IDENTIFYING RELEVANT SEGMENTS OF POTENTIAL BANKING CHATBOT USERS BASED ON TECHNOLOGY ADOPTION BEHAVIOR

IDENTIFICIRANJE RELEVANTNIH SEGMENATA POTENCIJALNIH KORISNIKA CHATBOTA U BANKARSTVU NA TEMELJU PONAŠANJA PRI PRIHVAĆANJU TEHNOLOGIJE

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Mónika-Anetta Alt[a], Vizeli Ibolya[b]

[a] Babeş-Bolyai University, Teodor Mihali No. 58-60, 400591 Cluj-Napoca, ROMANIA, e-mail: monika.alt@econ.ubbcluj.ro

[b] Babeş-Bolyai University, Teodor Mihali No. 58-60, 400591 Cluj-Napoca, ROMANIA, e-mail: ibolya.vizeli@stud.ubbcluj.ro

Abstract

Purpose – Chatbot technology is expected to revolutionize customer service in financial institutions. However, the adoption of customer service chatbots in banking remains low. Therefore, the aim of this paper is to identify relevant segments of potential banking chatbot users based on technology adoption behavior.

Design/Methodology/Approach – Data for the research was collected through an online questionnaire in Romania using the non-probability sampling method. The 287 questionnaires were analyzed using hierarchical and k-means cluster analysis.

Findings and implications – The analysis revealed three distinct segments: Innovators (26%), consisting of highly educated young women employed in the business sector; the Late Majority (55%), consisting of young women with higher education degrees who work in services-related fields; and Laggards (19%), consisting of educated middle-aged men employed in the business sector. New significant differences among demographic and banking

Sažetak

Svrha – Očekuje se da će chatbot tehnologija revolucionirati usluge korisnicima u financijskim institucijama. Međutim prihvaćenost chatbota među korisnicima usluga banaka još je uvijek niska. Stoga je cilj ovog rada identificirati relevantne segmente potencijalnih korisnika bankovnih chatbotova na temelju ponašanja pri usvajanju tehnologije.

Metodološki pristup – Podatci su prikupljeni u Rumunjskoj ne temelju neprobabilističke metode uzorkovanja putem online anketnog upitnika. Analizirano je 287 anketnih upitnika primjenom hijerarhijske i k-mean klasterske analize.

Rezultati i implikacije – Analizom su otkrivena tri različita segmenta: Inovatori (26%) koji su visokoobrazovani, mlade žene zaposlene u području poslovne ekonomije; Kasna većina (55%) koju čine mlađe žene s višom stručnom spremom zaposlene u područjima povezanim s uslugama; Kolebljivci (19%) koji su obrazovani, muškarci srednjih godina zaposleni u području poslovne ekonomije. Otkrivene su nove značajne razlike među profilima segmenata behavior variables were observed across the profiles of potential banking chatbot user segments.

Limitations – The study is based on a non-probability sample collected from only one country, with a rather small sample size.

Originality – Technology acceptance variables (perceived usefulness, perceived ease of use), expanded to include constructs such as awareness of service, perceived privacy risk, and perceived compatibility, were found to be appropriate for customer segmentation purposes in the context of chatbot applications based on artificial intelligence. The study also revealed a new innovator demographic profile.

Keywords – artificial intelligence (AI), chatbot, banking industry, technology acceptance, segmentation, customer segments

potencijalnih korisnika chatbota u bankarstvu vezane uz demografske te varijable ponašanja korisnika usluga u bankarstvu.

Ograničenja – Istraživanje se temelji na nepobabilističkom uzorku prikupljenom u samo jednoj zemlji, a veličina uzorka je prilično mala.

Doprinos – Utvrđeno je da su varijable prihvaćanja tehnologije (percipirana korisnost, percipirana jednostavnost korištenja) proširene s konstruktima kao što su svjesnost o usluzi, percipirani rizik privatnosti i percipirana kompatibilnost, prikladne za potrebe segmentacije korisnika u kontekstu chatbot aplikacija temeljenih na umjetnoj inteligenciji. Istraživanje je otkrilo novi demografski profil inovatora.

Ključne riječi – umjetna inteligencija (AI), chatbot, bankarska industrija, prihvaćenost tehnologije, segmentacija, segmenti korisnika

1. INTRODUCTION

It has been reported that 79% of banks expect technologies based on artificial intelligence (AI) to revolutionize the way financial institutions acquire information about their clients and interact with them; 29% think that offering products and services through assistants or messaging bots will be important in the future, and 76% believe that AI interfaces will become the primary interaction point between banks and customers in following years (Accenture, 2017). Consequently, the so-called chatbot technology is a frequently adopted form of AI in the financial and banking sector (Richad, Vivensius, Sfenrianto & Kaburuan, 2019).

A chatbot is a computer program that is able to carry out basic tasks (Nguyen & Sidorova, 2017). By using chatbots, businesses and government agencies can interact with customers (Shumanov & Johnson, 2021) 24/7 at a reduced cost, addressing them in a relevant and personalized manner (Zumstein & Hundertmark, 2017). One of the most common uses for chatbots is in customer service, which presents new possibilities for business communication, cost saving, and increasing sales (Heo & Lee, 2018). Moreover, AI-based chatbots are implemented in the financial industry with the expectation of enhancing customer experience, improving operational efficiency, and supporting existing personnel (Jang, Jung & Kim, 2021). Although chatbots have clear benefits for both banks and customers (Zumstein & Hundertmark, 2017), the implementation of chatbots in customer service is still in an early stage (Følstad, Nordheim & Bjørkli, 2018). Recent papers dealing with chatbots have analyzed factors determining technology adoption in the context of learning and higher education (Almahri, Bell & Merhi, 2020; Fryer, Nakao & Thompson, 2019), retail (Rese, Ganster & Baier, 2020), and tourism (Melián-González, Gutiérrez-Taño & Bulchand-Gidumal, 2021). However, findings obtained in various fields may not be transferable to the context of financial services (Cardona, Werth, Schönborn & Breitner, 2019). Thus, specific research is necessary in the relevant sectors such as banking.

