IJE TRANSACTIONS B: Applications Vol. 36, No. 05, (May 2023) 1012-1022

International Journal of Engineering

Journal Homepage: www.ije.ir

A Framework for Analysis of Predictors of Mobile-marketing Use by Expanding Unified Theory of Acceptance and Use of Technology and Artificial Neural Networks

N. Safaie*, H. Hamidi, M. Vali

Faculty of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran

PAPER INFO

Paper history:
Received 14 February 2022
Received in revised form 22 March 2023
Accepted 23 March 2023

Keywords:
Mobile Marketing
Technology Acceptance
Partial Least Squares
Artificial Neural Networks
Unified Theory of Acceptance
Use Technology

ABSTRACT

This study developed unified theory of acceptance and use technology (UTAUT) to examine the predictive factors of mobile marketing adoption. Variables such as personal innovativeness, hedonic motivations, performance expectancy, mobility, and social influence were studied for mobile marketing acceptance. The predicted artificial neural networks (ANN) approach was applied to evaluate the data, and the results of the data were used for comparison with path analysis. The ANN model was derailed by the linear statistical model and was able to show the importance of all predictors that could not be identified by the path analysis model. The results show that personal innovativeness is the most effective factor in mobile marketing acceptance. Subsequently, the hedonic motivations, performance expectancy, mobility, social influence, trust, and facilitating conditions play a vital role. Furthermore, the results illustrate that price value, perceived risk, and effort expectancy were not effective.

doi: *10.5829/ije.2023.36.05b.17*

1. INTRODUCTION

Over time, mobile marketing and mobile services businesses have grown rapidly to expand customer networks. Importantly, more than half of the world's population is online today [1]. Nowadays, many smartphone users are doing more sophisticated activities such as electronic payments, shopping, marketing services with their mobile devices, using voice services, etc. In 2022, Google's advertising revenue is estimated to be $ 224 billion[1]. These figures show evidence of the enormous growth and influence of mobile marketing. Therefore, developing countries such as Iran, with its high number of subscribers (123.7 million mobile subscribers) [2-4], as well as the potential and profits that are growing in this industry, need to be present seriously in this industry and commerce. Although China currently has the largest mobile payment market, developing countries such as India and Iran are being recognized as the future of mobile marketing owing to the rapid growth of their market and their large number of mobile users [5-8]. Figure 1 illustrated the average changes in media consumption in 2019 vs. 2011.

The benefits of mobile marketing include its ubiquitous availability, customization based on the time, place, and individual characteristics of users [9]. By reducing search costs for users, increased diversity of products offered, lower prices for both users and retailers, empowering consumers to make better choices, enhancing brand [10, 11] relationship after purchase. Mobile marketing also differentiates itself usefully from other marketing media such as television, radio, and newspapers as well as the website (due to its fully interactive nature). However, there are some challenges in mobile marketing, such as the concern of the lack of explicit written law to protect consumer rights in mobile marketing and advertising. Government agencies can help by taking steps to ensure the privacy of consumers, for example, the confidentiality of personal information and requesting permission to post ads before making extensive use of this tool [12].

The goals that we want to achieve in this research are:

*Corresponding Author Institutional Email: *nsafaie@kntu.ac.ir* (N. Safaie)

[1] https://www.statista.com/statistics/266249/advertising-revenue-of-google/

Please cite this article as: N. Safaie, H. Hamidi, M. Vali, A Framework for Analysis of Predictors of Mobile-marketing Use by Expanding Unified Theory of Acceptance and Use of Technology and Artificial Neural Networks, ***International Journal of Engineering, Transactions B: Applications***, Vol. 36, No. 05, (2023) 1012-1022

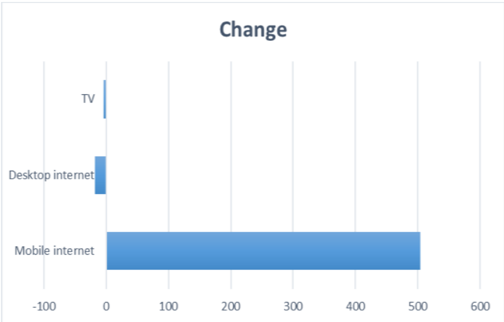

Figure 1. Average Changes in Media Consumption in 2019 vs. 2011

1. This study aims to explore the use of mobile marketing in Iranian consumer market, which is one of the fastest-growing mobile marketing markets. This is also the first study to examine mobile marketing for consumers in Iran.
2. This study aims to identify the important factors that can predict the use of mobile marketing based on the extended UTAUT model. This study adds variables of mobility, personal innovativeness, trust and perceived risk to the UTAUT model by using previous studies.
3. In this study, a more detailed analysis was performed using artificial neural networks. This approach provides a better prediction of conventional linear models for predicting mobile marketing acceptance by considering the nonlinear decision model. To this end, the results of the neural network have been compared with the analysis of linear statistical methods to determine which techniques can improve mobile marketing acceptance. It also responds to the call to apply analytical forecasting techniques to information systems research.

