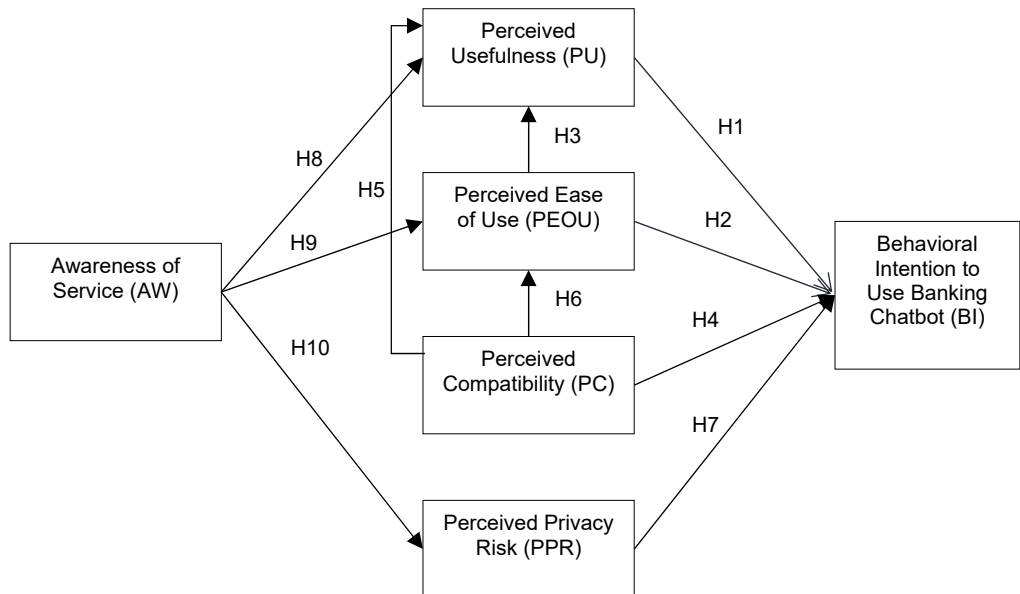
Authors	The aim of the study	Theories/Studied variables	Research method/sample	Data analysis
(Trivedi, 2019)	Examination of customer experience of using banking chatbots and its impact on brand love in India	Information Systems (IS) success model customer experience, brand love system quality, information quality, service quality, perceived risk	Quantitative Online questionnaire sent to Gen Z individuals, N=258 Data collected in India in 2018	SEM
(Sarbabidi a and Saha, 2020)	Examination of the role of chatbots in customer service of the banking industry of Bangladesh	customer service advisory services, ease of use and convenient service, cost effective and efficient service, customer-friendly service, customized service, relationship banking services, responsive service, trustworthy service, value based usefulness, security and privacy	Quantitative Judgment sampling method, N=125 Data collected in Bangladesh in 2019	Regression

Based on the reviewed literature regarding the adoption of chatbots applied in the banking industry, it can be concluded that this topic is in the early phase of research, mostly based on descriptive analysis (Table 1). Only one study (Richad et al., 2019) analysed chatbot acceptance based on theoretical models and analysed a conceptual model in order to identify the factors that have significant impact on adoption. Thus, the present study aims to fill this research gap by building a conceptual model of technology acceptance based on previous studies related to chatbots used in financial services (Cardona et al., 2019; Richad et al., 2019), and other technologies' acceptance in the financial sector (e.g. m-banking, i-banking).

3. Conceptual framework development

The aim of the paper is to identify those factors that have an influence on consumers' intention to use chatbot technology applied in the banking industry. Therefore, the proposed research model is based on technology acceptance (Davis' TAM, Venkatesh's UTAUT) in the context of the financial services. In order to provide a simple conceptual model, only those variables were included into the model, which were found to be relevant for different banking technologies' adoption. It is generally accepted that perceived usefulness (known as performance expectancy in Venkatesh's UTAUT) and perceived ease of use (known as effort expectancy in Venkatesh's UTAUT) are key determinants in financial technologies' acceptance and for banking chatbots as well (Richad et al., 2019). The basic TAM model will be extended with one more driver, namely with compatibility and one barrier, namely privacy risk. When introducing new services, banks tend to inform their customers as part of a communication campaign. Therefore, customers' awareness of the new technology is an important antecedent of technology acceptance. Knowledge about chatbot technology was examined in the context of insurance companies (Cardona et al., 2019). Figure 1 illustrates the proposed research model.

