Heliyon 9 (2023) e20686

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

The effect of Arabic language type on banking chatbots adoption

Hazar Hmoud [a,*], Farah Shishan [b], Zainah Qasem [b,c], Saleh Bazi [d]

[a] Department of Management Information Systems, School of Business, The University of Jordan, Amman, Jordan
[b] Department of Marketing, School of Business, The University of Jordan, Amman, Jordan
[c] Department of Marketing, School of Business, Effat University, Jeddah, Saudi Arabia
[d] Department of Marketing, School of Business, Yarmouk University, Irbid, Jordan

ARTICLE INFO

Kyewords:
UTAUT2
Chatbot
Arabic language
AI
Banking

ABSTRACT

Recently many banks around the world are adopting chatbots to communicate with their customers. However, the success of banking chatbots relay on customer adoption of this new technology. Although chatbots use in the banking sector is expanding globally, the Arabic world is still behind in using the technology, and chatbot applications in the Arab world are still immature. One reason behind this lag is the complexity of the Arabic language. This study comes to bridge the gap in the literature regarding what technology aspects affect customer adoption of bank chatbots in the Arabic world, and which type of Arabic language is the most effective in communicating with Arabic language speakers. UTAUT2 was used to figure what factors afect customer adoption. The data for this study was collected from two separate groups, with a total of 429 participants. Results showed that there is a significant difference between the model testing Arabic Fusha and Dialect Fusha. Results showed that Effort expectancy influences adoption only when dialect Arabic is used. Performance expectancy was also found to have no effect on the adoption of bank chatbot in both groups.

1. Introduction

In recent years, artificial intelligence (AI) has advanced rapidly thanks to the development of machine learning and deep learning algorithms [1–4]. AI agents or chatbots are AI application that was created to mimic human conversation and communicate automatically through text or verbal format [5,6]. Chatbots are already a common feature on websites and customer-facing applications across numerous sectors [7]. This is contributed to the chatbot's ability to provide a wide range of successful interpersonal interactions, easy to use interface, the absence of limitations on time and location, and the advancement of interactive teaching methods [8,9].

Recently many banks around the world are adopting chatbots to communicate with their customers. However, the success of banking chatbots relay on customer adoption of this new technology [10]. Chatbots are providing bank customers with efficient and easy-to-access 24/7 service activities [11], and fast answers to some of their questions. As a result, adopting chatbot by banks is expected to enhance the customer experience [12].

Although chatbots use in the banking sector is expanding globally, the Arabic world is still behind in using the technology, and chatbot applications in the Arab world are still immature [13]. One reason behind this lag is the complexity of the Arabic language.

Accordingly, this study comes to bridge the gap in the literature regarding what technology aspects affect customer adoption of

* Corresponding author.
E-mail addresses: h.hmoud@ju.edu.jo (H. Hmoud), f.shishan@ju.edu.jo (F. Shishan), z.qasem@ju.edu.jo, zqasem@effatuniversity.edu.sa (Z. Qasem), Saleh.bazi@yu.edu.jo (S. Bazi).

https://doi.org/10.1016/j.heliyon.2023.e20686
Received 27 June 2023; Received in revised form 22 September 2023; Accepted 4 October 2023
Available online 12 October 2023

chatbots in the Arabic world, and which type of Arabic language is the most effective in communicating with Arabic language speakers in the middle east. Jordanian Arabic is a dialect spoken by the population of the Hashemite Kingdom of Jordan and belongs to Levantine Arabic [14] which is spoken by more than 11 million person which is the population of Jordan and understood by over 44 million Arabic speakers of the Levant which consist of Palestine, Syria, Turkey and Lebanon. These statistics make Jordan a good representative of Arabic speakers.

The choice of Jordan as the focus of this study is pertinent since Jordan is at the forefront of technological innovation, and provides concrete support to institutions and technology companies alike, as well as aiming to set up a regulatory framework which will help technology drive and expand the Jordanian economy [15]. [16] note that Jordan was one of the first countries which liberalised its telecommunications sector, which was a major step in building a robust and strong ICT infrastructure. In 2020, the International Telecommunications Union published the results of its global regulatory survey for 2019. This survey highlighted the fact that the Jordanian Telecommunications Regulatory Authority was now ranked as having reached an advanced level in the category of countries with fourth-generation regulation - achieving a rate of 91%, and thus ranking first in the Arab world along with Saudi Arabia, followed by Morocco, Bahrain and Oman [17,18]. These technological developments demonstrate that Jordan is open and ready to accept innovative new technologies [19]. The Kingdom has already designed a national digital strategy, which will be launched soon, to set out how Jordan intends to benefit from emerging technologies, improve service provision throughout the country, and in the process lead the way towards improving its citizens' lives and living standards [20,21].

To answer this study's main questions the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) was adopted as the main theory. Participants were presented with two mock-up chatbot interfaces. The first interface was using Fusha Arabic and the second interface was using the Jordanian common dialect to test which type of language is the most effective.

1.1. *Importance of the study*

Generally speaking, the wide range of digital technologies has posed a significant challenge for organizations in terms of effectively stimulate innovation, enhance operational effectiveness, and secure a competitive edge in the market [22,23]. Investigating technology aspects that affect customer adoption of bank chatbots in the Arabic world, and which type of Arabic language is the most effective in communicating with Arabic language speakers is different from other research formerly carried out in the technology adoption literature. This holds true especially that the market for chatbots is expected to grow significantly from its size in 2016 of 190.8 million dollars to reach over 1.25 billion dollars in 2025 [24].

Furthermore, a survey measuring customers' preference to communicate with businesses using chatbots reported that 57 % of respondents are happy or very happy to deal with chatbots when contacting a business. On the other hand, 43 % of participants were not happy or not happy at all dealing with chatbots [25]. These numbers show that there is still a need to study what variables and chatbot characteristics are better influencing customers' adoption of chatbot technology when provided by a business.

In addition, Arabic is the fifth most spoken language globally [26]. There are more than 400 million Arabic speakers around the world and it is one of the UN's official six languages [27]. The Arabic language is also very important in the context of business and the global market. This importance is partially attributed to the role the middle east plays in the business world [28]. Therefore, it is very important to focus on building chatbots that communicate with Arabic speakers effectively.

In addition, there is little available literature on the factors which determine whether Jordanian customers decide to adopt AI in the banking sector. It is essential to create a research framework which will investigate chatbot adoption from the perspective of the customer. The study will play a positive role in helping bank managers to argue in favour of adopting AI and implementing it successfully within their banks. Finally, the study will provide a point of reference for future researchers into AI, both in Jordan itself and in Arabic-speaking developing countries which share a similar context with that of Jordan.

1.2. *Research setting*

The choice of Jordan as the focus of this study is pertinent since Jordan is at the forefront of technological innovation, and provides concrete support to institutions and technology companies alike, as well as aiming to set up a regulatory framework which will help technology drive and expand the Jordanian economy [16,29]. note that Jordan was one of the first countries which liberalised its telecommunications sector, which was a major step in building a robust and strong ICT infrastructure. In 2020, the International Telecommunications Union published the results of its global regulatory survey for 2019. This survey highlighted the fact that the Jordanian Telecommunications Regulatory Authority was now ranked as having reached an advanced level in the category of countries with fourth-generation regulation - achieving a rate of 91%, and thus ranking first in the Arab world along with Saudi Arabia, followed by Morocco, Bahrain and Oman [17,18]. These technological developments demonstrate that Jordan is open and ready to accept innovative new technologies. The Kingdom has already designed a national digital strategy, which will be launched soon, to set out how Jordan intends to benefit from emerging technologies, improve service provision throughout the country, and in the process lead the way towards improving its citizens' lives and living standards [20].

2. Literature

2.1. *Chatbots in the banking sector*

Chatbots have arisen as a significant technological innovation in the past few years, transforming the way businesses and customers interact [30]. Chatbots, also known as Artificial intelligence (AI) agents, are “conversational agent that interacts with users turn by turn using natural languages” [31] like English and Arabic. Chatbots mimic the human ability to communicate and to attend to customers’ requests expressed in oral or written methods [32].

In recent years more financial businesses are incorporating chatbots into their websites, especially text chatbots, which have changed the landscape of communication and interaction between financial organizations and their customers [11]. This is attributed to chatbots’ ability to offer numerous advantages over human-based services including being available 24 h a day with personalized assistance, faster response times, scalability, and cost-effectiveness [33]. Due to these advantages, chatbots are replacing humans in many financial service providers such as banks.

The use of chatbots in the banking industry has significantly increased in recent years. The banking industry has found using chatbots to be beneficial since they can help their customers to achieve different tasks such as account enquiries, transaction processing, and answering FAQs efficiently. Using Chatbots in the banking sector is expected to save up to 7.3 billion US dollars globally by 2023 [34].

Despite their advantages, chatbots in the banking sector also face several challenges. The majority of financial businesses are still in the learning stage of implementing AI and its applications such as chatbots [35] Therefore, there is a need to continue researching the best ways to incorporate different AI systems into their operational processes, and this has prompted the need for a more thorough theoretical understanding of what factors affect chatbot adoption among banking customers.

In the literature, many recent studies concentrated on understanding the relationship between chatbots in the banking sector and their customers. The majority of the studies have focused mainly on one of two topics: customer experience, and technology adoption.

For example [36], examine the usage of chatbots in customer support by banks. The study reported that banks using chatbots to provide reliable and convenient assistance to their customers have seen an enhancement in their relationship with their customers which lead to loyalty. Another study by Ref. [37] intended to examine the effect of bank chatbots on customer satisfaction has reported that perceived performance, perceived trust and corporate reputation significantly affect customer satisfaction with chatbot use. In a third study [10], used the diffusion of innovation theory to look at the causes and effects of customer brand engagement when employing banking chatbots. The findings indicate that trialability, compatibility, and interactivity have a positive effect on customer brand engagement through a chatbot, therefore, affecting satisfaction with the brand experience and customer brand usage intention.