2. LITERATURE REVIEW

As mentioned in the previous section, the internet plays an important role in people's activities today. In examining the determinants of technology acceptance, researchers often consider behavior or approach as an important part of understanding actual behavior [13, 14]. Users often accept applying technologies suggested by their social and business partners. Therefore, the advice of users to other people can be extremely important in increasing the influence and development of mobile marketing in Iran. In addition to the recommendation, the study also explored a proposal to expand UTAUT2, taking into account the degree of risk and trust considered as a factor [15]. Since mobile marketing and its technology adoption in developing countries is a valuable topic, the proposed model is presented in Figure 2.

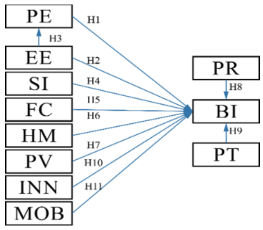

Figure 2. The proposed model

2. 1. Performance Expectancy The performance expectancy is a set of different features of information systems that can explain the benefits to users and is quite similar to the perceived usefulness of TAM technology adoption. It is generally agreed that people are more inclined to use new technology that they think will be useful [16-18]. In the context of mobile marketing, the performance expectancy means that the consumer realizes that using mobile marketing can be beneficial and optimal for completing business transactions. However, since the expected performance goes beyond being useful, it also includes aspects of relative advantage and extrinsic motivation [19]. The following hypothesis is proposed:

H 1: Performance expectancy positively affects the behavioral intention of mobile marketing acceptance.

2. 2. Effort Expectancy Effort expectancy is defined as "the degree of easy to interact with technology for users" [20, 21]. This topic is similar to the discussion of the perceived ease of use and users' understanding of the application in TAM, which illustrates how comfortable the users are with the application. In the context of mobile marketing, the degree of effort and performance can be described as the ability to complete a mobile marketing transaction with minimal effort. In such a situation, consumers can easily make mobile marketing deals within these applications. However, recent studies on the adoption of other mobile technologies have found no direct and significant relationship between effort expectancy and behavioral intention [22-28]. Instead, it is expected that it has an indirect effect on behavioral intention on acceptance through its positive effect on performance expectancy [29-31]. Since ease of use is considered to have a great impact on mobile marketing, the following hypothesis is proposed:

H 2: Effort expectancy positively influences behavioral intention on mobile marketing acceptance.

H 3: Effort expectancy has a positive effect on performance expectancy.

2. 3. Social Influence Social influence is significant to the extent that it can be said that users are strongly influenced by their family [32]. When other users' feedbacks are positive, they are encouraged to use that technology and, in turn, misuse the other people's feedbacks. Previous studies have shown that social influence has a significant impact on consumers'

acceptance of mobile marketing solutions [33, 34]. For this reason, this study assumes that:
H 4: Social influence positively influences behavioral intention on mobile marketing acceptance.

2. 4. Facilitating Conditions In other words, facilitation conditions can be perceived by consumers about environmental barriers or available resources that make it easy to use mobile marketing solutions. The early concept of UTAUT examined facilitating conditions only as a predictor of behavior. However, Imtiaz [35] in UTAUT2 showed that facilitating conditions is also a behavioral approach for technology adoption. However, the generalization of this relationship is controversial, as some studies have shown significant conditions[1]. While others have found no significant association of facilitation conditions. Do not have a behavioral approach [36]. Despite these contradictory results, this study examines facilitation conditions according to studies conducted by Kalinic and Marinkovic [37], they stated facilitating conditions significantly influence the behavioral intention to accept using a technology. Facilitating conditions have a significant impact on mobile Internet use[2], which can have had a great impact on mobile marketing adoption because mobile internet is a vital part of mobile marketing transactions. So, this research assumes that:
H 5: Conditions of facilitation positively influence behavioral intention on mobile marketing acceptance.