Figure 1: Proposed research model for intention to use banking chatbots



3.1 Behavioral Intention to Use Banking Chatbot (BI)

It was found that behavioral intention is a strong predictor of an individual's actual usage behavior (Venkatesh et al., 2003). BI is defined as "the strength of one's intention to perform a specified behavior" (Fishbein and Ajzen, 1975 p. 288). As banking chatbots are a relatively new type of technology, currently being in the phase of adoption, actual system usage would be difficult to measure. Thus, the present study will analyze customers' intention to use banking chatbots. In the banking technology adoption literature, perceived usefulness (Koenig-Lewis et al., 2010; Safeena et al., 2012; Martins et al., 2014; Alalwan et al., 2018; Farah et al., 2018), perceived ease of use (Safeena et al., 2012; Martins et al., 2014; Alalwan et al., 2018; Farah et al., 2018), perceived compatibility (Kolodinsky et al., 2004; Koenig-Lewis et al., 2010), perceived privacy risk (Akturan and Tezcan, 2012; Giovanis et al., 2012; Arif et al., 2016; Shankar and Kumari, 2016), and awareness of the service (Sathye, 1999; Pikkarainen et al., 2004; Al-somali et al., 2009) were identified as predictors of behavior intention to use the technology.

3.2 Perceived Usefulness (PU)

Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989 p. 320). PU is considered to be similar to the performance expectancy construct in the UTAUT model (Li and Kishore, 2006), which was adopted and found to be a strong predictor of usage intention in several banking technology (e.g. m-banking i-banking and m-payment) adoption studies. Several studies on the adoption of

m-banking (Koenig-Lewis et al., 2010; Safeena et al., 2012; Farah et al., 2018; Giovanis et al., 2019) and the adoption of i-banking (Martins et al., 2014; Alalwan et al., 2018) found that PU had a direct, positive effect on intention to use the studied technology. Moreover, Richad et al. (2019) found that perceived usefulness of the banking chatbot had significant effect on behavioral intention. Therefore, the first hypothesis is proposed:

H1: Perceived usefulness has a significant and positive effect on customers' intention to use banking chatbot.

3.3 Perceived ease of use (PEOU)

Perceived ease of use is defined as “the degree to which a person believes that using a particular system would be free from effort” (Davis, 1989 p. 320). PEOU is considered to be similar to the effort expectancy construct in the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Li and Kishore, 2006), which was studied and found to be a strong predictor of usage intention in several banking technology (e.g. m-banking, i-banking and m-payment) adoption studies. First, existing literature on the adoption of m-banking (Safeena et al., 2012; Farah et al., 2018; Giovanis et al., 2019) and the adoption of i-banking (Alalwan et al., 2018; Martins et al., 2014) found that PEOU had a direct, positive effect on intention to use the studied technology. Second, studies showed that lower levels of effort expectations improved performance expectations of m-banking (Akturan and Tezcan, 2012; Koenig-Lewis et al., 2010) and i-banking (Martins et al., 2014) activities. In addition (Richad et al., 2019) concluded that perceived ease of use of the banking chatbot had significant effect on behavioral intention. Therefore, the second and third hypotheses are proposed:

H2: Perceived ease of use has a significant and positive effect on customers' intention to use banking chatbot.

H3: Perceived ease of use has a significant and positive effect on perceived usefulness.

3.4 Perceived compatibility (PC)

Innovations that are compatible with the lifestyle of an individual, have a faster adoption rate (Rogers, 1983). Perceived compatibility is “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers, 1983 p. 42). Several studies on m-banking (Koenig-Lewis et al., 2010; Giovanis et al., 2019;) and i-banking (Kolodinsky et al., 2004) adoption concluded that perceived compatibility had direct and positive effect on intention to use the certain technology. Moreover, some studies on m-banking (Koenig-Lewis et al., 2010) and i-banking (A. N. Giovanis et al., 2012) adoption found that perceived compatibility had a direct and positive effect on perceived usefulness, respectively on perceived ease of use. Thus, the fourth, fifth and sixth hypotheses are proposed:

H4: Perceived compatibility has a significant and positive effect on customers' intention to use banking chatbot.

H5: Perceived compatibility has a significant and positive effect on perceived usefulness.

H6: Perceived compatibility has a significant and positive effect on perceived ease of use.