2.2. Chatbot adoption in the banking sector

Although chatbots are increasingly being used in customer service, research on their use in customer assistance is still in its early stages especially [38] in the banking sector where customers are still feeling uncomfortable and not willing to use chatbots. Moreover, the banking industry has a significant commitment to investing in different enterprise systems recognizing it as a crucial tool to gain a competitive edge in the contemporary business environment [39–41]. Therefore, it is important to examine what factors influence customers’ adoption of bank chatbots [42].

Several authors have made efforts to research how chatbot technology is used in various contexts such as tourism (e.g. Refs. [43,44]), education (e.g. Ref. [45]), healthcare (e.g. Ref. [46]), transportation (e.g. Ref. [47]), and financial service including banks (e.g. Ref. [48]).

To study customers’ adoption of chatbots in financial services and banking, some technology acceptance models and theories were utilized. For example [33], have studied customers’ adoption of chatbots in the banking sector using the technology acceptance model (TAM). In their study [33], studied the effect of TAM constructs on ease of use and perceived usefulness in addition to two other factors perceived compatibility and perceived privacy risk. The results of their study identified two factors that had a significant impact on customers’ intention to adopt bank chatbots these are perceived usefulness and perceived compatibility. Similar results were reported by Ref. [12] study which searched for factors that influence millennials’ technology acceptance of chatbots in the banking industry in Indonesia. Perceived usefulness, perceived ease of use and attitude in addition to innovativeness were found to influence the intention to adopt bank chatbots among Indonesian millennials.

To identify the determinants of acceptance of banking chatbots among Malaysian millennials [42] relied on UTAUT2. The results of this study showed that all variables of UTAUT2 (performance expectancy, hedonic aspects, facilitating condition, habit, effort expectancy, social influence) in addition to perceived compatibility affects Malaysian millennials’ intention to adopt chatbots.

The Literature of technology acceptance presents several theories and models that where utilized to explain consumer adoption of new technology (e.g., Technology acceptance model ([41,49–51]), IS success model ([52,53]), and the UTAUT ([54]).

UTAUT is a robust model that proved validity, and stability in explaining technology acceptance in involuntary working context [55]. However, to understand what factors affect the intention to adopt technology in voluntary contexts like customers context [56] have introduced UTAUT2 which is an expansion of the original UTAUT model and incorporates a number of novel factors that were absent from the earlier model [56]. UTAUT2 is extensively utilized in the field of information systems research and has been applied in a variety of contexts to comprehend users’ acceptance and utilization of new technologies [57].

Different studies suggested that UTAUT2 was able to predict customers intention to adopt new technology in different domains such as Telebanking (e.g., Ref. [58]), Financial services (e.g. Ref. [59], and recently chatbot acceptance in fields like education (e.g., Ref. [60]), telecommunication (e.g., Ref. [61]), and financial services (e.g., Ref. [7]).

[56] designed UTAUT2 to provide a rigorous framework for explaining technology acceptance and use, predominantly in the consumer context. UTAUT2 enhanced the predictability of behavioural intention and actual use of new technology in comparison to UTAUT [57], indicating that the theory is robust and well-validated. Because UTAUT2 is a robust and well-established theory that can predict individuals’ acceptance and use of technology in a consumer voluntary setting, it will be used to explain consumer acceptance

and adoption of bank chatbots among Arabic speakers [57].

According to UTAUT2, four key factors influence individual's intention to use technology: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic aspects, and price. In this study, both price and facilitating conditions were not studied. This is contributed to the fact that bank chatbots are free hence, there is no price aspect. And customers will not receive any items or speak to the service providers regarding any errors with chatbots hence, facilitating conditions construct has no effect on the intention to adopt bank chatbots in this study. Moreover, the original UTAUT model includes moderating demographic variables, including age, gender, and experience that were not studied in this research. By excluding demographic variables, the research findings may be more broadly applicable to a wider range of users, transcending specific demographic groups and can lead to the identification of universal adoption drivers that are applicable across diverse user groups. This can provide valuable insights for technology designers and marketers. And for the purpose of this research excluding demographic variables will allow researchers to focus on core language-based variables driving technology adoption without distractions from external influences.

2.2.1. Performance expectancy and intention to adopt chatbot

One of the key predictors of technology adoption intention and acceptance is "performance expectancy", namely the extent to which users believe that the system will enable them to carry out their job role more efficiently [49]. Performance expectancy concerning chatbots refers to the degree to which users believe that chatbots will help them in meeting their goals [62]. Several studies have found a positive link between performance expectancy and the intention to adopt chatbots (for example, [63]).

[64] investigated the impact of performance expectancy on the intention to adopt chatbots in e-commerce and found a positive link. The authors added that the chatbots' speedy responses to customer enquiries, and the efficient support they offered, could increase their perceived value in the eyes of the users and thus make them more likely to adopt chatbots. In a similar vein, it is also found that performance expectancy was a major predictor of the intention to adopt chatbots in the healthcare sector [65]. The authors noted that the chatbots' ability to suggest personalized health recommendations, provide reminders and take part in monitoring patients could increase users' perceived performance expectancy - and result in a higher intention to adopt. Once again, the authors pointed out that the chatbots' ability to offer speedy and efficient customer support could raise users' levels of performance expectancy- and thus their intention to adopt.

As a result, the literature suggests that performance expectancy is a significant predictor of the intention to adopt chatbots. The capabilities of chatbots, such as personalized advice, quick responses, and efficient support, can increase users' perceived value and performance expectancy. This work suggests that performance expectancy should be created to expand the intention to adopt chatbots.

H1. Performance expectancy will positively influence intentions to adopt chatbots.

2.2.2. Effort expectancy and intention to adopt chatbot

Another major predictor of technology acceptance is "effort expectancy", or the ease with which the system can be used [49]. Concerning chatbots refers to their perceived ease of use and the amount of effort users have to make to interact with the technology.

Several research studies have focussed on the link between effort expectancy and the intention to adopt chatbots. A study by Ref. [46], which investigated chatbots in e-commerce, also found that effort expectancy had a positive impact on the intention to adopt chatbots. These authors noted that the chatbots' ability to offer speedy and straightforward support increased users' perceived ease of use, and reduced the perception that the technology was complex, which led to an increased intention to adopt.

In addition, a study conducted by Ref. [65], in the context of healthcare, concluded that ease of use was an important predictor of the intention to adopt chatbots. The researchers found that the chatbots' user-friendly interface and clear language could increase perceived ease of use, and raise intentions to adopt. Furthermore [7], study, which examined chatbots in the context of financial services, came to an identical conclusion. Perceived ease of use had a major impact on the intention to adopt chatbots, whose ability to offer simple financial help could increase users' perceived ease of use, and raise their intention to adopt.

As a result, the research highlights the importance of effort expectancy in the intention to adopt chatbots. Many studies have reported that effort expectancy has a significant impact on the intention to adopt chatbots. This work suggests that effort expectancy should be created to expand the intention to adopt chatbots.

H2. Effort expectancy will positively influence intentions to adopt chatbots.

2.2.3. Social norms and intention to adopt a chatbot

Social norms are a set of expectations and beliefs about how people should act in a specific context [56]. The relationship between social norms and the intention to adopt chatbots has been the subject of several research studies [66]. found that subjective norms - namely, the degree to which an individual considers the opinions of others, regarding whether or not they should act in a certain way, as important - have a positive effect on the intention to adopt chatbots. The authors argued that behavioural intentions were invariably shaped by the influence of social groups, and thus individuals would be more inclined to adopt chatbots if they saw that people who were important to them supported the adoption of chatbots.

Likewise [67], study of chatbots in the context of e-commerce determined that friends also significantly influenced decisions to adopt chatbots. The authors concluded that individuals were more likely to adopt chatbots if they saw that their friends were already using them to good effect and found them beneficial. Similarly [68], found that social norms had a positive impact on the intention to adopt chatbots in the healthcare sector. The study stated that if healthcare professionals recommended the use of chatbots and had a positive view of them, this could increase individuals' perception of the positive benefits of chatbots, and result in a higher intention to adopt.

As a result, the research highlights the importance of social norms in the intention to adopt chatbots. Many studies have reported that social norms have a significant impact on the intention to adopt chatbots. This work suggests that social norms should be created to expand the intention to adopt chatbots.

H3. Social norms will positively influence intentions to adopt chatbots.

2.2.4. Hedonic motivation and intention to adopt chatbot

Hedonic motivation describes the emotional bond which consumers feel towards technology. Since chatbots are being popularised and introduced into various sectors, and many companies are harnessing their features to upgrade customer service, it is vital to investigate the relationship between hedonic motivation and the intention to adopt chatbots. The present literature review sets out to assess previous studies on the relationship between hedonic motivation and the intention to adopt chatbots.

The relationship between hedonic motivation and the intention to adopt chatbots has been evaluated in several studies. For example [69], found that hedonic motivation is a strong predictor of the intention to adopt chatbots, in the field of online shopping. In addition [70], found that those users who perceived chatbots as highly hedonically trustworthy also had a higher intention to adopt them.

A further study, by Ref. [71] analysed students' responses to the adoption of chatbots in educational environments and found that hedonic motivation was the key factor. Similarly [66], study of millennials found a clear positive correlation between hedonic trust, and the intention to adopt chatbots, and argued that the existence of an emotional bond with chatbots can influence individuals' decision to adopt them. Moreover [72], study discovered that hedonic motivation has a positive and important impact on the intention to adopt chatbots in the customer service sector. The authors also highlighted the fact that mastering the use of chatbots and trusting their performance are both factors which mediate the relationship between hedonic motivation and intention to adopt.