Identifying distinct consumer groups based on their innovation adoption behavior (Rogers, 1983) can help banks to plan and implement appropriate strategies for addressing different customer needs. Therefore, segmenting customers based on their behavioral characteristics (e.g., innovation adoption) has become a widely researched topic in the literature. In the banking context, several authors have attempted to segment customers based on factors that influence the adoption of m-banking (Alavi & Ahuja, 2016; Chawla & Joshi, 2017) and i-banking (Patsiotis, Hughes & Webber, 2012). Although these studies provide a useful contribution to customer segmentation based on technology adoption factors within the banking industry, there is limited knowledge on the acceptance of banking chatbot technology. While certain studies have examined chatbot adoption within the financial (Cardona et al., 2019) and banking (Richad et al., 2019) industries, research in this area remains scarce. Moreover, in those studies, respondents were not grouped into distinct consumer segments based on their technology acceptance behavior, but were perceived as a single group.

Therefore, this paper aims to address this research gap by segmenting potential banking chatbot users based on the Technology Acceptance Model (TAM). The originality of this paper is threefold. First, it examines a relatively new type of technology applied in the banking industry, namely chatbot technology. Research related to chatbots is very scarce and, to our knowledge, a segmentation approach has not yet been studied. Second, it further expands the literature on customer segmentation based on technology acceptance behavior. Usually, consumer segmentation is based on descriptive characteristics, with consumer profiles being described with the use of behavioral variables. A modern segmentation approach promotes clustering with behavioral variables, such as technology acceptance, and describes consumer segments based on descriptive characteristics. Finally, it identifies a new innovator profile with regard to technology acceptance in the financial industry.

The paper is structured as follows. First, the literature review section examines the adoption of chatbot technology, as well as technology adoption and customer segmentation in the context of financial services. Next, the sample and the measures applied are described in the research methodology section. Thereafter, the results and a discussion of the results are provided. Finally, the conclusions are formulated, including the contribution made and its implications for theory and practice, and the limitations of the study, as well as possible directions for further research are presented.

2. LITERATURE REVIEW

2.1. Chatbot technology adoption

The term "chatbot", consisting of the words "chat" and "robot", was originally used for a computer program which replicated human language with the help of a text-based dialogue system (Zumstein & Hundertmark, 2017). Chatbots are implemented into messaging platforms (Araujo, 2018), such as Facebook Messenger and WhatsApp, as well as the websites of service providers. Thus, chatbots are able to offer fast and reliable responses to customer requests, representing a resource-efficient channel for the service providers (Følstad et al., 2018), and can have an important role in developing and strengthening consumer-brand relationships (Youn & Jin, 2021).

Although chatbots are becoming widely implemented in customer service, research on the adoption of this technology in customer assistance is still in an early stage (Følstad et al., 2018). Several authors have attempted to study the adoption of chatbot technology in different contexts. For instance, Almahri and others (2020) applied a modified UTAUT2 model in order to examine the adoption of chatbots in higher education. The results showed that performance expectancy, effort expectancy, and habit predicted participants' behavioral intention to use chatbot technology. Rese and others (2020) studied the acceptance of chatbots in the retail industry by applying the technology acceptance model (TAM) and the uses and gratifications (U&G) theory. The results indicated that utilitarian factors (e.g., authenticity of conversation, perceived usefulness) and hedonic factors (e.g., perceived enjoyment) had a positive effect on the acceptance of the studied chatbot. Privacy concerns and the immaturity of the technology, on the other hand, had a negative effect on usage intention and frequency of usage. Melián-González and others (2021) studied the adoption of chatbots in tourism by adopting the UTAUT2 model. They found that performance expectancy, hedonic motivation, habit, attitude towards the use of self-service technologies, and anthropomorphism had a positive impact on the intention to use chatbots, while inconvenience and problems relating to communication with the chatbot led to negative effects (Melián-González et al., 2021). Although research on the adoption of chatbots in different contexts provides useful insights for the study of chatbot adoption in banking, these results may not be directly transferable to financial and banking services (Cardona et al., 2019).

As established by Cardona et al. (2019), potential customers in the financial sector, which is highly conservative and regulated, may express affective and behavioral reactions towards the adoption of chatbots that differ from those in other usage contexts (e.g., tourism, health care, higher education, or retail). The study in question found that relative advantages and information system infrastructure are the most critical factors for the adoption and diffusion of chatbot technology in the insurance context. It was also shown that, although the majority of the study participants were familiar with chatbot technology and would prefer to use it at the beginning of the advisory process, one third of them completely rejected the adoption of chatbots due to a low level of trust. The findings were based on semi-structured expert interviews and a web-based survey, yet mostly descriptive statistical analysis was carried out. Only one study in Asia applied and analyzed a conceptual model based on TAM in order to examine the adoption of banking chatbots (Richad et al., 2019). The findings showed that innovativeness positively influenced perceived usefulness and perceived ease of use, which had a positive effect on attitude towards chatbot use. Ultimately, attitude led to positive effects on the usage intention of chatbot technology.