3.5 Perceived Privacy Risk (PPR)

Consumers tend to have concerns about the security and privacy of their financial information in online environments. Moreover, consumers are also concerned about the banks sharing their personal information with other companies (Kolodinsky et al., 2004). Perceived privacy risk refers to an individual's concern about potential loss of control over personal information, such as when information about an individual is used without that person's awareness (Akturan and Tezcan, 2012). Several studies on the acceptance of i-banking found that customers' perception of privacy risk (also referred as credibility) was an inhibitor of i-banking acceptance (A. N. Giovanis et al., 2012). Other studies on m-banking (Arif et al., 2016; Shankar and Kumari, 2016) adoption found that perceived privacy risk had a direct and negative effect on attitude toward the technology and on usage intention. Therefore, the seventh hypothesis is proposed:

H7: Perceived privacy risk has a direct and negative effect on customers' intention to use banking chatbot.

3.6 Awareness of service (AW)

Awareness of a new product or services is an important adoption factor of innovative technologies (Sathye, 1999). It was found that the amount of information that customers have about online banking, is a major factor influencing online banking adoption (Pikkarainen et al., 2004). Whereas, low awareness of online banking is a significant variable in causing people not to adopt online banking technology (Sathye, 1999). Al-somali et al. (2009) found that the awareness of online banking and its benefits had significant effects on the perceived usefulness and perceived ease of use of online banking acceptance. Furthermore, awareness of i-banking also decreased all aspects of perceived risk (Hanafizadeh and Khedmatgozar, 2012). Therefore, the eighth, ninth and tenth hypothesis are proposed:

H8: Awareness of service has a significant and positive effect on perceived usefulness.

H9: Awareness of service has a significant and positive effect on perceived ease of use.

H10: Awareness of service has a significant and negative effect on perceived privacy risk.

4. Research method

4.1 Procedure

The survey method was used to test the proposed research model based on a Romanian sample. Previous research is focused mostly on Asian countries, therefore data from an East Central European country will extend the actual literature.

In Romania, there are 32 banks (Curs BNR, 2020) out of whom five institutions have implemented banking chatbots so far. Data were collected from April to May in 2020. It should be outlined that this was a pandemic period in Romania because of COVID-19. Therefore, the use of digital channels were highly recommended for all services. The questionnaire was distributed online through the Facebook platform. 307 questionnaires were collected. Data were assessed for multivariate outliers using a Mahalanobis Distance Test (Tabachnick and Fidell, 2007). Twenty multivariate outliers were identified and removed, the final sample contains 287 questionnaires. The present study follows a two-step approach to the analysis of the data obtained, including the assessment of measurement and structural models using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) (Ringle et al., 2015).

4.2 Measure items

Measurement items used in this study were adapted from previously validated measures or developed on the basis of the literature review. Applying a forward-backward method, the questionnaire was translated from English into Romanian. A five-point Likert scale ranging from totally disagree (1) to totally agree (5) was used in all statements. A pilot test of the measures was carried out on a sample of 5 randomly chosen people. Questionnaire statements were modified based on the results of the pilot test. The final questionnaire items that were used in order to measure each construct are presented in Table 2.

Table 2: Summary of measurement scales

Constructs	Measures	Source
Perceived usefulness (PU)	PE1	I find the banking chatbot useful in my daily life.
	PE2	Using the banking chatbot increases my chances of achieving things that are important to me.
	PE3	Using the banking chatbot helps me accomplish things more quickly.
	PE4	Using the banking chatbot increases my productivity.
Perceived ease of use (PEOU)	EE1	Learning how to use the banking chatbot is easy for me.
	EE2	My interaction with the banking chatbot is clear and understandable.
	EE3	I find the banking chatbot easy to use.
	EE4	It is easy for me to become skillful at using the banking chatbot.
Perceived compatibility (PC)	PC1	Using the banking chatbot fits well with my lifestyle.
	PC2	Using the banking chatbot fits well with the way I like to interact with companies.
	PC3	I would appreciate using the banking chatbot instead of alternative modes of customer service.
Perceived privacy risk (PPR)	PPR1	Privacy information could be misused, inappropriately shared, or sold when using the banking chatbot.
	PPR2	Personal information could be intercepted or accessed when using the banking chatbot.