2. 5. Hedonic Motivations Hedonic motivation is the pleasure that is given to the consumer through the use of technology. In fact, users are increasingly concerned about the overall experience of using precision technology. So, whether it enjoys it or not or in other words, whether communicating with technology or not for users can change the way technology is used. Even if support for the relationship between hedonic motivations and behavioral approach has not been fully elucidated, many other studies confirm the significant role of this factor in proving and explaining hedonic motivations for predicting goals have been argued in different technologies adoption [38, 39]. As such, this research assumes that:
H 6: Hedonic motivations for positively influences on behavioral intention to mobile marketing acceptance.

2. 6. Price Value In the context of mobile marketing, this factor can be considered as the advantage of using business applications that are more valuable than the financial costs of conducting similar transactions in an in-person transaction or other types of transactions. Given the potential benefits of using different mobile marketing applications as introduced in UTAUT2. However, there are also studies that have found that financial value is not significant in predicting behavioral approach [40]. Therefore, this study shows that:
H 7: Price value has a positive effect on behavioral intention on mobile marketing acceptance.

2.7. Extended UTAUT2

2. 7. 1. Perceived Risk Perceived risk refers to individual conclusions about the risks and negative consequences of using technology. researches shows that the risks posed by users' use of Internet technologies have a significant negative impact on their decision to use electronic systems [40]. Researches have shown that building trust between consumers and vendors and providing a degree of control over the disclosure of personal information online can alleviate privacy risk concerns [38]. Because privacy issues in online settings affect the attitudes and goals of website use [39], risk-taking increases the amount of mobile activity associated with providing information to companies, and the content will be accessed. Therefore, this study shows that:
H 8: Perceived risk has a significant negative impact on behavioral intention on m-marketing acceptance.

2. 7. 2. Perceived Trust When a significant amount of trust is provided and guaranteed for an application, the user is more likely to use that application and system and is then persuaded to provide personally identifiable information and other sensitive information to the m-marketing service provider. As such, this research assumes that:
H 9: Perceived trust has a significant positive effect on behavioral intention on m-marketing acceptance.

2. 7. 3. Personal Innovativeness and Mobility Consumer innovativeness has been used to study the acceptance behavior of new products and services [40]. The level of personal innovativeness is often referred to as a personality structure, which has been used to predict innovative consumer tendencies to embrace different types of technological innovations. To accurately conceptualize the structure of "innovativeness" some scholars separate the concepts of "inherent innovativeness" and "real innovativeness" [37]. The following hypothesis is developed on this basis:
H 10: Consumer's personal innovativeness positively influences behavioral intention on mobile marketing acceptance.
H 11: Mobility has a significant and positive effect on behavioral intention to accept m-marketing. Table 1 also presents summarizes of previous studies as reported in literature.

[1] https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2018/MISR-2018-Vol-1-E.pdf

[2] https://wearesocial.com/blog/2019/01/digital-2019-global-internet-use-accelerates