Although the reviewed studies (Table 1) have significant implications for the understanding of chatbot adoption in banking and financial services, they examined only one consumer group that would either reject or accept chatbot technology. However, in order for innovations to be successful, they must be adopted by all relevant groups, which might differ from each other in their needs and technology perceptions (Plouffe, Vandenbosch & Hulland, 2001). It can be concluded that there is limited knowledge on the acceptance of chatbot technology across different consumer groups. Therefore, further research needs to be conducted taking account of multiple groups in the adoption process of chatbot technology.

As the study of chatbot adoption is in an early stage, there is limited knowledge on the factors that affect the acceptance of chatbot technology among consumers in the banking sector. Thus, we believe that previous research on the acceptance of other banking innovations (e.g., i-banking and m-banking) could provide important insights for studying chatbot adoption in the banking industry.

TABLE 1: Summary of studies regarding chatbot adoption

Authors	The aim of the study/context	Theories / Studied variables	Results
(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	51% of the respondents were familiar with chatbot technology. 47% would prefer the use of chatbots at the beginning of the advisory process, 33% rejected the adoption. Relative advantages and IS infrastructure were the most critical adoption factors.
(Richad et al., 2019)	Acceptance of chatbots in the Indonesian banking industry	TAM: perceived usefulness, perceived ease of use, attitude towards usage, behavioral intention Additional variable: innovativeness	Innovativeness explained 23% of perceived ease of use. Innovativeness and perceived ease of use explained 52% of perceived usefulness. Perceived usefulness and perceived ease of use explained 24% of the attitude towards usage, and attitude towards usage explained 59% of behavioral intention.

Authors	The aim of the study/context	Theories / Studied variables	Results
(Almahri et al., 2020)	Acceptance and usage of chatbots in higher education in the UK	UTAUT2: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, behavioral intention, use	Performance expectancy, effort expectancy, and habit predicted behavioral intention to use chatbots.
(Rese et al., 2020)	Analysis of the acceptance of chatbot technology in the German retail industry	TAM: perceived usefulness, perceived ease of use, perceived enjoyment, behavioral intention U&G: convenience, authenticity of conversation, enjoyment, pastime, privacy concerns, immature technology, behavioral intention	Authenticity of conversation, perceived usefulness, and perceived enjoyment positively influenced chatbot adoption. Privacy concerns and the immaturity of the technology had negative effects on usage intention and frequency of usage. The predictive power of both models (U&G, TAM) was similar, but U&G gave alternative insights into the customers' motivation to use the chatbot.
(Melián-González et al., 2021)	Intention to use chatbots in the Spanish tourism industry	UTAUT2: performance expectancy, effort expectancy, social influence, hedonic motivation, habit, usage intention Additional variables: perceived innovativeness, attitude towards SSTs, inconveniences, anthropomorphism, automation	Performance expectancy, habit, hedonic motivation, the predisposition to use SSTs, social influence, and anthropomorphism positively influenced chatbot usage intention. Inconvenience and problems relating to communication with the chatbot had a negative effect on usage intention. The factors explained 49.5% of the variance in usage intention.

2.2. Technology adoption in the banking industry

Not only have technological advancements in recent decades had a profound effect on the banking industry, but it is believed that the development of AI-based chatbots will alter the relationship between consumers and financial institutions even further (De Bruyn, Viswanathan, Beh, Brock & von Wangenheim, 2020). The performance of customer service tasks through chat interfaces is being increasingly prioritized in the banking sector. Thus, reviewing prior research regarding technology acceptance in the banking industry could provide valuable insights for studying banking chatbot adoption.

An extensive literature review on i-banking and m-banking adoption found a positive attitude towards the technology, behavioral intention to use, and the actual technology usage to be the key dependent variables (Shaikh & Karjaluoto, 2015; Yousafzai, 2012). Behavioral intention has also been applied in previous chatbot adoption studies (Almahri et al., 2020; Melián-González et al., 2021; Rese et al., 2020; Richad et al., 2019). Since banking chatbot technology is currently in an early adoption phase, behavioral intention would be the most appropriate measure for explaining adoption.

Perceived ease of use and perceived usefulness, as fundamental variables of TAM, were also found to be key factors explaining usage intention towards a new type of technology implemented in the financial and banking industry (Dahlberg, Guo & Ondrus, 2015; Shaikh & Karjaluoto, 2015). Moreover, these two factors proved to be significant ascendants of attitude towards banking chatbots, which ultimately affected usage intention (Richad et al., 2019). Thus, it is expected that usefulness and ease of use will also influence banking chatbot adoption. In addition, perceived compatibility, which is part of the diffusion of innovation theory, was also found to be a key determinant for m-banking (Giovanis, Athanasopoulou, Assimakopoulos & Sarmaniotis, 2019), i-banking (Giovanis, Binioris & Polychronopoulos, 2012), and chatbot adoption in the insurance sector (Cardona et al., 2019). Hence, it is expected that compatibility will also influence the acceptance of banking chatbots. Moreover, Sathye (1999) found that, apart from the standard technology acceptance variables, the awareness of a new product and its benefits is also an important adoption factor when it comes to innovative technologies. As chatbot technology is a relatively new technological trend (Rese et al., 2020), it is possible that many potential banking customers are not yet aware of its existence and benefits. Thus, greater customer awareness of the service is expected to influence the adoption of banking chatbots. On the other hand, the acceptance of a new technology might be inhibited directly or indirectly (Moldovan & Saplacan, 2018) by several factors. For instance, perceived privacy risk was found to be a barrier for the adoption of m-banking (Arif, Afshan & Sharif, 2016) and i-banking (Giovanis et al., 2012). Also, privacy concerns had a negative effect on chatbot usage intention in the retail (Rese et al., 2020) and insurance (Cardona et al., 2019) sectors. Therefore, it is assumed that perceived privacy risk could also hinder the adoption of banking chatbots.