Constructs	Measures	Source
	PPR3 Personal information could be collected, tracked, and analyzed when using the banking chatbot.	
	PPR4 Privacy could be exposed or accessed when using the banking chatbot.	
Awareness of service (AW)	AW1 My bank has communicated a banking chatbot usage policy to me.	(Al-somali et al., 2009)
	AW2 My bank has a strategy regarding the usage of the banking chatbot.	(Guesalaga, 2016)
	AW3 I have received sufficient information from my bank regarding the usage of the banking chatbot.	
	AW4 I have received recommendations from my bank on the use of the banking chatbot in the context of the COVID-19 pandemic.	
Behavioral intention to use (BI)	BI1 Given the opportunity, I will use the banking chatbot.	(Davis, 1989)
	BI2 I am likely to use the banking chatbot in the near future.	(Venkatesh and Davis, 2000)
	BI3 I am willing to use the banking chatbot in the near future.	(Gefen et al., 2003)
	BI4 I intend to use the banking chatbot when the opportunity arises.	(Schierz et al., 2010)

5. Data analysis

5.1 Respondents' demographic profile

Descriptive statistics were used to picture the demographic characteristics of the survey respondents. Table 3 illustrates the demographic profile of the respondents in terms of gender, age, education levels, occupation, field of work/study and residence.

Table 3: Demographic profile of survey sample

Respondents characteristics	Frequency (n=287)	Percentage (%)
<i>Gender</i>		
Male	114	39.7
Female	173	60.3
Total	287	100.0
<i>Age</i>		
24 and younger	148	51.6
25-44	99	34.5
45 and older	40	13.9
Total	287	100.0
<i>Education</i>		
High school	88	30.7
Superior studies	199	69.3
Total	287	100.0

Respondents characteristics	Frequency (n=287)	Percentage (%)
<i>Occupation</i>		
Employed (including business owner, freelancer)	173	60.3
Student	108	37.6
Other (unemployed, retired)	6	2.1
Total	287	100.0
<i>Field of work</i>		
Business (e.g. Accounting, Consulting, Finance, HR, Marketing)	110	38.3
Engineering & Computer Science (e.g. IT)	42	14.6
Services related activities (e.g. Hospitality)	97	33.8
Other	38	13.2
Total	287	100
<i>Residence</i>		
County seat	99	34.5
City	129	44.9
Village	59	20.6
Total	287	100.0
<i>Satisfaction with financial situation</i>		
(1) very dissatisfied	3	1.0
(2) dissatisfied	22	7.7
(3) neutral	127	44.3
(4) satisfied	106	36.9
(5) very satisfied	29	10.1
Total	287	100.0

Results show that the majority of respondents are female (60.3%) and the largest proportion (51.6%) of respondents by age groups, were those in the 24 years and younger category. 69.3% of respondents finished superior studies and 60.3% of respondents are employed, while 37.6% are students. In terms of field of work/study, the majority of the respondents work or study in the business field (38.3%). The vast majority lives in county seats (34.5%) and cities (44.9%). Overall, 47% of survey respondents are either satisfied or very satisfied with their financial situation.

Table 4 summarizes the descriptive statistics for survey respondents in terms of chatbot usage. Respondents reported that m-banking (44.9%) and i-banking (34.9%) are the technologies that they are commonly using for banking purposes. Seventy respondents (24.4%) stated that they have previously used a banking chatbot, while 75.6% of survey respondents haven't used such a system. The majority of those who have used banking chatbots, used it with a personal banking account (80%) and 30% used it for the first time in the last six months. Finally, 47% of the respondents who have not used a banking chatbot before, stated that they are aware of the existence of the technology.

Table 4: Descriptives of chatbot technology usage among respondents

Respondents characteristics	Frequency	Percentage (%)
<i>Usage of banking technologies</i>	n=287	
I-banking	146	30.9%
M-banking	194	41.1%
M-payment technology	94	19.9%
Other	35	7.4%
None	3	0.6%
Total	472	100%
<i>Have used banking chatbot technology</i>	n=287	
Yes	70	24.4
No	217	75.6
Total	287	100.0
<i>Use of chatbot for different types of banking</i>	n=70	
Personal account	56	80
Business account	4	5.7
Both	10	14.3
Total	70	100
<i>First usage of a banking chatbot</i>	n=70	
This month	7	100
A month ago	11	15.7
6 months ago	21	30
A year ago	13	18.6
More than one year ago	18	25.7
Total	70	100
<i>Awareness of the banking chatbot</i>	n=217	
Yes	102	47.0
No	88	40.6
Don't know	27	12.4
Total	217	100

5.2 Validation of the measurement scale

The analysis of the data was carried out employing a two-phase approach in order to assess the reliability and validity of the measurement items using the Partial Least Squares-Structural Equation Modeling (PLS-SEM). The first phase consisted of the measurement model's analysis, while in the second step, structural relations between latent constructs were tested. The analysis of the measurement model involved the estimation of indicator reliability, internal consistency reliability, composite reliability, convergent validity and discriminant validity (Ringle et al., 2015).