TABLE 1. Summarizes of previous studies

Source	Base model	Factors	Findings
Duarte and Pinho [21]	UTAUT2	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Personal Interests, Price value, Risk, Trust	• The positive impact of perceived risk, perceived trust, and personal attachment • In the context of the environment, the key factors for the adoption of e-commerce in Cameroon are the social influence and facilitating conditions
Chong [12]	UTAUT	Trust, Performance Expectancy, Effort Expectancy, Perceived Value, Perceived Enjoyment, Personal Innovation, Facilitating Conditions, Social Influence, Perceived Ease of Use, Demographic Factors	Based on ANN analysis, perceived value is the most important predictor of mobile commerce usage, followed by performance expectancy, social influence, trust, perceived ease of use, age, perceived enjoyment, education level, personal innovativeness, facilitating conditions and gender.
Dai and Palvia [17]	TAM	Perceived Usefulness, Perceived Ease of Use, Perceived Privacy, Perceived Cost, Compatibility, Perceived Enjoyment, and Perceived Added Value	In the Chinese model, innovation, perceived usefulness, perceived ease of use, perceived cost, and subjective norms significantly influence consumers' intentions to use mobile commerce.
Alalwan [3]	TAM	Perceived usefulness, perceived ease of use, trust, innovation, perceived enjoyment	Perceived enjoyment is the strongest predictor of consumers' decisions. Perceived enjoyment also has a significant impact on the perceived usefulness of Saudi customers in the conceptual model. This means that as long as the customers feel that it is enjoyable to use mobile internet, they will positively perceive mobile internet as productive and useful.
Benbasat and Barki [7]	TAM	Perceived Usefulness, Perceived Ease of Use, Trust, Mobility, Customization, Customer engagement	The results show that customization and customer engagement are the strongest predictors of behavioral intention to use mobile commerce.
Herrero et al. [27]	UTAUT2	Perceived Value, Personal Innovativeness, Performance Expectancy, Perceived Privacy, Perceived Personal Risk, Perceived Transaction Risk,	Perceived value replaces price value to represent the value of an IT product that does not have direct costs associated with it, as a compromise between privacy concerns and performance expectations.
Faqih and Jaradat [23]	TAM	Perceived Usefulness of Mobile Online Stores for Searching Information, Perceived Usefulness of Mobile Online Stores for Shopping,	This study aims to examine the processes of understanding consumer concepts by examining the processes of online shopping in Europe.
Carlsson et al. [10]	UTAUT	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Enjoyment, Perceived Risk, Personal Innovativeness in Accepting Different E-Commerce Categories.	Performance expectancy includes improvements in performance, productivity, greater convenience through the use of e-commerce applications.
Gao et al. [24]	TAM	Risk acceptance, personal dependence instead of the perceived ease of use of the old model,	Providing information and content availability in both the US and Pakistan have a positive impact on mobile marketing acceptance.

This study developed UTAUT to examine the predictive factors of mobile marketing adoption. Variables such as personal innovativeness, hedonic motivations, performance expectancy, mobility, and social influence were studied for mobile marketing acceptance.

3. METHODOLOGY

UTAUT2 is a validated model and comprises a comprehensive structure of diverse findings in various contexts [26, 27]. For this reason, it is important to continually review and refine UTAUT2 to enhance its generalizability, and it is particularly important in mobile marketing since different studies show similar results for similar variables [11, 29].

This information was collected in the spring of 2019. In this article, a convenient tool for student information gathering was applied using a questionnaire. As well as, participation in this questionnaire was completely optional. Table 2 summarized the details of demographic characteristics.

The results of the questionnaire analysis are shown in Figure 3. This figure shows the percentage of respondents in each factor separation based on the Likert scale. As shown in the Figure 3, most participants believe that the use of mobile marketing will be useful in everyday life in general. They also find it easy to learn how to use mobile marketing. More than half of users believe that facilitating conditions such as the resources and knowledge they need, helping others, or adapting to other technologies make it possible for them to use mobile marketing. Moreover, more than 80 percent of users believe that they are interested in using new technologies, and among their peers, they usually use technology earlier than others.

TABLE 2. The details of demographic characteristics

Characteristics		Number	Percentage
Gender	Male	154	44%
	Female	196	56%
Age	18-20	65	19%
	21-30	245	70%
	31-40	26	7%
	>40	14	4%
Marriage	Single	241	68%
	Married	33	9%
Education level	Diploma	63	18%
	Bachelor	154	44%
	Master	113	32%
	Ph.D. and higher	20	5%

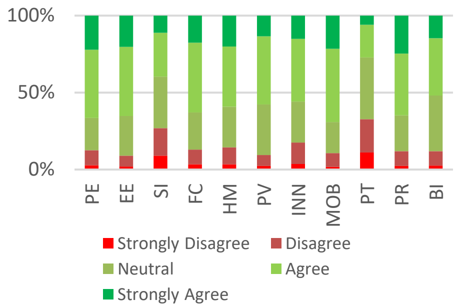

Figure 3. Distribution of responses

3. 1. Survey Development The survey questions in this study were designed using the opinions of experts and previous studies. Questions for the main variables of UTAUT2 including PE, EE, SI, FC, HM, and PV come from [26], and have been privatized by the technology used in the study of mobile marketing acceptance. Other questions come from [11, 13, 26] in the context of mobile marketing has been extracted.