Based on the reviewed literature on innovation adoption in banking and prior research of chatbot acceptance, this paper attempts to segment potential banking chatbot users based on the key variables of TAM (perceived usefulness, perceived ease of use), which have been expanded to include perceived compatibility, awareness of service, and perceived privacy risk.

2.3. Customer segmentation in the financial services context

Market segmentation can be defined as the process of identifying and profiling heterogeneous groups of consumers, which differ in terms of their needs and wants (Kotler & Keller, 2012). The consumer segmentation process in the context of financial services and the banking industry is generally based on the traditional methods of segmentation, such as demographic characteristics (Henrique & de Matos, 2015), potential value of current customers (Ekinci, Uray & Ülengin, 2014), and customer lifetime value (Estrella-Ramón, Sánchez-Pérez, Swinnen & VanHoof, 2017).

Factors determining the adoption of a new technology might vary among different consumer segments (Chawla & Joshi, 2017). As Rogers (1983) suggested, the adoption of innovation may take time and distinct groups can be identified based on their adoption behavior which, in most populations, shows the following pattern: innovators (2%), early adopters (14%), the early majority (34%), the late majority (34%), and laggards (16%). Thus, increased emphasis was placed on the application of behavioral characteristics, such as information channel preference, purchase channel preference, and technology acceptance, in customer segmentation in the financial services context (Alt, Săplăcan, Benedek & Nagy, 2021). Moreover, studies on the adoption of i-banking (Patsiotis et al., 2012) and m-banking (Alavi & Ahuja, 2016; Chawla & Joshi, 2017) found that distinct customer segments can be identified based on technology acceptance behavior (Table 2) in the banking context.

TABLE 2: Customer segmentation based on technology adoption factors in the banking industry

Authors	Analyzed technology	Factors used for segmentation	Obtained segments
(Patsiotis et al., 2012)	i-banking	interactivity, knowledge, human interaction, emotional elements, lack of trial	Advanced users The concerned majority The unconcerned majority
(Alavi & Ahuja, 2016)	m-banking	perceived usefulness, perceived ease of use, perceived as alternative option, perceived risk and cost, need for information	Cognizant indubitables Conservative apprehensives Internet-savvy inquisitives
(Chawla & Joshi, 2017)	m-banking	ease of use, convenience, efficiency, trust, lifestyle	Technology adoption leaders Technology adoption followers Technology adoption laggards
This study	banking chatbot	perceived usefulness, perceived ease of use, perceived compatibility, awareness of service, perceived privacy risk	-

Based on the reviewed literature on the adoption of chatbots and other innovations in the banking industry, the first hypothesis is formulated as follows:

H1: Potential banking chatbot users can be segmented based on the dimensions of technology adoption behavior: perceived usefulness, perceived ease of use, perceived compatibility, awareness of service, and perceived privacy risk.

Building on to the literature on customer segmentation based on technology acceptance behavior in the banking industry (Alavi & Ahuja, 2016; Chawla & Joshi, 2017; Patsiotis et al., 2012; Zadeh, Faraahi & Mastali, 2011), the present study makes use of the following demographic covariates in order to identify the profile of the potential banking chatbot users based on their adoption behavior: gender, age, education, occupation, residence, and satisfaction with financial situation. In line with the opinion of industry experts, the study aims to include the field of work as a demographic variable in the profiling process, thus expanding on the existing literature on customer segmentation in the banking industry. Finally, selected channels used for accessing banking services (i-banking, m-banking, m-payment, banking chatbots) were also included in the customer profiling process (Chawla & Joshi, 2017). Therefore, the following hypotheses are formulated:

H2.1: Potential banking chatbot users are distinct in terms of gender.

H2.2: Potential banking chatbot users are distinct in terms of age.

H2.3: Potential banking chatbot users are distinct in terms of education.

H2.4: Potential banking chatbot users are distinct in terms of occupation.

H2.5: Potential banking chatbot users are distinct in terms of residence.

H2.6: Potential banking chatbot users are distinct in terms of satisfaction with their financial situation.

H2.7: Potential banking chatbot users are distinct in terms of field of work/study.

H2.8: Potential banking chatbot users are distinct in terms of i-banking usage.

H2.9: Potential banking chatbot users are distinct in terms of m-banking usage.

H2.10: Potential banking chatbot users are distinct in terms of m-payment usage.

H2.11: Potential banking chatbot users are distinct in terms of chatbot usage.

3. RESEARCH DESIGN AND METODOLOGY

The present study aims to segment potential banking chatbot users based on the factors that influence consumer intention to use banking chatbot technology. This study is part of a project exploring the adoption of banking chatbot technology.