Cronbach's Alpha and composite reliability (CR) were used to measure the reliability, while factor loadings (outer loadings) and Average Variance Extracted (AVE) were applied to measure the convergent validity. The results revealed that the questions measuring the constructs had reasonably acceptable reliability, and

the measures of the latent variables had high levels of convergent validity. As shown in Table 5, the values of Cronbach's Alpha, composite reliability (CR) and factor loadings (outer loadings) were above the threshold value of 0.7, the values of Average Variance Extracted (AVE) were all above the recommended value of 0.5, respectively.

Table 5: Psychometric properties of the constructs

Construct	Indicator	Outer Weights	Outer Loadings	Cronbach's α	CR	AVE
Awareness of service (AW)				0.902	0.907	0.932
	AW 1	0.299	0.914			
	AW 2	0.307	0.822			
	AW 3	0.289	0.921			
	AW 4	0.242	0.858			
Perceived usefulness (PU)				0.928	0.929	0.949
	PE 1	0.26	0.89			
	PE 2	0.283	0.901			
	PE 3	0.273	0.906			
	PE 4	0.286	0.931			
Perceived ease of use (PEOU)				0.933	0.934	0.952
	EE 1	0.259	0.902			
	EE 2	0.289	0.921			
	EE 3	0.275	0.926			
	EE 4	0.273	0.9			
Perceived Compatibility (PC)				0.871	0.876	0.921
	PC 1	0.394	0.887			
	PC 2	0.385	0.916			
	PC 3	0.342	0.871			
Perceived privacy risk (PPR)				0.894	0.935	0.926
	PPR 1	0.288	0.857			
	PPR 2	0.244	0.896			
	PPR 3	0.232	0.814			
	PPR 4	0.379	0.912			
Behavioral intention to use Banking Chatbot (BI)				0.926	0.928	0.947
	BI 1	0.301	0.916			
	BI 2	0.264	0.908			
	BI 3	0.269	0.892			
	BI 4	0.272	0.901			

It has been found that the "Heterotrait-Monotrait ratio (HTMT)" is a significant measure for testing the discriminant validity (Henseler et al., 2015). As shown in Table 6, all the HTMT ratio values were below the suggested value of 0.85, which indicated that all the items satisfied the criteria for good discriminant validity. Thus, the measurement model is verified, and the evaluation of the structural model can be carried out.

In order to confirm and validate the measurement instruments and to define the relationships between observed and unobserved variables, a measurement model consisting of six constructs has been established. Results showed that the fitted

measurement model provided a fairly reasonable fit, the value of NFI being 0.874, which is greater than the threshold value of 0.8 for the model to be considered good (Forza and Filippini, 1998), while the value of SRMR being 0.049 (Hair et al., 2017).

Table 6: Discriminant validity of constructs - Heterotrait-Monotrait Ratio (HTMT)

	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	

5.3 Examination of research hypotheses

The structural model was evaluated by examining the path coefficients beta weight (β) and coefficient of determination (R^2). The β value indicates the strength of the relationships between the dependent and independent variables, while the R^2 value describes the variance explained by independent variables which can be interpreted as the predictive power of the model. The evaluation of the research hypothesis can be seen in Table 7, while Figure 2 shows the statistical analysis' results of the research model.

Results indicate that seven variables have significant statistical support. First, awareness of service is correlated significantly and positively with perceived usefulness ($\beta = 0.143$; $p \leq 0.001$) and perceived ease of use ($\beta = 0.25$; $p \leq 0.001$), and it has a significant and negative effect on perceived privacy risk ($\beta = -0.173$; $p \leq 0.05$). Second, perceived ease of use has significant and positive effect on perceived usefulness ($\beta = 0.168$; $p \leq 0.001$). Perceived compatibility has significant and positive effect on both perceived usefulness ($\beta = 0.581$; $p \leq 0.001$) and perceived ease of use ($\beta = 0.421$; $p \leq 0.001$). Last, intention to use is significantly and positively influenced by perceived usefulness ($\beta = 0.176$; $p \leq 0.05$) and perceived compatibility ($\beta = 0.484$; $p \leq 0.001$). Also, results indicate that perceived ease of use and perceived privacy risk are not correlated with intention to use. Therefore, H1, H3, H4, H5, H6, H8, H9 and H10 were supported by the empirical data, while H2 and H7 were rejected.