As a result, the research highlights the importance of hedonic motivation in the intention to adopt chatbots. Many studies have reported that hedonic motivation has a significant impact on the intention to adopt chatbots. This work suggests that hedonic motivation should be created to expand the intention to adopt chatbots.

H4. Hedonic motivation will positively influence intentions to adopt chatbots.

2.2.5. Bank chatbot adoption among Arabic speakers

Even though Arabic chatbot implementations exist, little research has been conducted on their adoption by customers. Arabic language has many challenges for chatbot developers for example, it is rich in morphology, has orthographic variations, and it has a high degree of ambiguity [6,73]. Furthermore, written Arabic text can be categorized into three types. First, the Quranic Arabic is the language of the Quran. Second, Modern Standard Arabic (Fusha) is considered the formal Arabic used in formal and official communication such as news and business. And finally, the dialectal Arabic, which is used by the public in their daily written and spoken personal and informal communication which varies between countries and regions [74]. Having three groups of language is putting chatbot developers under the pressure of deciding on which type of language is the most effective when communicating with bank customers.

Dialect Arabic is frequently used for spoken communication and daily interactions like customer service interaction. On the other hand, Fusha is used for written communication. Chatbots are expected to replace service provider however it is using written language [75]. Therefore, comes the question of the type of language used affects customers' intention to adopt bank chatbots. Hence, we hypothesise that:

H5. type of Arabic language moderates the relationship between UTAUT2 variables and intention to adopt bank chatbots.

3. Methodology

This research's main objective is to understand the effect of different chatbot features on Arabic speakers' potential customers' intention to adopt chatbots in banking services. To achieve this objective this study has produced two images representing a conversation between a chatbot named "Alia" and a participant.

The first image represents an automated conversation. To achieve the latter the chatbot "Alia" used "Fosha Arabic" (formal Arabic), and did not ask for the participant's name. The conversation also did not use any emojis and asked the participant to press a number to choose a specific requirement. The participant was not provided with any indication that his/her message is being answered such as "typing dots", and participants were not provided with the option of speaking to a human agent (see appendix for conversation image and translation).

The second image represented a more humanized encounter with the chatbot. To achieve the latter the chatbot "Alia" used slang language. As Arabic slang has many dialects and each dialect has different words and to overcome this problem the words chosen to represent the conversation were common words in many dialects in Jordan. The chatbot asked the participant to provide his/her name and welcomed the participant using the first and second names. Chatbot also used emojis and provided "typing dots" to signal that the question is being answered.

The data was collected using a convenience sampling approach and total of 429 questionnairs were collected. To validate the proposed conceptual model, empirical data was collected by creating two separate online self-administered questionnaires using google forms. The first questionnaire had image one and the second questionnaire had image two. The questionnaire aimed at generating answers regarding participants' intention to adopt a chatbot for banking service using the primary variables of UTAUT2

(PE, EE, H, PV, and BI). Each questionnaire was distributed using a different platform to assure that the questionnaire is answered by a different group of people.

Notably, the primary variables of UTAUT2 (PE, EE, H, PV, and BI) were measured using scales adapted from Ref. [56]. To measure the participant's responses to the primary variables of UTAUT2, this study adopted a five-point Likert scale ranging from strongly agree to strongly disagree.

Finally, to measure the effect of different features, participants were proposed with the two conversations and asked to evaluate the effect of each feature using a five-point Likert scale ranging from strongly agree to strongly disagree.

The questionnaire concluded with six closed-ended questions aiming to collect demographic data (age, gender, income, marital status, education level, experience with online banking, and previous experience with chatbots).

4. Results

4.1. Data analysis

The PLS-SEM method [76] and the Smartly 4 software [77] were utilized by our team to develop, estimate, and evaluate the underlying conceptual model. PLS-SEM is a causal-predictive approach to SEM, which allows researchers to assess the results' predictive quality [78]. It can be applied to both reflective and formative measurement models [79]. Hence, PLS-SEM is especially helpful if the goal of the researchers is to estimate a structural model that explains a major target construct of interest [80]. To be more explicit, composite-based PLS-SEM places more emphasis on maximizing the prediction of the endogenous constructs rather than the model fit [81]. In contrast, factor- or covariance-based SEM (CB-SEM) places more emphasis on the model fit [82].

We decided to use a PLS-SEM technique since one of the goals of our study is to forecast intention to use based on a variety of chatbot determinants, and not because we want to test a theory in and of itself.

4.2. Findings

4.2.1. Sample profile and the two groups

The sample profile (see Table 1) indicates that the majority of respondents (n = 266, 62 %) were female. There were few respondents whose aged are above 45 (n = 4, 1 %), while the majority were younger between 18 and 25 (n = 325, 75.8 %). Almost ninety percent (n = 386) of the sample were single. The sample was dominated by the educated respondent who held a bachelor degree (n = 388, 78.8 %). There was a slice of unemployed participants (n = 172, 40.1 %), and then the majority of respondents (n = 296, 69 %) earned between JD 500–701 per month. Two-hundred and eleven participants were informal data and two-hundred and nineteenth were formal data.

Table 1
Sample characteristics.

Variable	Frequency (N)	Percentage (%)
Gender (N = 429)		
Female	266	62
Male	163	38
Age		
18-24	325	75.8
25-30	41	9.6
31-37	47	11
38-44	12	2.8
45-50	2	0.5
51-56	2	0.5
Martial Status		
Single	386	90
Married	43	10
Education		
High School	18	4.2
Diploma	20	4.7
Bachelor	338	78.8
Higher Diploma	53	12.4
Employment		
Full time	135	31.5
Part-time	96	22.4
Self-employed	26	6.1
Unemployed	172	40.1
Monthly Income		
250-500	296	69
501-750	52	12.1
851-999	19	4.4
1000+	62	14.5

To provide a more relevant comparison of the data, we grouped the data into two groups, informal data (n = 211, 49 %) and formal data (n = 219, 51 %). We used the G*Power program [83] to conduct a power analysis and determine the minimal sample size necessary for the multi-group analysis. Given 10 predictors, an alpha level of 5 %, and a power of 80 %, the projected minimum sample size to detect a moderate effect size was 55. Hence, the sample sizes for each kind of chatbot met these criteria.

4.2.2. Measurement model assessment

We, first, examine the measurement model for the entire sample [84]. Table 2 presents the factor-item loading, composite reliability (CR), Cronbach's alpha reliability (α), and average variance extracted (AVE). All of the factor-item loading items were greater than the 0.70 cut-off point, except one item of social norm, which was dropped due to low loading. Thus, the measurement model was internally consistent. All constructs' AVE, Cronbach's alpha, and CR values were above the thresholds of 0.50, 0.70, and 0.70, respectively, which reflected that the measurement model was convergently valid [85].

Following [85,86], we tested the discriminant validity using the heterotrait-monotrait ratio (HTMT) of the correlations. As shown in Table 3, all HTMT ratios were less than 0.85, which indicates that the measurement model has discriminant validity. Appendix A illustrates the measurement model assessment and the discriminant validity for the two groups respectively.

To ensure the differences in the findings were not due to measurement invariance, we employed the measurement invariance of the composite models (MICOM) [87]. We followed [86] three ways procedures: (1) "configural invariance assessment", (2) "compositional invariance assessment", and (3) the "assessment of equal means and variances". The results in Table 4A, 4B, and 4C demonstrated the evidence of full measurement invariances that allowed us to test the Standardized path coefficients can be compared across the two groups.

4.2.3. Structural model assessment

After establishing the reliability and validity of the measurement models and ensuring measurement invariance across the two groups, our emphasis switched to the structural model. We utilized the PLSpredict method to evaluate the predictive potential of the performance expectancy, effort expectancy, social norm, and hedonic motivation with respect to the intention to use the combined sample across the two groups. The PLS-SEM model had lower RMSE values than the nave LM benchmark, indicating that the model has a high predictive potential. The results of Q^2predict showed a value of 0.716, 0.752, 0.663 for the entire sample, informal group, and formal group respectively, which present a high predictive power for the PLS model [88]. The findings of the hypotheses of the entire sample and the multigroup analysis are presented in Table 5.

5. Discussion

In recent years, there has been a significant increase in the financial industry's use of chatbot technology to improve customer service and streamline banking operations. With the increased adoption of artificial intelligence (AI) and natural language processing (NLP), chatbots have emerged as useful tool for providing personalized assistance to consumers, answering their questions, and facilitating transactions. Despite the large population of Arabic-speaking consumers and the unique linguistic characteristics of the Arabic language, there has been little research conducted on Arabic-speaking bank chatbots [6,89]. Moreover, scholars need to focus

Table 2
Measurement model assessment for the entire sample.

Variable and Measurement items	Factor-item loading	CR	α	AVE
Effort Expectancy (EE)		0.891	0.837	0.674
EE1	0.745			
EE2	0.850			
EE3	0.849			
EE4	0.835			
Performance Expectancy (PE)		0.941	0.916	0.800
PE1	0.879			
PE2	0.918			
PE3	0.881			
PE4	0.898			
Social Norm (SN)		0.914	0.858	0.778
SN2	0.897			
SN3	0.924			
SN4	0.823			
Hedonic (HB)		0.965	0.946	0.901
HB1	0.955			
HB2	0.947			
HB3	0.949			
Intention to use (IN)		0.932	0.902	0.774
IN1	0.904			
IN2	0.870			
IN3	0.899			
IN4	0.845			

Table 3
Discriminant validity assessment for the entire sample.