3.1. Sample and data

Data collection took place in Romania, where 4 out of 32 banking institution (Curs BNR, 2020) had already implemented banking chatbots by 2020. A total of 307 questionnaires were collected via an online survey between April and May 2020. The study period coincided with the pandemic, when the use of digital channels was highly recommended for all services. Data was assessed for multivariate outliers using the Mahalanobis distance test (Tabachnick & Fidell, 2007). Twenty multivariate outliers were identified and removed, leaving 287 questionnaires in the final sample (Table 3).

Cluster analysis was employed to segment consumers based on five constructs measuring banking chatbot adoption behavior. This is a popular and widely used approach for establishing market segments; however, there are no universally recognized guidelines for the sample size required for cluster analysis (Dolnicar, 2002). According to Formann (1984), the minimum sample size should be no less than 2^k instances, where k is equal to the number of variables included in the analysis; ideally, the sample should be least $5*2^k$. Dolnicar, Grün, Leisch, and Schmidt (2014) recommend that the sample size should be around 70 times the number of variables included in the study for the cluster analysis findings to be appropriate. As a result, the sufficient sample size was determined to be between 160 and 350. The current study's final sample size was 287, which was deemed acceptable for conducting the cluster analysis s.

3.2. Variables and measures

The questionnaire consisted of 25 questions covering general banking technology usage

TABLE 3: Sample demographics

Demographics	Frequency	%	Demographics	Frequency	%
Gender			*Field of work*		
male	114	39.7	business	110	38.3
female	173	60.3	engineering	42	14.6
Age			services-related	97	33.8
24 and younger	148	51.6	other	38	13.2
25-44	99	34.5	*Residence*		
45 and older	40	13.9	county seat	99	34.5
Education			city	129	44.9
secondary education	88	30.7	village	59	20.6
higher education	199	69.3	*Satisfaction with financial situation*		
Occupation			(1) very dissatisfied	3	1.0
employed	173	60.3	(2) dissatisfied	22	7.7
student	108	37.6	(3) neutral	127	44.3
other	6	2.1	(4) satisfied	106	36.9
			(5) very satisfied	29	10.1

behavior and technology acceptance behavior with regard to banking chatbots and demographics. The measurement items used in the study were adapted from previously validated measures or developed based on the literature review. The questionnaire items and their sources are presented in Table 4. Applying a forward-backward method, the questionnaire was translated from English into Romanian. A five-point Likert scale ranging from "completely disagree" (1) to "completely agree" (5) was used in all statements. A pilot test of the measures was carried out on a sample of five randomly chosen individuals. Questionnaire statements were modified based on the results of the pilot test.

TABLE 4: Results of the factor analysis

Construct	Observed variable	Factor loading	Cronbach's α
Factor 1: Perceived usefulness (Davis, 1989; Venkatesh, Thong & Xu, 2012)	I find the banking chatbot useful in my daily life.	0.820	0.928
	Using the banking chatbot increases my chances of achieving things that are important to me.	0.782	
	Using the banking chatbot helps me accomplish things more quickly.	0.819	
	Using the banking chatbot increases my productivity.	0.824	
Factor 2: Perceived ease of use (Davis, 1989; Venkatesh et al., 2012)	Learning how to use the banking chatbot is easy for me.	0.862	0.933
	My interaction with the banking chatbot is clear and understandable.	8.43	
	I find the banking chatbot easy to use.	0.865	
	It is easy for me to become skillful at using the banking chatbot.	0.845	
Factor 3: Perceived compatibility (Moore & Benbasat, 1991; Schierz, Schilke & Wirtz, 2010)	Using the banking chatbot fits well with my lifestyle.	0.593	0.871
	Using the banking chatbot fits well with the way I like to interact with companies.	0.650	
	I would appreciate using the banking chatbot instead of alternative modes of customer service.	0.781	
Factor 4: Perceived privacy risk (Yang, Liu, Li & Yu, 2015)	Private information could be misused, inappropriately shared, or sold when using the banking chatbot.	0.852	0.894
	Personal information could be intercepted or accessed when using the banking chatbot.	0.903	
	Personal information could be collected, tracked, and analyzed when using the banking chatbot.	0.827	
	Privacy could be exposed or intruded on when using the banking chatbot.	0.878	

Construct	Observed variable	Factor loading	Cronbach's α
Factor 5: Awareness of service (Al-somali, Gholami & Clegg, 2009; Guesalaga, 2016)	My bank has communicated a banking chatbot usage policy to me.	0.884	0.902
	My bank has a strategy regarding the usage of the banking chatbot.	0.728	
	I have received sufficient information from my bank regarding the usage of the banking chatbot.	0.901	
	I have received recommendations from my bank on the use of the banking chatbot in the context of the COVID-19 pandemic.	0.874	
Factor 6: Behavioral intention (Davis, 1989; Venkatesh et al., 2012)	Given the opportunity, I will use the banking chatbot.	0.804	0.925
	I am likely to use the banking chatbot in the near future.	0.853	
	I am willing to use the banking chatbot in the near future.	0.832	
	I intend to use the banking chatbot when the opportunity arises.	0.829	

Note: KMO=0.897, 80.80% of the variance explained.

3.3. Methodology

During the customer profiling process, a series of behavioral variables was included. For the multi-item behavioral variables, principal component exploratory factor analysis was performed applying Euclidean distance with Varimax rotation. The conditions for the application of factor analysis were satisfied (KMO=0.897; $\chi2$ for Bartlett's test of sphericity = 5473.457; DF=253; $p<0.05$). The factor analysis revealed six factors (KMO=0.897; 80.80% of the variance explained). Table 4 illustrates the results of the factor analysis.