Table 7: Assessment of the structural model

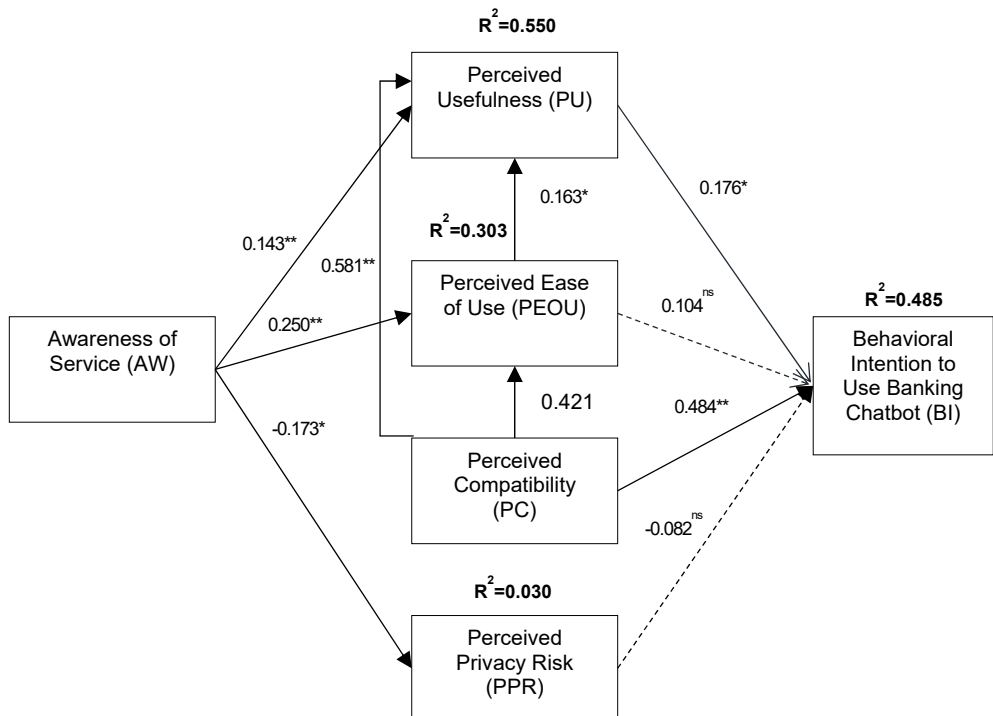
No.	Hypothesis path	Path coefficient (β)	STDEV	t-Value	p- Value	Supported?
H1	PU \rightarrow BI	0.176	0.068	2.601	0.010*	yes
H2	PEOU \rightarrow BI	0.104	0.055	1.909	0.057 ^{ns}	no
H3	PEOU \rightarrow PU	0.168	0.052	3.23	0.001*	yes
H4	PC \rightarrow BI	0.484	0.06	8.116	0.000**	yes
H5	PC \rightarrow PU	0.581	0.047	12.451	0.000**	yes

No.	Hypothesis path	Path coefficient (β)	STDEV	t-Value	p- Value	Supported?
H6	PC \rightarrow PEOU	0.421	0.054	7.807	0.000**	yes
H7	PPR \rightarrow BI	-0.082	0.045	1.81	0.071 ^{ns}	no
H8	AW \rightarrow PU	0.143	0.038	3.763	0.000**	yes
H9	AW \rightarrow PEOU	0.25	0.051	4.896	0.000**	yes
H10	AW \rightarrow PPR	-0.173	0.066	2.63	0.009*	yes

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

The results show that awareness of service, perceived ease of use and perceived compatibility together explain 55% of the variance in perceived usefulness. Moreover, awareness of service and perceived compatibility together explain 30.3% of the variance in perceived ease of use. Also, awareness of services explains 3% of the variance in perceived privacy risk. Finally, perceived usefulness and perceived compatibility together explain 48.5% of the variance in behavioral intention.