	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
Effort Expectancy					
Hedonic	0.6045				
Intention to use	0.7156	0.7894			
Performance Expectancy	0.6851	0.6214	0.7345		
Social Norm	0.7728	0.7007	0.8909	0.7968	

Table 4A
Compositional invariance

Informal vs. formal	C = 1	95 % CI	CIE?
Effort Expectancy	0.9990	[0.9973:1.000]	YES
Hedonic trust	1.0000	[0.9999:1.000]	YES
Intention to use	0.9999	[0.9997:1.000]	YES
Performance Expectancy	0.9996	[0.9995:1.000]	YES
Social Norm	0.9998	[0.9990:1.000]	YES

Notes: C = 1: correlation value = 1; CI: confidence interval; CIE: compositional invariance established?.

Table 4B
Equal variances assessment.

Informal vs. formal	R = 0	95 % CI	EV?
Effort Expectancy	0.0992	[-0.3770; 0.3505]	YES
Hedonic	0.2591	[-0.2743; 0.2932]	YES
Intention to use	0.2847	[-0.3511; 0.3812]	YES
Performance Expectancy	0.0425	[-0.3822; 0.3433]	YES
Social Norm	0.2029	[-0.4017; 0.4012]	YES

Notes: R = 0: logarithm of the composite's variances ratio (R = 0); CI: confidence interval; EV: equal variances.

Table 4C
Equal mean assessment.

Informal vs. formal	D = 0	95 % CI	EMV?
Effort Expectancy	−0.0701	[-0.1965; 0.1854]	YES
Hedonic	−0.0261	[-0.1990; 0.1870]	YES
Intention to use	−0.0286	[-0.1966; 0.1895]	YES
Performance Expectancy	−0.0577	[-0.1836; 0.1904]	YES
Social Norm	−0.0114	[-0.1996; 0.1919]	YES

Notes: D = 0: difference in the composite's mean value (=0); CI: confidence interval; EMV: equal Mean values.

on comprehending the various elements that play a significant role in the adoption of chatbots [90].

This paper aims to fill this research gap by investigating what factors affect Arabic-speaking bank chatbot adoption in the Arabic sector taking into consideration one major aspect which is the difference in the type of Arabic language (Fusha or dialect) used to communicate with customers. To achieve this study's objectives UTAUT2 was adopted as the main theory. The present study investigated the relationships between the model's constructs using samples from two groups. The first group was presented with a mock-up chatbot conversation in Fusha Arabic and the second group was presented with a mock-up chatbot in Jordanian dialect.

The effect of Effort expectancy on intention to adopt bank chatbots in groups presented with mock-up chatbot conversations in Fusha Arabic was not supported. This indicates that the difficulty of using chatbot that uses Fusha is not a concern for potential users. The literature provided similar results in adopting technologies that people are familiar with. For example [91], has reported a non-significant relationship between effort expectancy and adoption of e-wallets [92]. has also reported a reported a non-significant relationship between effort expectancy and adoption of try on technology among Generation Z members which was contributed to the familiarity of users with the technology.

On the other hand, the effect of effort expectancy in the second group which was presented with mock-up chatbots in Jordanian

Table 5
Results of the structural model and Multigroup analysis.

		Entire sample				Informal sample				Formal sample			
H. No	Path	*B*	t-value	*p*-value	Supported?	*B*	t-value	*p*-value	Supported?	β	t-value	*p*-value	Supported?
1	Effort Expectancy - > Intention to use	0.090	2.3054	0.021	YES	0.1119	2.2213	0.026	YES	0.061	1.052	0.293	NO
2	Hedonic - > Intention to use	0.336	7.9951	0.000	YES	0.3949	6.9682	0.000	YES	0.254	4.151	0.000	YES
3	Performance Expectancy - > Intention to use	0.110	2.3908	0.017	YES	0.1100	1.8026	0.072	NO	0.124	1.765	0.078	NO
4	Social Norm - > Intention to use	0.439	8.5014	0.000	YES	0.3949	5.8698	0.000	YES	0.496	6.923	0.000	YES
R2		0.721				0.764				0.678			
Q^2predict		0.716				0.752				0.663			

dialect was supported. This result means that those who were exposed to bank chatbots using dialect Arabic seems to be concerned about the simplicity or difficulty of using a chatbot in. The positive relationship between Effort expectancy and intention to adopt new technology comes in align with [56] findings. The relationship was also supported in the literature. For example [58], has reported a positive relationship between effort expectancy and adoption of internet banking.

The results show a difference between how each group perceive effort expectancy. Those who were exposed to bank chatbots using dialect Arabic seems to be concerned about the simplicity or difficulty of using a chatbot in comparison to those who were exposed to bank chatbot in Fusha Arabic. The significance of effort expectancy and intention to adopt a technology could be contributed to users knowledge of the technology [93]. However, in this study the compared technology is the same therefore, then difference in result could be contributed to the difference in used language to communicate the service.

The different significance results of effort expectancy between both groups could be contributed to the fact that Arab users are used to using Fusha in business communication. Effort expectancy refers "the degree of ease associated with consumers' use of technology" [56] therefore when proposed with Fusha chatbot users did not associate any difficulty with understanding the conversation. On the contrary when presented with dialect Arabic chatbot they had to spend more time to process the information therefore, effort expectancy was significant.

Performance expectancy was found to not influence the intention to adopt bank chatbots in both groups which was an unexpected result. The definition of performance expectancy is "the degree to which using a technology will provide benefits to consumers in performing certain activities" [56]. Looking at the definition of performance expectancy the insignificant result shows that bank customers do not consider the usability of chatbots as an influencer to decide regardless of the type of Arabic used. This might be contributed to the fact that customers have not been prepared enough by banks in the Arabic world to accept this new technology in banking. Hence, they do not have enough knowledge of its capabilities and its usefulness in performing different banking tasks. Therefore, regardless of the type of Arabic used customers are still in the stage where they are trying to understand the uses and benefits of the technology As a result, performance expectancy has no role in influencing their intention to adopt bank chatbots regardless of the language [94].

The hedonic motivation influence on intention to adopt bank chatbots was supported in both groups. This result is similar to other studies results. This result was supported in the literature, for example, [56]. Reported that hedonic motivation is expected to play a significant role in creating intention among users [56]. [95] have reported the effect of hedonic motivation on intention to adopt new technology in financial service.

Chatbots in banking sector is a newly introduced technology in the Arabic world. As this technology is new hedonic motivation is expected to paly a significant role in creating intention among users [56]. However, this role is expected to fadeaway after users get more familiar with the technology [96]. Therefore, it I important to know which type of Arabic language is perceived as more enjoyable by Arabic users in order to sustain the effect of hedonic motive.

Social norm was found to influence the intention to adopt bank chatbots in both groups. Social norms represent the degree to which an individual values the opinion of those who are important to them when deciding to adopt a specific technology [56]. The literature has reported different results on this factor. For example [97], found no significant relationship between social influence and intention to adopt m-banking. On the other hand, a significant relationship between social influence and intention to adopt financial technology was reported by Ref. [95]. The results of this study come to support findings that reports a significant relationship between social influence and the intention to adopt technology. The opinion of family and friend are expected to affect users' intention to adopt using services [98] which banking chatbots belongs to specially in such as sensitive field. In addition, the Arabic culture is a collectivist culture which in general cares for the opinion of others [99]. As most Arabic speakers belongs to an Arabic collectivist culture other's opinion on adopting bank chatbots is significantly influencing the decision to adopt the technology.

6. Implications and limitations

Banks and consumers have benefited from the integration of chatbots in the banking industry. Chatbots enable customers to access banking services such as checking account balances, transferring funds, and paying bills in a fast and convenient manner. Additionally, this technology has drastically reduced wait times and eliminated the need for consumers to visit physical branches. Chatbots have streamlined the customer service operations of banks by providing around-the-clock assistance and freeing up employees to concentrate on more complex issues. In addition, chatbots have reduced operational expenses for banks, which has increased their profitability. The use of chatbots in the banking industry has revolutionized how consumers interact with their banks, making banking faster, more efficient, and more accessible to all. Looking at all of these benefits banks management needs to know what factors will enhance customers' adoption of.

This research comes to bridge a gap in the literature on what factors are affecting Arabic-speaking customers to adopt banks chatbot. The results of this study are of great significant for bank managers. The results show that Arabic-speaking bank customers prefer to communicate with chatbots writing in Fusha Arabic. Hence, it is very important to consider Fusha Arabic when building chatbots as the main type of Arabic when communicating in text chatbots. Results have also shown that more efforts should be created to introduce bank customers to chatbot technology and to create awareness of the benefits this technology will bring to the customers.

Practical implications for this research can vary. For software developers, understanding how different language aspects influence chatbot adoption allows software developers to create more user-friendly and intuitive interfaces. In addition, analyzing language effects enables the customization of chatbot responses based on users' language choices, preferred dialects, and communication styles.

For managers, adapting to users' language preferences can lead to higher adoption rates as users find the technology more accessible and relatable, and can provide more accurate and contextually relevant support, addressing user queries effectively. This results in better customer satisfaction and reduced support costs.

For normal users, Language-sensitive chatbots can assist users in decision-making processes by providing information and recommendations in a language style that aligns with users' preferences.

Although the results of this study are of significance there are still some limitations to be reported. For example, this study used the Jordanian dialect which is only one dialect from so many others used by other regions like GCC and Egypt. This study might be replicated to see if the same results will appear in other Arabic countries. It would be crucial to include other variables such as cultural effect because Arabic language often incorporates cultural nuances and references so Chatbots need to be culturally sensitive, recognizing and respecting cultural references while engaging users. Moreover, Arabic language identified by its Morphological Complexity with words have the same spelling but different meanings across the same and different cultures. This implies that chatbots need sophisticated linguistic algorithms to handle word forms, stemming, and morphology to ensure accurate understanding and response generation.