In order to carry out the segmentation procedure, hierarchical cluster analysis (Hair, Black, Babin & Anderson, 1998) was conducted with the aim of gaining insight into the number of potential clusters. Afterwards, k-means cluster analysis (Hartigan & Wong, 1979) was carried out using the average scores of variables that influence banking chatbot adoption. Three clusters were identified and appropriately labeled based on the innovation adoption behavior proposed by Rogers (1983).

As the next step, comparisons of the behavioral intention to use banking chatbots were made, using a one-way analysis of variance to examine whether it varied across the obtained clusters. In case a significant difference was found, a post hoc test was conducted to examine the degree of difference between various cluster pairs. Also, one-way ANOVA and Chi-square tests were used to analyze possible variations in the three clusters, specifically concerning the demographic variables, such as gender, age, education, occupation, field of work, residence, satisfaction with financial situation, and banking technology usage variables including i-banking, m-banking, m-payment, and banking chatbot usage behavior. Based on the results, a cluster profile was developed using a similar approach to that adopted by Chawla and Joshi (2017).

4. RESULTS AND DISCUSSION

Based on the results, three distinct segments with distinguishable intention to use banking chatbot technology were identified: Innovators (26%), the Late Majority (55%), and Laggards (19%). The results indicated that the three clusters distinctly differed from each other in terms of the importance they assigned to the five dimensions of banking chatbot adoption (Table 5). Similar results were obtained by previous research on customer segmentation in the context of i-banking (Patsiotis et al., 2012) and m-banking (Alavi & Ahuja, 2016; Chawla & Joshi, 2017). Consequently, potential banking chatbot users could be segmented based on technology acceptance behavior (perceived usefulness, perceived ease of use, awareness of service, perceived privacy risk, and perceived compatibility) when it comes to banking chatbots. Thus, H1 was accepted.

Furthermore, in order to better understand the adoption of banking chatbots, the three identified clusters were analyzed with respect to the factor of behavioral intention to use banking chatbot technology (Table 6). A significant difference in the average scores for usage intention was observed among the three clusters, so the intention to use banking chatbots varied across the three clusters. The usage intention of the Innovators was significantly higher than that of the Late Majority and Laggards. Similarly, the intention of the Late Majority was significantly higher than that of the Laggards. These results are consistent with previous research on customer segmentation in terms of i-banking (Patsiotis et al., 2012) and m-banking adoption (Chawla & Joshi, 2017).

TABLE 5: Final cluster centers indicating difference in average scores of chatbot adoption dimensions across clusters

Banking chatbot adoption dimensions	Cluster 1 (Innovators)	Cluster 2 (Late Majority)	Cluster 3 (Laggards)
Perceived usefulness	3.85	3.34	1.74
Perceived ease of use	4.26	3.63	2.86
Awareness of service	3.85	2.23	1.99
Perceived privacy risk	2.79	3.12	3.23
Perceived compatibility	3.70	3.18	1.82
No of cases (N)	75	158	54

Note: A five-point Likert scale ranging from "completely disagree" (1) to "completely agree" (5) was used.

TABLE 6: Significant one-way ANOVA test and post hoc test results between average scores of behavioral intention to use banking chatbots and clusters

Dependent variable	DF	F-statistic	Significance	Independent groups (n)	Mean difference
Behavioral intention to use banking chatbots	2	57.098	0.000	Innovators – Late Majority	0.55215*
				Late Majority – Laggards	1.49296*
				Innovators – Laggards	0.94081*

Note: * ($p<0.05$)

Moreover, the existence of a relationship existed between the obtained clusters and different demographic variables was also tested (Table 7). First, the relationship between the obtained clusters and gender was studied. Despite previous research findings (Chawla & Joshi, 2017; Patsiotis et al., 2012), the current study's results showed that there was a significant difference ($\chi2=8.305$; $p<0.05$) in the degree of banking chatbot adoption between male and female respondents. Second, the relationship between the three clusters and age was tested. In line with previous research (Chawla & Joshi, 2017), the results pointed to a significant difference ($\chi2=21.993$; $p<0.05$) in the degree of banking chatbot adoption between the different age groups. Third, the relationship between the identified clusters and field of work was analyzed, revealing a significant difference ($\chi2=19.716$; $p<0.05$) in the degree of banking chatbot adoption between the different fields of study or work, and thus expanding on the literature on the segmentation of potential banking customers with a new demographic covariate. Therefore, H2.1, H2.2 and H2.7 were accepted. Lastly, the relationship between the three clusters on the one hand and education, occupation, residence, and satisfaction with financial situation on the other was tested. In contrast with previous research on customer segmentation based on i-banking (Patsiotis et al., 2012) and m-banking adoption (Chawla & Joshi, 2017), this study did not find a significant difference between the clusters in terms of those demographic characteristics. Therefore, H2.3, H2.5, and H2.6 were rejected.