Figure 2. Proposed research model for attitude toward banking chatbots



Note: * ($p < 0.05$); ** ($p < 0.001$); ^{ns} and dashed arrows (paths coefficients that are not statistically significant)

6. Discussion

Artificial intelligence based chatbot applications have become a very popular form automatizing customer service processes in the financial sector, transforming communication between banks and consumers. Many banks have implemented chatbots in order to reduce costs and to improve services quality. Thus, it is essential for these institutions to identify factors that influence customer adoption of this technology.

The present study identified two factors that significantly impact customers' intention to use banking chatbots in the Romanian banking industry including, perceived usefulness and perceived compatibility. Moreover, the proposed research model explained 48.5% of the behavioral intention to use banking chatbots, the value being higher than that of 40% found in several studies that adopted TAM (Venkatesh and Davis, 2000).

Among the two identified factors, perceived compatibility has the strongest effect on customers' intention to use banking chatbots which is consistent with earlier findings of i-banking (A. N. Giovanis et al., 2012) and m-banking (Koenig-Lewis et al., 2010) adoption research. The results indicate that the higher is consumers' perception of the banking chatbot being compatible with their lifestyle, the higher their willingness is to adopt the technology. This indicates that it is important to develop and implement banking chatbots in a way that is compatible with the lifestyle and values of the bank's customers. Moreover, the findings of this study indicate that perceived compatibility also has an indirect and significant effect on intention to use chatbots through perceived usefulness and perceived ease of use, meaning that compatibility leads consumers to perceive banking chatbots as being more useful and easier to use. These findings are in line with previous research on i-banking (A. N. Giovanis et al., 2012) and m-banking (Koenig-Lewis et al., 2010) adoption.

Perceived usefulness was also found to be an important antecedent of customers' behavioral intention to use banking chatbots. These findings support observation of previous research into i-banking (Martins et al., 2014) and m-banking (Farah et al., 2018; Koenig-Lewis et al., 2010; Safeena et al., 2012) adoption. Consumers perception of the banking chatbot being useful and representing a quicker and easier way to manage their finances, leads to a higher level of intention to use the banking chatbot.

The effect of perceived ease of use on behavioral intention is disputable in banking technology adoption research. Several studies on i-banking (Alalwan et al., 2018; Martins et al., 2014) and m-banking (Safeena et al., 2012; Farah et al., 2018) adoption found that perceived ease of use significantly and positively influenced usage intention, whereas other studies on i-banking (Pikkarainen et al., 2004) and m-banking (Koenig-Lewis et al., 2010) adoption found no significant results in this regard. The findings of the current study are consistent with the findings of Pikkarainen et al. (2004) on i-banking and the results of Koenig-Lewis et al. (2010) on m-banking who found that perceived ease of use had no significant effect on usage intention. Moreover, the results of the current study indicate that perceived ease of use has a significant indirect effect on behavioral intention to use banking chatbots through perceived usefulness. Several studies found that perceived ease of use has less impact on technology acceptance than perceived

usefulness (Davis, 1989; Venkatesh and Davis, 2000) since perceived ease of use influences technology acceptance through perceived usefulness (Pikkarainen et al., 2004).

Contrary to previous expectations, perceived privacy risk had no significant effect on behavioral intention to use banking chatbots. Even though several studies on the acceptance of i-banking (Giovanis et al., 2012) and m-banking adoption concluded that perceived privacy risk had a direct and negative effect on intention to use (Arif et al., 2016; Shankar and Kumari, 2016), the present study did not find significant relationship in this regard. These results are in line with the findings of Akturan and Tezcan (2012) on m-banking adoption who concluded that perceived privacy risk had no significant effect on usage intention. That lack of evidence on this matter has two explanations. First, in i-banking adoption studies, the dimensions of the perceived risk factor are classified into six groups including, time, financial, performance, social, security, and privacy risks (Hanafizadeh and Khedmatgozar, 2012). According to Aldás-Manzano et al. (2009), not all the risk dimensions are relevant in the context of online banking services. The results of the current study indicate that perceived privacy risk is a risk dimension that is not applicable in banking chatbot adoption. Second, the sample of the current research consisted predominantly of individuals aged 24 or younger with a higher education degree. This age and educational demographic generally has considerable experience of online banking, mobile phone usage and other internet-related activities (Akturan and Tezcan, 2012). Thus, the non-significant relation between perceived privacy risk and behavioral intention can be explained by the age of the respondents of the current study.