In addition, it would be beneficial to conduct further elaboration on specific linguistic challenges that identify the complexity of the Arabic language as a reason for lagging chatbot adoption in the Arabic world. Those linguistic challenges are not exclusive to dialetic diversity and the use of formal and informal language but also include: the use of synonyms and semantic nuances as chatbots must be capable of recognizing and adapting to different language registers to ensure natural and contextually appropriate interactions, the use of Arabic grammar as Arabic grammar is intricate, with features like case endings, verb conjugations, and agreement rules and accordingly, chatbots must possess advanced grammatical analysis to generate coherent and grammatically correct responses, enhancing user satisfaction.

Another limitation is that this study was being performed using a mock-up platform therefore trust variable was not accounted for. Different results might appear if performed on a functioning bank chatbot. A functioning chatbot would be beneficial in capturing the dynamic and real-time nature of actual chatbot conversations, understanding the Actual user reactions, confusion, or suggestions for improvement, identifying the diverse range of language inputs and variations that users might use when interacting with a chatbot, and investigating trust as a variable because people might engage differently when they know they are interacting with a functional chatbot instead of mock screens. Hence, it is recommended to replicate this study on functioning bank chatbot users to validate the results.

Lastly, performing a longitudinal study across a duration of time would enable researchers to monitor the progression of customers' viewpoints and sentiments regarding chatbots. This approach can yield a more holistic comprehension of the variables shaping the long-term acceptance of chatbot technology. Also, subsequent studies should take into account a broader and more inclusive sample to enhance the applicability of the results to a wider context.

Data availability statement

Data associated with this research has not been deposited into a publicly available repository. Data will be available upon request.

CRediT authorship contribution statement

Hazar Hmoud: Conceptualization, Writing – original draft, Writing – review & editing. **Farah Shishan:** Investigation, Visualization, Writing – original draft. **Zainah Qasem:** Methodology, Writing – original draft, Writing – review & editing, Methodology, Writing – original draft, Writing – review & editing. **Saleh Bazi:** Data curation, Formal analysis, Validation, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e20686.

Appendix A

Table 1
Measurement items correlations (entire sample)

	PE1	PE2	PE3	PE4	EE1	EE2	EE3	EE4	S1	S2	S3	S4	IN1	IN2	IN3	IN4	H1	H2	H3
PE1	1																		
PE2	0.7644	1																	
PE3	0.6735	0.7443	1																
PE4	0.7091	0.7691	0.7335	1															
EE1	0.3907	0.4054	0.3917	0.4152	1														
EE2	0.447	0.493	0.5162	0.4923	0.4802	1													
EE3	0.4634	0.4963	0.4865	0.4583	0.4885	0.6379	1												
EE4	0.3786	0.4321	0.3743	0.3993	0.4664	0.6377	0.6694	1											
S1	0.3257	0.3251	0.3677	0.3572	0.3313	0.3067	0.3329	0.4743	1										
S2	0.5181	0.5407	0.5103	0.5589	0.357	0.5229	0.4759	0.3569	0.3895	1									
S3	0.5691	0.6102	0.5892	0.6094	0.4104	0.57	0.5334	0.3268	0.3748	0.7829	1								
S4	0.5479	0.5549	0.553	0.5216	0.3681	0.4953	0.5214	0.2129	0.3079	0.5875	0.6313	1							
IN1	0.5105	0.528	0.5031	0.4572	0.4269	0.5016	0.4368	0.2601	0.4791	0.5762	0.664	0.5521	1						
IN2	0.5558	0.5875	0.5612	0.5327	0.4056	0.4883	0.504	0.4874	0.4758	0.6866	0.746	0.6127	0.6929	1					
IN3	0.5159	0.5216	0.5365	0.4805	0.4263	0.4862	0.436	0.3881	0.5137	0.617	0.6893	0.5931	0.7817	0.7146	1				
IN4	0.4783	0.5024	0.4939	0.5146	0.4849	0.5146	0.3828	0.348	0.4171	0.4846	0.624	0.4483	0.706	0.6288	0.6619	1			
H1	0.4633	0.4512	0.4718	0.5722	0.4171	0.552	0.379	0.3931	0.3381	0.4987	0.6096	0.3894	0.6269	0.571	0.5857	0.6228	1		
H2	0.4901	0.5079	0.5105	0.4934	0.4415	0.4671	0.359	0.4019	0.4392	0.5556	0.654	0.4207	0.5946	0.6131	0.5747	0.6262	0.8595	1	
H3	0.5065	0.497	0.5236	0.525	0.4867	0.4262	0.3866	0.373	0.4226	0.5449	0.6361	0.4475	0.6435	0.6097	0.5918	0.6462	0.8593	0.8395	1

Table 2
Cross-loading (entire sample)

	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
EE1	**0.7452**	0.4419	0.5188	0.4483	0.4297
EE2	**0.8501**	0.5181	0.5594	0.545	0.6012
EE3	**0.8491**	0.3949	0.5024	0.5326	0.5775
EE4	**0.8349**	0.4098	0.4654	0.4432	0.5424
H1	0.5219	**0.9537**	0.6829	0.5153	0.5729
H2	0.5074	**0.9467**	0.6843	0.5708	0.6231
H3	0.5133	**0.9485**	0.7073	0.5612	0.6208
IN1	0.5647	0.6549	**0.9036**	0.575	0.6798
IN2	0.5993	0.6298	**0.87**	0.6367	0.7756
IN3	0.5307	0.6151	**0.8986**	0.578	0.7195
IN4	0.5039	0.6654	**0.8446**	0.5592	0.5939
PE1	0.5138	0.5127	0.5871	**0.8787**	0.6171
PE2	0.5583	0.5112	0.6097	**0.9177**	0.6451
PE3	0.5429	0.5289	0.5966	**0.8812**	0.6244
PE4	0.5407	0.5161	0.5992	**0.8984**	0.64
S2	0.5553	0.5615	0.6758	0.5951	**0.8974**
S3	0.6225	0.6669	0.7763	0.665	**0.9242**
S4	0.5587	0.4418	0.6301	0.6088	**0.8233**

Table 3
Cross Loading (informal group)

	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
EE1	**0.7655**	0.4659	0.5305	0.4518	0.422
EE2	**0.8559**	0.56	0.6277	0.5627	0.6436
EE3	**0.8444**	0.346	0.4967	0.4889	0.5636
EE4	**0.8375**	0.4032	0.475	0.4059	0.5288
H1	0.5262	**0.9631**	0.7126	0.5	0.5695
H2	0.5094	**0.9532**	0.7365	0.5415	0.6241
H3	0.5351	**0.9584**	0.7589	0.563	0.6322
IN1	0.6106	0.7136	**0.9061**	0.596	0.6839
IN2	0.6093	0.6777	**0.8854**	0.6023	0.7935
IN3	0.5705	0.6383	**0.9021**	0.5846	0.7212
IN4	0.5254	0.7059	**0.8643**	0.5977	0.6255
PE1	0.5434	0.5289	0.6369	**0.9085**	0.6249
PE2	0.5343	0.492	0.6081	**0.919**	0.6065
PE3	0.5097	0.5009	0.5922	**0.8912**	0.6233
PE4	0.5359	0.5094	0.5936	**0.9174**	0.6593
S2	0.5745	0.5943	0.7181	0.6097	**0.9205**
S3	0.6073	0.6442	0.7698	0.6294	**0.9342**
S4	0.5838	0.4494	0.6355	0.6153	**0.8185**

Table 4
Cross Loading (formal group)

	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
EE1	**0.7259**	0.416	0.5046	0.4445	0.4399
EE2	**0.8408**	0.4678	0.4751	0.5271	0.5509
EE3	**0.8556**	0.4493	0.5128	0.5747	0.5962
EE4	**0.8319**	0.4182	0.4552	0.4833	0.5596
H1	0.5206	**0.9430**	0.6436	0.5366	0.579
H2	0.5059	**0.9392**	0.6206	0.6046	0.624
H3	0.4927	**0.9376**	0.6476	0.5611	0.6092
IN1	0.513	0.5798	**0.9003**	0.5527	0.6759
IN2	0.5926	0.5732	**0.8529**	0.6785	0.7547
IN3	0.4877	0.5858	**0.8953**	0.5733	0.7198
IN4	0.483	0.6216	**0.8214**	0.5209	0.5613
PE1	0.4862	0.496	0.5333	**0.8467**	0.6098
PE2	0.5866	0.5343	0.6145	**0.9175**	0.6897
PE3	0.5769	0.5628	0.6056	**0.8732**	0.63
PE4	0.5483	0.5319	0.6168	**0.8882**	0.6324
S2	0.5364	0.5227	0.6257	0.5827	**0.8681**
S3	0.6425	0.6948	0.7859	0.7045	**0.9148**
S4	0.534	0.4334	0.6254	0.6017	**0.8296**

Table 5
Measurement model assessment for the entire sample

Variable and Measurement items	Factor-item loading	Mean	Std. Deviation	CR	α	AVE
Effort Expectancy (EE)				0.891	0.837	0.674
EE1	0.745	1.8462	0.9440			
EE2	0.850	1.8904	0.8699			
EE3	0.849	1.8485	0.7476			
EE4	0.835	2.0000	0.8645			
Performance Expectancy (PE)				0.941	0.916	0.800
PE1	0.879	2.2145	0.8163			
PE2	0.918	1.9114	0.8471			
PE3	0.881	1.7622	0.9201			
PE4	0.898	1.8881	0.8981			
Social Norm (SN)				0.914	0.858	0.778
SN2	0.897	1.9138	0.9056			
SN3	0.924	1.9674	0.9626			
SN4	0.823	1.7576	0.8808			
Hedonic (HB)				0.965	0.946	0.901
HB1	0.955	2.2214	1.0332			
HB2	0.947	2.2774	1.0622			
HB3	0.949	2.3427	1.0803			
Intention to use (IN)				0.932	0.902	0.774
IN1	0.904	2.2051	0.9988			
IN2	0.870	1.9371	0.8573			
IN3	0.899	2.0746	0.9627			
IN4	0.845	2.3473	1.1519			