TABLE 7: Demographic profile of identified clusters (%)

Demographics	Innovators	Late Majority	Laggards	Total	χ2 / F	p-value
Sample size*	26	55	19	100		
Gender					8.305	0.016
male	30.7[a]	38.6[a, b]	55.6[b]	39.7		
female	69.3[a]	61.4[a, b]	44.4[b]	60.3		
Age					21.993	0.015
24 and younger	49.3[a, b]	58.2[b]	35.2[a]	51.6		
25-44	34.7[a]	31.6[a]	42.6[a]	34.5		
45 and older	16.0[a]	10.1[a]	22.2[a]	13.9		
Education					2.255	0.324
secondary education	33.3[a]	32.3[a]	22.2[a]	30.7		
higher education	66.7[a]	67.7[a]	77.8[a]	69.3		
Occupation					4.897	0.298
employed	69.3[a]	55.7[a]	61.1[a]	60.3		
student	29.3[a]	42.4[a]	35.2[a]	37.6		
other	1.3[a]	1.9[a]	3.7[a]	2.1		
Field of work					19.716	0.003
business	56.0[a]	32.3[b]	31.5[b]	38.3		
engineering	9.3[a]	13.9[a]	24.1[a]	14.6		
services-related activities	29.3[a]	38.0[a]	27.8[a]	33.8		
other	5.3[a]	15.8[a]	16.7[a]	13.2		
Residence					3.982	0.408
county seat	29.3[a]	35.4[a]	38.9[a]	34.5		
city	45.3[a]	47.5[a]	37.0[a]	44.9		
village	25.3[a]	17.1[a]	24.1[a]	20.6		
Satisfaction with financial situation					.581	.560
Mean	3.56	3.44	3.46			

Notes: *N=287; [a] Post-hoc comparison revealed significant difference ($p<0.05$) from Innovators; [b] Post-hoc comparison revealed significant difference ($p<0.05$) from the Late Majority.

Whether or not the three clusters differed in terms of selected banking technology usage behavior was also examined. Respondents were asked to select the technologies they used for banking purposes from a list provided to them. Afterwards, the relationship between the obtained clusters and usage behavior with respect to the selected banking technology was tested (Table 8). A significant difference in terms of i-banking usage ($\chi2=7.367$; $p<0.05$), m-banking usage ($\chi2=11.398$; $p<0.05$), and banking chatbot usage ($\chi2=50.819$; $p<0.05$) was found to exist between the three clusters. Thus, H2.8, H2.9, and H2.11 were accepted. In terms of m-payment usage behavior, no significant difference was revealed between the studied clusters; therefore, H2.10 was rejected.

previous research indicating that, in the innovator groups, men are in the majority (Chawla & Joshi, 2017; Patsiotis et al., 2012). Moreover, this segment is aged 24 years or younger (49.3%), while earlier findings (Chawla & Joshi, 2017; Patsiotis et al., 2012) indicate that innovators mainly belong to the age group of between 25 and 35. Similar to earlier findings (Chawla & Joshi, 2017; Patsiotis et al., 2012), this segment has higher education qualifications (66.7%). The results also indicate that this group consists of employed persons (69.3%), working mainly in business-related fields (56%) and living in cities (45.3%). On a scale of 1 to 5, their average score given to satisfaction with their financial situation is above 3.5, the highest of all three segments. In line with previous research (Chawla & Joshi, 2017), the seg-

TABLE 8: Cross-tabulation of the identified clusters with usage of selected banking technology services (%)

Technology used	Innovators	Late Majority	Laggards	Total	χ2	p-value
Sample size*	26	55	19	100		
i-banking usage					7.367	0.025
Yes	58.7[a]	43.7[a]	61.1[a]	50.9		
No	41.3[a]	56.3[a]	38.9[a]	49.1		
m-banking usage					11.398	0.003
Yes	80.0[a]	67.1[a, b]	51.9[b]	67.6		
No	20.0[a]	32.9[a, b]	48.1[b]	32.4		
m-payment usage					4.442	0.109
Yes	41.3[a]	31.6[a]	24.1[a]	32.8		
No	58.7[a]	68.4[a]	75.9[a]	67.2		
Banking chatbot usage					50.819	0.000
Yes	54.7[a]	12.7[b]	16.7[b]	24.4		
No	45.3[a]	87.3[b]	83.3[b]	75.6		

Notes: *N=287; [a] Post-hoc comparison revealed significant difference ($p<0.05$) from Innovators;

[b] Post-hoc comparison revealed significant difference ($p<0.05$) from the Late Majority.

The profile of the respondents in the obtained clusters below. Cluster 1, labelled as Innovators (26%), is the second-largest obtained segment. The majority of the respondents in the Innovators segment are female (69.3%). One recent study revealed that women perceived themselves to have a higher level of financial knowledge than men (Lučić, Barbić & Uzelac, 2020). However, these results are inconsistent with ment's average scores for perceived usefulness, perceived ease of use, awareness of service, and perceived compatibility constructs are close to or above 4, representing the highest values of the three segments. Moreover, the average score for perceived privacy risk stands below 3, representing the lowest value of the three clusters. The segment's intention towards banking chatbot usage is also high (4.03), indicating that this segment is willing to adopt banking chatbots, which supports earlier findings (Chawla & Joshi, 2017). Lastly, in terms of selected banking technology usage behavior, the majority have used i-banking (58.7%), m-payment (41.3%), and banking chatbots (54.7%). M-banking usage has the highest score among Innovators (80%), in line with previous research findings (Chawla & Joshi, 2017).