Regarding the indirect relationships between the studied constructs, it was found that awareness of the service has an indirect effect on behavioral intention through perceived usefulness. Consistent with the results of Al-somali et al. (2009) on online banking adoption, the more information consumers have about the service, the more useful they find it. Moreover, awareness of the service also has significant and positive effect on perceived ease of use, and significant and negative effect on perceived privacy risk which is in line with the findings of Al-somali et al. (2009) and Hanafizadeh and Khedmatgozar (2012) on online banking. Therefore, high awareness of banking chatbots is a critical factor in banking chatbot adoption.

6.1 Theoretical implications

Results of the current study offer useful insights for academic perspective. First, the present analysis extended technology adoption research to the area of banking chatbot technology with the following variables: perceived usefulness, perceived ease of use, compatibility, privacy risk and awareness. Compatibility and awareness are innovative factors in studying chatbot adoption. Overall, 48.5% of the variance of behavioral intention to use banking chatbots is explained by the proposed conceptual model. Perceived compatibility and perceived usefulness were identified as factors that have direct effect on banking chatbot adoption. Second, results highlight the importance of awareness of service in the context of banking chatbot adoption as the construct has an indirect effect on usage intention through perceived usefulness. Even if this study did not find evidence for the effect of perceived ease of use and perceived privacy risk on behavioral intention, it is

unequivocal that awareness has direct effects on these two variables as well. These results emphasize the importance of awareness of the service and its benefits in the context of technology adoption in the banking industry. Thus, the current study was able to contribute to existing literature on technology adoption in the banking industry, and in the field of chatbot technology adoption.

6.2 Managerial implications

There are several managerial implications of this study for the banking sector. First, significant effects of perceived compatibility and perceived usefulness on behavioral intention indicate that consumers expect banking chatbots to be compatible with their lifestyle and to provide benefits for them. Therefore, communication campaigns should contain this type of information. Second, the role of awareness of the services has indirect effect on usage intentions, which indicate the importance of informing consumers about the existence and benefits of using the banking chatbots. Thus, banks and developers of banking chatbot applications should devote great effort to the factors of utility and compatibility when designing, implementing and upgrading such systems. Moreover, marketing campaigns that emphasize the usefulness and benefits of banking chatbots, namely 24/7 availability of the service, high convenience, ease of use, and the time and cost saving aspect of the application, may attract consumers' attention and could drive the acceptance and use of the technology. As awareness of the service, its features and its benefits could be a key factor in banking chatbot adoption, banks should focus on providing information about the system and communication with consumers in order to encourage the adoption.

6.3 Limitations and future research directions

While the current study adds to the existing literature, its limitations should be acknowledged. First, the questionnaire respondents were mainly young, highly educated individuals whose actions may vary somewhat from the population average. Thus, the study sample is not representative and the findings are not generalizable. Second, this research is not specific to a single banking chatbot application or specific bank. Future research should investigate specific banking chatbot systems as these systems could have unique service features depending on the banks that have implemented them. There could be specific variables that are unique for each chatbot, and other adoption factors that have significant impact on adoption, such as relative advantage, which was not investigated, however, future research is encouraged to fill this gap. Future research also needs to investigate the proposed research model in a different geographic location with special emphasis on rural areas and the model should be tested on a different sample.

7. Conclusion

The adoption of technologies applied in the banking industry are widely studied in the literature. However, a more and more popular and frequently implemented technology, namely chatbot technology in the context of the banking industry, has

received limited attention. To address this research gap, the present study was conducted with the aim of identifying the main factors that influence customers' intention to use the banking chatbot technology. The proposed research model was built by adopting concepts from the TAM model, extending it with compatibility, customers' perceived privacy risk and awareness of the service. Data for the present analysis was collected from 287 consumers via online, applying a self-administrated survey method. The findings supported the conceptual model by predicting 48.5% of variance in the behavioral intention. Perceived usefulness and perceived compatibility significantly predicted the customers' intention to use the banking chatbot. Awareness of the service had an effect on perceived ease of use, perceived privacy risk, and it indirectly affected usage intention through perceived usefulness. Also, perceived ease of use influenced perceived usefulness, and perceived compatibility had an effect on both perceived ease of use and perceived usefulness. Yet, perceived ease of use and perceived privacy risk were not found to be significant determinants of behavioral intention. As a result, the current study was able to make a significant contribution to the field for both academics and practitioners.

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