Table 6
Measurement model assessment for the for each group

Variable and Measurement items	Factor-item loading for informal group	Mean	Std. Deviation	CR	α	AVE	Factor-item loading for formal group	Mean	Std. Deviation	CR	α	AVE
Effort Expectancy (EE)				0.891	0.837	0.674				0.888	0.823	0.665
EE1	0.766	2.2202	0.9272				0.726	1.8578	0.8368			
EE2	0.856	1.9450	0.8277				0.841	1.8957	0.8590			
EE3	0.844	1.7844	0.7629				0.856	1.7915	0.9257			
EE4	0.838	1.9220	0.8450				0.832	1.9431	0.8356			
Performance Expectancy (PE)				0.941	0.916	0.800				0.933	0.904	0.778
PE1	0.909	1.8349	0.7958				0.847	2.2085	0.9609			
PE2	0.919	1.8853	0.8354				0.918	1.8768	0.9102			
PE3	0.891	1.9037	0.9111				0.873	1.7393	0.7307			
PE4	0.917	2.0550	0.9514				0.888	1.8531	0.8828			
Social Norm (SN)				0.914	0.858	0.778				0.904	0.842	0.760
SN2	0.921	1.8991	0.8561				0.868	1.9289	0.9537			
SN3	0.934	1.9862	0.9310				0.915	1.9479	0.9939			
SN4	0.819	1.7661	0.8542				0.830	1.7488	0.9073			
Hedonic (HB)				0.965	0.946	0.901				0.958	0.934	0.883
HB1	0.963	2.2294	0.9446				0.943	2.2133	1.1173			
HB2	0.953	2.3165	1.0072				0.939	2.2370	1.1146			
HB3	0.958	2.3349	1.0461				0.938	2.3507	1.1144			
Intention to use (IN)				0.932	0.902	0.774				0.924	0.891	0.753
IN1	0.906	2.2339	0.9214				0.900	2.1754	1.0721			
IN2	0.885	1.9312	0.8127				0.853	1.9431	0.9011			
IN3	0.902	2.0826	0.8792				0.895	2.0664	1.0419			
IN4	0.864	2.3716	1.1311				0.821	2.3223	1.1725			

Table 7
Constructs correlations (entire sample)

Construct	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
Effort Expectancy	1	0.5415	0.6267	0.6029	0.6569
Hedonic	0.5415	1	0.7284	0.5784	0.6379
Intention to use	0.6267	0.7284	1	0.6691	0.7904
Performance Expectancy	0.6029	0.5784	0.6691	1	0.7066
Social Norm	0.6569	0.6379	0.7904	0.7066	1

Table 8
Constructs correlations (informal group)

Construct	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
Effort Expectancy	1	0.5465	0.652	0.5842	0.6583
Hedonic	0.5465	1	0.7686	0.5589	0.6358
Intention to use	0.652	0.7686	1	0.6691	0.7957
Performance Expectancy	0.5842	0.5589	0.6691	1	0.6911
Social Norm	0.6583	0.6358	0.7957	0.6911	1

Table 9
Constructs correlations (formal group)

	Effort Expectancy	Hedonic	Intention to use	Performance Expectancy	Social Norm
Effort Expectancy	1	0.5387	0.6003	0.6249	0.6595
Hedonic	0.5387	1	0.6782	0.6032	0.6424
Intention to use	0.6003	0.6782	1	0.6736	0.7862
Performance Expectancy	0.6249	0.6032	0.6736	1	0.7269
Social Norm	0.6595	0.6424	0.7862	0.7269	1

References

[1] H. Yaseen, A.S. Al-Adwan, M. Nofal, H. Hmoud, R.S. Abujassar, Factors influencing cloud computing doption among SMEs: the Jordanian context, Inf. Dev. 39 (2) (2023) 317–332, https://doi.org/10.1177/02666669211047916.
[2] O.M. Horani, A.S. Al-Adwan, H. Yaseen, H. Hmoud, W.M. Al-Rahmi, A. Alkhalifah, The critical determinants impacting artificial intelligence adoption at the organizational level, Inf. Dev. (2023), 02666669231166889, https://doi.org/10.1177/02666669231166889.
[3] B. Abu-Salih, P. Wongthongtham, G. Morrison, K. Coutinho, M. Al-Okaily, A. Huneiti, Short-term renewable energy consumption and generation forecasting: a case study of Western Australia, Heliyon 8 (3) (2022), https://doi.org/10.1016/j.heliyon.2022.e09152.
[4] S. Khrais, M. Shidwan, Investigating the factors affecting chatbots adoption intention: an empirical study in the healthcare sector, Health Policy and Technol 9 (1) (2020) 1–9.
[5] H. Hmoud, A.S. Al-Adwan, O. Horani, H. Yaseen, J. Zoubi, Factors influencing business intelligence adoption by higher education institutions, J. of Open Innovation: Technol., Mark., and Complex. 9 (3) (2023), 100111, https://doi.org/10.1016/j.joitmc.2023.100111.
[6] A. Ahmed, N. Ali, M. Alzubaidi, W. Zaghouani, A. Abd-alrazaq, M. Househ, Arabic chatbot technologies: a scoping review, Comput. Methods and Programs in Biomedicine Update 2 (2022), 100057, https://doi.org/10.1016/j.cmpbup.2022.100057.
[7] M. Sugumar, S. Chandra, Do I desire chatbots to be like humans? exploring factors for adoption of chatbots for financial services, J. of International Technol. and Inf. Manag. 30 (3) (2021) 38–77.
[8] L. Zhou, J. Gao, D. Li, H.Y. Shum, The design and implementation of xiaoice, an empathetic social chatbot, Computational Linguist 46 (1) (2020) 53–93, https://doi.org/10.1162/COLI_a_00368.
[9] H.D. Wube, S.Z. Esubalew, F.F. Weldesellasie, T.G. Debelee, Text-based chatbot in financial sector: a systematic literature review, Data Sci. Financ. and Econ. 2 (3) (2022) 232–259.
[10] H. Hari, R. Iyer, B. Sampat, Customer brand engagement through chatbots on bank websites–Examining the antecedents and consequences, Int. J. Hum. Comput. Interact. 38 (13) (2022) 1212–1227, https://doi.org/10.1080/10447318.2021.1988487.
[11] P. Gatzioufa, V. Saprikis, A literature review on users' behavioral intention toward chatbots' adoption, Appl. Comput.and Inform. (2022) (ahead-of-print).
[12] R. Richad, V. Vivensius, S. Sfenrianto, E.R. Kaburuan, Analysis of factors influencing millennial's technology acceptance of chatbot in the banking industry in Indonesia, Int. J. Civ. Eng. Technol. 10 (4) (2019) 1270–1281, https://doi.org/10.34218/IJM.10.3.2019.011.
[13] A. Almurayh, The challenges of using Arabic chatbot in Saudi universities, IAENG Int. J. Comput. Sci. 48 (1) (2021).
[14] H. Palva, A General Classification for the Arabic Dialects Spoken in Palestine and Transjordan, vol. 55, Studia Orientalia Electronica, 1984, pp. 357–376.
[15] A.S. Al-Adwan, N. Khdour, Exploring student readiness to MOOCs in Jordan: a structural equation modelling approach, J. of Inf. Technol. Education 19 (2020) 223–242, https://doi.org/10.28945/4542.
[16] A. Alsharkawi, M. Al-Fetyani, M. Dawas, H. Saadeh, M. Alyaman, Poverty classification using machine learning: the case of Jordan, Sustain. Times 13 (3) (2021) 1412, https://doi.org/10.3390/su13031412.
[17] R.E. Jordan, P. Adab, K. Cheng, Covid-19: risk factors for severe disease and death, Bmj 368 (2020).
[18] S. Sari, R. Anjani, I. Farida, M.A. Ramdhani, Using android-based educational game for learning colloid material, J. Phys. Conf. Ser. 895 (No. 1) (2017, September), 012012, https://doi.org/10.1088/1742-6596/895/1/012012. IOP Publishing.
[19] H. Alqudah, A.A. Al-Qudah, A.F. Alkhwaldi, Examining the critical factors of computer-assisted audit tools and techniques adoption in the post-COVID-19 period: internal auditors perspective, VINE J. of Inf. and Knowl. Manag. Syst. (2022), https://doi.org/10.1108/VJIKMS-12-2021-0311 ahead-of-print No. ahead-of-print.
[20] M.A. Alqudah, L. Muradkhanli, Artificial intelligence in electric government; ethical challenges and governance in Jordan, Electron. Res. J. of Soc. Sci. and Humanities 3 (2021) 65–74.
[21] M. Al-Okaily, A. Al-Okaily, An empirical assessment of enterprise information systems success in a developing country: the Jordanian experience, The TQM J 34 (6) (2022) 1958–1975, https://doi.org/10.1108/TQM-09-2021-0267.
[22] A. Habibi, M.F.M. Yaakob, A.S. Al-Adwan, m-Learning management system use during Covid-19, Inf. Dev. 39 (1) (2023) 123–135, https://doi.org/10.1177/02666669211035473.
[23] O. Horani, A. Khatibi, A. AL-Soud, J. Tham, A.S. Al-Adwan, Determining the factors influencing business analytics adoption at organizational level: a systematic literature review, Big Data Cogn. Comput. 7 (3) (2023) 125, https://doi.org/10.3390/bdcc7030125.
[24] Statista, Size of the Chatbot arket Worldwide from 2021 to 2030, 2023 [online][18.4.2023]. available online: https://www.statista.com/statistics/656596/worldwide-chatbot-market/.
[25] Dencheva,V.Statista, Consumer Satisfaction with Chatbot Customer Service in the United States as of June 2022, 2023 [online][18.4.2023]. available online: https://www.statista.com/statistics/657148/united-states-consumer-satisfaction-with-chatbot-service/.
[26] C. Morgan, The experiences of disabled people in the United Arab Emirates: barriers to participation in higher education and employment, Disabil. Soc. 38 (3) (2023) 421–444, https://doi.org/10.1080/09687599.2021.1930520.