Cluster 2, labelled as the Late Majority (55%), consists mostly of women (61.4%). Similar to previous research (Chawla & Joshi, 2017; Patsiotis et al., 2012), this segment represents young adults aged 24 years or younger (58.2%) who have participated in higher education (67.7%). The results indicate that they are also employed (55.7%), with the majority working in services-related fields (38.0%) and living in cities (47.5%). The segment's average score for satisfaction with their financial situation is 3.44, which is the lowest of all three segments. In line with earlier research (Chawla & Joshi, 2017), this segment's average scores for perceived usefulness, perceived ease of use, awareness of service, and perceived compatibility constructs fall between 3.12 and 3.63, indicating that the segment is moderately positively inclined towards banking chatbot technology (Chawla & Joshi, 2017). Moreover, the average value for perceived privacy risk stands at 3.12, which suggests that respondents have concerns regarding data privacy. In line with Chawla and Joshi (2017), their intention towards banking chatbot usage is moderate (3.47). Lastly, in terms of selected banking technology usage behavior, fewer respondents have used i-banking (43.7%), m-banking (67.1%), m-payment (31.6%), and banking chatbots (12.7%) compared to the Innovators segment. These results correlate with the findings of Chawla and Joshi (2017).

Cluster 3, labelled as Laggards (19%), represents the smallest identified segment, which is in line with the findings of Chawla and Joshi (2017). This group mostly consists of men (55.6%) aged between 25 and 44 years (42.6%) who have participated in higher education (77.8%), who are employed (61.1%) mostly in business-related fields (38.0%), and live in county seats (38.9%). These results support earlier findings on banking customer segmentation based on m-banking adoption (Chawla & Joshi, 2017). The segment's average score for satisfaction with their financial situation is above 3.46, which is slightly higher than in the case of the Late Majority segment, which can be explained by the higher average age of the group. Similarly, the average scores for perceived usefulness, perceived ease of use, awareness of service, and perceived compatibility constructs fall between 1.82 and 2.86, indicating that the segment has little knowledge about the existence of banking chatbots and does not perceive them as being useful, easy to use, or compatible with their lifestyles. These results support previous findings on customer segmentation based on m-banking adoption (Chawla & Joshi, 2017). Moreover, the average value for perceived privacy risk stands at 3.23, showing that this segment has the greatest concerns regarding data privacy. Their intention towards banking chatbot usage is very low (2.53), indicating that they are not willing to adopt banking chatbots (Chawla & Joshi, 2017). Lastly, in terms of selected banking technology usage behavior, Internet banking was found to be popular (61.1%), representing the highest value of the identified clusters. This is in contrast with the findings of Chawla and Joshi (2017), who found that i-banking usage is higher in the case of innovators. Also, only a smaller part of the segment has used m-banking (51.9%), m-payment (24.1%), or banking chatbots (16.7%).

5. IMPLICATIONS FOR THEORY AND PRACTICE, LIMITATIONS AND FUTURE RESEARCH

From a theoretical perspective, this study provides novel insights into the segmentation of potential banking customers based on their behavioral characteristics. The results indicate that the technology acceptance variables (perceived usefulness, perceived ease of use), expanded to include constructs such as awareness of service, perceived privacy risk, and perceived compatibility, are appropriate for consumer segmentation purposes in the context of AI-based chatbot applications. Moreover, the demographic covariate, as well as field of work/study, was found to be a significant variable in profiling consumers.

The research results also have managerial implications for financial institutions, outlining the importance of awareness of service in the technology adoption process. Therefore, when implementing new types of technology, banks should focus their communication on the benefits of the technology, highlighting important factors such as ease of use, high level of usefulness and compatibility, and low level of risk and data privacy issues associated with the use of the system. Offering all the information necessary and implementing incentives to reward the actual usage could be an important driver of the adoption phase. Moreover, financial institutions and banks may consider identifying distinct consumer segments, based on chatbot adoption behavior and the consumer profiles of the obtained segments, to develop appropriate communication and marketing strategies for different segments in order to further encourage chatbot adoption.

Finally, the limitations of the research study should be acknowledged. Its results are based on a sample in which the young and well-educated generation (aged 24 or younger, with higher education qualifications) is overrepresented, and their perception and usage intention may differ from the average population. Although the findings provide valuable insights into consumer behavior with respect to banking chatbot adoption, the sample size was rather small, limiting the generalizability of the results. Therefore, further research should focus on studying user segments based on technology acceptance factors among other generations and on a larger sample, in order to gain a deeper understanding of the topic and to identify similarities and discrepancies between generations. Since the sample was collected from only one country, and the analysis focused on the banking sector, the topic could also be further examined by replicating the entire research study for AI-based chatbots applied in different industries. Differences in user behavior, adoption and use of chatbots for various purposes may provide interesting opportunities for future research.

6. CONCLUSIONS

The primary objective of this study was to identify relevant segments of potential banking chatbot users based on their technology adoption behavior. The results are based on 287 responses from a convenience sample. The segmentation analysis revealed three distinct user segments: Innovators (26%), who are highly educated young women employed in the business sector; the Late Majority (55%), who are young women with higher education degrees working in services-related fields; and Laggards (19%), who are educated middle-aged men working in the business sector. The largest segment is represented by the Late Majority, who do not reject the use of chatbot technology, but are slower in their adoption than the Innovators. The results also revealed differences across the obtained segments with regard to demographic variables, such as gender, age, and field of work, as well as the usage of selected banking technologies such as i-banking and banking chatbot technology. Moreover, the study highlights the importance of awareness of service when it comes to usage intention in the obtained segments: the Late Majority and Laggards reported very low scores for this dimension, meaning that they are not fully aware of the existence and benefits of banking chatbots.

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