[27] UNESCO, World Arabic Language Day, 2022 [online][21.4.2023]. available online: https://www.unesco.org/en/days/world-arabic-language#:~:text=It%20is%20one%20of%20the,more%20than%20400%20million%20people.

[28] L. Najarian, CCCI. Arabic in the Context of Business and the Global Market, 2021 [online][21.4.2023]. available online: https://ccci.am/the-arabic-languages-global-business-significance/.

[29] S.F. Alhashmi, S.A. Salloum, S. Abdallah, Critical success factors for implementing artificial intelligence (AI) projects in Dubai Government United Arab Emirates (UAE) health sector: applying the extended technology acceptance model (TAM), in: Int. Conf. On Adv. Intel. Syst. and Inform., Springer International Publishing, Cham, 2019, October, pp. 393–405.

[30] N.I.M. Rahim, N.A. Iahad, A.F. Yusof, M.A. Al-Sharafi, AI-Based chatbots adoption model for higher-education institutions: a hybrid PLS-SEM-Neural network modelling approach, Sustain. Times 14 (19) (2022), 12726, https://doi.org/10.3390/su141912726.

[31] B.A. Shawar, E. Atwell, Different measurement metrics to evaluate a chatbot system, in: Proc. Of the Workshop on Bridg. the, gap: Acad. and Ind. Res. in dialog technol., 2007, April, pp. 89–96, https://doi.org/10.1145/3477314.3507255.

[32] A. Abdulquadri, E. Mogaji, T.A. Kieu, N.P. Nguyen, Digital transformation in financial services provision: a Nigerian perspective to the adoption of chatbot, J. of Enterp. Communities: People and Places in the Glob. Econ. 15 (2) (2021) 258–281, https://doi.org/10.1108/JEC-06-2020-0126.

[33] M.A. Alt, I. Vizeli, Z. Săplăcan, Banking with a chatbot–A study on technology acceptance, Studia Universitatis Babes-Bolyai Oeconomica 66 (1) (2021) 13–35.

[34] Juniper research, Bank Cost Savings via Chatbots to Reach $7.3 Billion by 2023, as Automated Customer Experience Evolve, 2023 [online][28.4.2023]. available online: https://www.juniperresearch.com/press/bank-cost-savings-via-chatbots-reach-7-3bn-2023.

[35] E. Mogaji, N.P. Nguyen, Managers' understanding of artificial intelligence in relation to marketing financial services: insights from a cross-country study, Int. J. Bank Market. 40 (6) (2022) 1272–1298.

[36] S. Sarbabidya, T. Saha, Role of chatbot in customer service: a study from the perspectives of the banking industry of Bangladesh, Int. Rev. of Bus. Res. Pap. 16 (1) (2020) 231–248.

[37] B.A. Eren, Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey, Int. J. of Bank Mark. 39 (2) (2021) 294–311, https://doi.org/10.1108/IJBM-02-2020-0056.

[38] M.A. Alt, V. Ibolya, Identifying relevant s a egments of potential banking chatbot users based on technology adoption behavior, Market-Tržište 33 (2) (2021) 165–183, https://doi.org/10.22598/mt/2021.33.2.165.

[39] A.A. Al-Qudah, A. Hamdan, M. Al-Okaily, L. Alhaddad, The impact of green lending on credit risk: evidence from UAE`s banks, Environ. Sci. Pollut. Res. 30 (22) (2023) 61381–61393, https://doi.org/10.1007/s11356-021-18224-5.

[40] R. Alghazzawi, A.F. Alkhwaldi, A. Al-Okaily, The effect of digital accounting systems on the decision-making quality in the banking industry sector: a mediated-moderated model, Glob. Knowl., Mem. and Commun. (2022), https://doi.org/10.1108/GKMC-01-2022-0015 (ahead-of-print).

[41] A. Al-Okaily, M. Al-Okaily, A.P. Teoh, M.M. Al-Debei, An empirical study on data warehouse systems effectiveness: the case of Jordanian banks in the business intelligence era, EuroMed J. Bus. (2022), https://doi.org/10.1108/EMJB-01-2022-0011.

[42] T.J. Toh, L.Y. Tay, Banking chatbots: a study on technology acceptance among millennials in Malaysia, J. of Logist., Inform. and Serv. Sci. 9 (3) (2022) 1–15, https://doi.org/10.33168/LISS.2022.0301.

[43] D.C. Ukpabi, B. Aslam, H. Karjaluoto, Chatbot adoption in tourism services: a conceptual exploration, in: Robot., Artif. Intell., and Serv. Autom. In Travel, Tour. and Hospitality, Emerald Publishing Limited, 2019, https://doi.org/10.1108/978-1-78756-687-320191006.

[44] R. Pillai, B. Sivathanu, Adoption of AI-based chatbots for hospitality and tourism, Int. J. of Contemp. Hospitality Manag. 32 (10) (2020) 3199–3226, https://doi.org/10.1108/IJCHM-04-2020-0259.

[45] N. Sandu, E. Gide, Adoption of AI-Chatbots to enhance student learning experience in higher education in India, in: 2019 18th Int. Conf. On Inf. Technol. Based High. Education and Train, IEEE, 2019, September, pp. 1–5, https://doi.org/10.1109/ITHET46829.2019.8937382 (ITHET).

[46] S. Laumer, C. Maier, F.T. Gubler, Chatbot Acceptance in Healthcare: Explaining User Adoption of Conversational Agents for Disease Diagnosis, 2019.

[47] S. Kuberkar, T.K. Singhal, Factors influencing adoption intention of AI powered chatbot for public transport services within a smart city, Int. J. of Emerg. Technol. in Learning 11 (3) (2020) 948–958.

[48] M. Al-Okaily, A.R. Al Natour, F. Shishan, A. Al-Dmour, R. Alghazzawi, M. Alsharairi, Sustainable FinTech innovation orientation: a moderated model, Sustain. Times 13 (24) (2021), 13591, https://doi.org/10.3390/su132413591.

[49] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. (1989) 319–340.

[50] A.S. Al-Adwan, H. Berger, Exploring physicians' behavioural intention toward the adoption of electronic health records: an empirical study from Jordan, Int. J. Healthc. Technol. Manag. 15 (2) (2015) 89–111, https://doi.org/10.1504/IJHTM.2015.074538.

[51] A.S. Al-Adwan, N. Li, A. Al-Adwan, G.A. Abbasi, N.A. Albelbisi, A. Habibi, Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms, Educ. Inf. Technol. (2023) 1–33, https://doi.org/10.1007/s10639-023-11816-3.

[52] A.S. Al-Adwan, M. Nofal, H. Akram, N.A. Albelbisi, M. Al-Okaily, Towards a sustainable adoption of E-learning systems: the role of self-directed learning, J. of Info. Technol. Educ.: Res. 21 (2022), https://doi.org/10.28945/4980.

[53] A. Al-Okaily, M. Al-Okaily, F. Shiyyab, W. Masadah, Accounting information system effectiveness from an organizational perspective, Manag. Sci. Lett. 10 (16) (2020) 3991–4000, https://doi.org/10.5267/j.msl.2020.7.010.

[54] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. (2003) 425–478, https://doi.org/10.2307/30036540.

[55] S.T. Alharbi, Trust and acceptance of cloud computing: a revised UTAUT model, 2, in: Comput. Sci. And Comput. Intell. (CSCI), 2014 International Conference on, IEEE, 2014, March, pp. 131–134, https://doi.org/10.1109/CSCI.2014.107.

[56] V. Venkatesh, J.Y. Thong, X. Xu, Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology, MIS Q. (2012) 157–178, https://doi.org/10.2307/41410412.

[57] Z. Qasem, Factors influencing the adoption of E-ticketing in Arabic frontier markets: conceptual extension of UTAUT, Emerg. Mark. from a Multidiscip. Perspect.: Chall., Oppor. and Res. Agenda (2018) 195–208.

[58] A.A. Alalwan, Y.K. Dwivedi, N.P. Rana, R. Algharabat, Examining factors influencing Jordanian customers' intentions and adoption of internet banking: extending UTAUT2 with risk, J. of Retail. and Consum. Serv. 40 (2018) 125–138, https://doi.org/10.1016/j.jretconser.2017.08.026.

[59] V. Soodan, A. Rana, Modeling customers' intention to use e-wallet in a developing nation: extending UTAUT2 with security, privacy and savings, J. of Electron. Commer. in Organ. (JECO) 18 (1) (2020) 89–114, https://doi.org/10.4018/JECO.2020010105.

[60] F.A.J. Almahri, D. Bell, M. Merhi, Understanding student acceptance and use of chatbots in the United Kingdom universities: a structural equation modelling approach, in: 2020 6th Int. Conf. On Inf. Manag. (ICIM), IEEE, 2020, March, pp. 284–288.

[61] P. Ganesa, S. John, A.S. Mane, Behavioural intention of AI-chatbots by telecom customers–UTAUT2 perspective with trust, in: Proc. Of 04th Int. Conf. on Mark., Technol. & Soc., 2020.

[62] A. Przegalinska, L. Ciechanowski, A. Stroz, P. Gloor, G. Mazurek, In bot we trust: a new methodology of chatbot performance measures, Bus. Horiz. 62 (6) (2019) 785–797, https://doi.org/10.1016/j.bushor.2019.08.005.

[63] M. Goli, A.K. Sahu, S. Bag, P. Dhamija, Users' acceptance of artificial intelligence-based chatbots: an empirical study, Int. J. Technol. Hum. Interact. 19 (1) (2023) 1–18, https://doi.org/10.4018/IJTHI.318481.

[64] B. Zhang, Y. Zhu, J. Deng, W. Zheng, Y. Liu, C. Wang, R. Zeng, I Am here to assist your tourism": predicting continuance intention to use AI-based chatbots for tourism. Does gender really matter? Int. J. Hum. Comput. Interact. 39 (9) (2023) 1887–1903, https://doi.org/10.1080/10447318.2022.2124345.

[65] R. Yang, S. Wibowo, S. Mubarak, An Investigation into Domestic Violence Victims' Adoption of Chatbots for Help-Seeking: Based on the UTAUT2 and Health Belief Models, 2023.

[66] A. Singh, N.P. Rana, S. Parayitam, Role of social currency in customer experience and co-creation intention in online travel agencies: moderation of attitude and subjective norms, Int. J. of Inf. Manag. Data Insights 2 (2) (2022), 100114, https://doi.org/10.1016/j.jjimei.2022.100114.

[67] Y.S. Huang, W.K. Kao, Chatbot service usage during a pandemic: fear and social distancing, Serv. Ind. J. 41 (13–14) (2021) 964–984, https://doi.org/10.1007/978-3-030-95346-1_38.
[68] Hsu, Y.P., Chih-Hsi, Y. and Hsu, W.C., Factors Influencing Users' Willingness to Consult Chatbots for Health Information..
[69] M.C. Han, Y. Kim, Chatbot commerce: hype or revolution? Pan-Pacific J. of Bus. Res. 11 (2) (2020) 30–45.
[70] Q. Gao, X. Xing, Study on the impact of chatbot characteristics of online shopping mall on customer satisfaction and reuse intention in China: hedonic motivation and utilitarian motivation as moderating variables, J. of Int. Trade & Commer. 19 (1) (2023) 51–67.
[71] C.L. Moraes, Chatbot as a Learning Assistant: Factors Influencing Adoption and Recommendation, Doctoral dissertation, Universidade NOVA de Lisboa, 2021 (Portugal)).
[72] B.P. Wicaksono, A. Zahra, Design of the use of chatbot as a virtual assistant in banking services in Indonesia, IAES Int. J. Artif. Intell. 11 (1) (2022) 23, https://doi.org/10.11591/ijai.v11.i1.pp23-33.
[73] N.A. Alhassan, A. Saad Albarrak, S. Bhatia, P. Agarwal, A novel framework for Arabic dialect chatbot using machine learning, Comput. Intell. Neurosci. (2022), https://doi.org/10.1155/2022/1844051, 2022.
[74] S. AlHumoud, A. Al Wazrah, W. Aldamegh, Arabic chatbots: a survey, Int. J. Adv. Comput. Sci. Appl. 9 (8) (2018), https://doi.org/10.14569/ijacsa.2018.090867.
[75] A.M.S. Alsubayhay, M.S.H. Salam, F.B. Mohamed, A review on approaches in Arabic chatbot for open and closed domain dialog, Int. J. Adv. Comput. Sci. Appl. 13 (11) (2022), https://doi.org/10.14569/IJACSA.2022.0131117.
[76] H.O.A. Wold, Soft modeling: the basic design and some extensions, in: K.G. Jöreskog, H.O.A. Wold (Eds.), Systems under Indirect Observations: Part II, North-Holland, Amsterdam, 1982, pp. 1–54.
[77] C.M. Ringle, S. Wende, J.-M. Becker, SmartPLS 4. Oststeinbek: SmartPLS GmbH, 2022. Retrieved from, http://www.smartpls.com.
[78] M. Sarstedt, J.F. Hair, M. Pick, B.D. Liengaard, L. Radomir, C.M. Ringle, Progress in partial least squares structural equation modeling use in marketing research in the last decade, Psychol. & Mark. 39 (5) (2022) 1035–1064, https://doi.org/10.1002/mar.21640.
[79] M. Sarstedt, J.F. Hair, C.M. Ringle, K.O. Thiele, S.P. Gudergan, Estimation issues with PLS and CBSEM: where the bias lies, J. Bus. Res. 69 (10) (2016) 3998–4010. https://10.1016/j.jbusres.2016.06.007.
[80] P.N. Sharma, B.D. Liengaard, M. Sarstedt, J.F. Hair, C.M. Ringle, Extraordinary claims require extraordinary evidence: a comment on "recent developments in PLS", Commun. Assoc. Inf. Syst. (2021).
[81] P.N. Sharma, G. Shmueli, M. Sarstedt, N. Danks, S. Ray, Prediction-oriented model selection in partial least squares path modeling, Decis. Sci. 52 (3) (2021) 567–607, https://doi.org/10.1111/deci.12329.
[82] G. Dash, J. Paul, CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting, Technol. Forecasting and Soci. Change 173 (2021), 121092, https://doi.org/10.1016/j.techfore.2021.121092.
[83] F. Faul, E. Erdfelder, A. Buchner, A.-G. Lang, Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses, Behav. Res. Methods 41 (4) (2009) 1149–1160, https://doi.org/10.3758/BRM.41.4.1149.
[84] J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), Sage, Thousand Oaks, CA, 2017.
[85] J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), Sage publications, 2021.
[86] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. of the Acad. of Mark. Sci. 43 (1) (2015) 115–135. https://10.1007/s11747-014-0403-8.
[87] J.F. Hair, M. Sarstedt, C.M. Ringle, S.P. Gudergan, Advanced Issues in Partial Least Squares Structural Equation Modeling, SAGE Publications, Thousand Oaks, CA, 2018.
[88] G. Shmueli, M. Sarstedt, J.F. Hair, J.-H. Cheah, H. Ting, S. Vaithilingam, C.M. Ringle, Predictive model assessment in PLS-SEM: guidelines for using PLSpredict, Eur. J. of Mark. 53 (11) (2019) 2322–2347, https://doi.org/10.1108/EJM-02-2019-0189.
[89] E.S. AL-Hagbani, M.B. Khan, Support of existing chatbot development framework for Arabic language: a brief survey, in: 5th Int. Symp. On Data Min. Appl., Springer International Publishing, 2018, pp. 26–35.
[90] Z. Jiang, M. Rashik, K. Panchal, M. Jasim, A. Sarvghad, P. Riahi, E. DeWitt, F. Thurber, N. Mahyar, CommunityBots: creating and evaluating A multi-agent chatbot platform for public input elicitation, Proc. of the ACM on Hum.-Comput. Interact. 7 (CSCW1) (2023) 1–32.
[91] Q. Hammouri, A. Aloqool, B. Saleh, H. Aldossary, S. Frejat, M. Halim, D. Almajali, J. Al-Gasawneh, S. Darawsheh, An empirical investigation on acceptance of e-wallets in the fintech era in Jordan: extending UTAUT2 model with perceived trust, Int. J. of Data and Netw. Sci. 7 (3) (2023) 1249–1258, https://doi.org/10.5267/j.ijdns.2023.4.013.
[92] Z. Qasem, The effect of positive TRI traits on centennials adoption of try-on technology in the context of E-fashion retailing, Int. J. Inf. Manag. 56 (2021), 102254, https://doi.org/10.1016/j.ijinfomgt.2020.102254.
[93] S. Dhingra, S. Gupta, Behavioural intention to use mobile banking: an extension of UTAUT2 model, Int. J. of Mob. Hum. Comput. Interact. (IJMHCI) 12 (3) (2020) 1–20, https://doi.org/10.4018/IJMHCI.2020070101.
[94] D. Pal, S. Patra, University students' perception of video-based learning in times of COVID-19: a TAM/TTF perspective, Int. J. Hum. Comput. Interact. 37 (10) (2021) 903–921, https://doi.org/10.1080/10447318.2020.1848164.
[95] M. Farzin, M. Sadeghi, F. Yahyayi Kharkeshi, H. Ruholahpur, M. Fattahi, Extending UTAUT2 in M-banking adoption and actual use behavior: does WOM communication matter? Asian J. of Econ. and Bank. 5 (2) (2021) 136–157, https://doi.org/10.1108/AJEB-10-2020-0085.
[96] K. Tamilmani, N.P. Rana, Y.K. Dwivedi, Consumer acceptance and use of information technology: a meta-analytic evaluation of UTAUT2, Inf. Syst. Frontiers 23 (2021) 987–1005, https://doi.org/10.1007/s10796-020-10007-6.
[97] K.O. Kwateng, K.A.O. Atiemo, C. Appiah, Acceptance and use of mobile banking: an application of UTAUT2, J. of enterp. Inf. manag. 32 (1) (2018) 118–151, https://doi.org/10.1108/JEIM-03-2018-0055.
[98] A.S. Mbrokoh, Exploring the factors that influence the adoption of internet banking in Ghana, J. Internet Bank. Commer. 21 (2) (2016) 1.
[99] G. Hofstede, Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations, SAGE Publications, Thousand Oaks, CA, 2001, 978-0-8039-7323-7. OCLC 45093960.