3. 2. Data Analysis SEM is a technique that estimates the relationships between variables [36]. SEM can be implemented using two methods: covariance-based method (such as EQS, AMOS, and LISREL) and variance-based PLS. According to literature [13, 26], partial least squares techniques are less restrictive than structural equation modeling, capable of simultaneously analyzing structural model and evaluation, and are more suitable for small-scale research and predictive purposes. The PLS method is principally used to analyze models that contain several different dimensions and the number of pathways is small [35]. Based on the conditions of this study (statistical population of 350 people and not using mobile marketing in Iran), the PLS method is preferred to SEM. According to Hamidi and Chavoshi [26], methods such as PLS and SEM consider complex human decisions so simple, including the tendency to use new technologies. Therefore, there exists a need to apply new artificial intelligence approaches such as ANNs for solving this problem. The partial least squares method is also not capable of analyzing nonlinear relationships. In fact, using the combination of artificial neural networks and partial least squares (PLS-ANN) makes the advantages of both methods better for data analysis. Therefore, in this study, this approach was implemented using SPSS and Smart PLS. The details of the data analysis and the steps to do this are schematically shown in Figure 4.

3. 3. Outer Model: Validity and Reliability The outer model is used to assess the validity and reliability of the questionnaire. Validity determines that the questions in the questionnaire measure the same concept as that of the researchers, and for its evaluation, convergent and discriminant validity must be tested [26]. Validity is meant to show the degree of reasonableness of the survey questions for the relevant factor, and reliability indicates that the questions related to each factor measure precisely and yield similar results at different times and conditions [30].

According to Chavoshi and Hamidi [11], to measure reliability, factor loadings of all indices must be greater than 0.5, and the corresponding t-statistic should be greater than ±1.96% and composite reliability (CR) greater than 0.7. Also, calculating internal consistency reliability is critical. For this purpose, the Cronbach's alpha correlation coefficient should be calculated, the closer this value shows a higher degree of internal consistency reliability. Table 3 shows the values of factor loadings, alpha correlation coefficient and composite reliability for this study. Accordingly, the reliability of the questionnaire is confirmed.

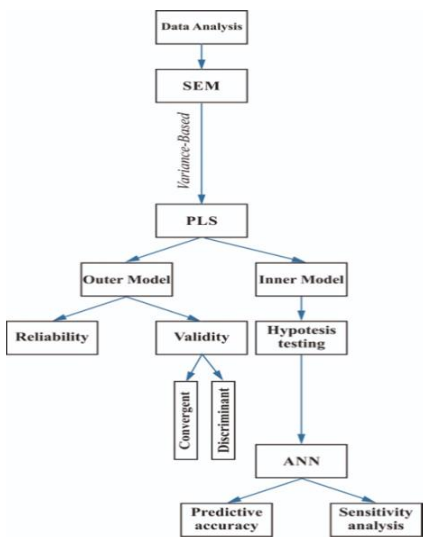

Figure 4. Data Analysis Schema [26]

TABLE 3. Outer Model

Construct	Indicator	Factor Loading	t-statistics	Cronbach's alpha	CR	AVE
Performance Expectancy	PE1	0.849	41.776	0.830	0.887	0.663
	PE2	0.847	45.259			
	PE3	0.796	25.509			
	PE4	0.764	29.054			
Effort Expectancy	EE1	0.819	32.519	0.847	0.897	0.686
	EE2	0.847	37.886			
	EE3	0.833	34.790			
	EE4	0.812	31.244			
Social Influence	SI1	0.798	23.916	0.734	0.849	0.653
	SI2	0.743	21.258			
	SI3	0.879	57.612			
Facilitating Conditions	FC1	0.767	26.171	0.702	0.834	0.626
	FC2	0.779	25.462			
	FC3	0.827	32.878			
Hedonic Motivations	HM1	0.834	36.594	0.727	0.847	0.650
	HM2	0.881	58.987			
	HM3	0.693	14.268			
Price Value	PV1	0.790	23.482	0.761	0.861	0.674
	PV2	0.868	47.883			
	PV3	0.804	19.946			
Perceived Risk	PR1	0.856	2.996	0.704	0.870	0.771
	PR2	0.899	3.379			
Perceived Trust	PT1	0.808	34.225	0.842	0.894	0.678
	PT2	0.831	29.741			
	PT3	0.846	39.745			
	PT4	0.809	35.794			
Personal Innovativeness	INN1	0.754	24.885	0.777	0.856	0.599
	INN2	0.693	17.830			
	INN3	0.811	34.502			
	INN4	0.830	41.015			
Mobility	MOB1	0.866	48.459	0.846	0.897	0.686
	MOB2	0.874	39.756			
	MOB3	0.840	16.999			
	MOB4	0.725	41.776			
Behavioral intention	BI1	0.880	62.348	0.891	0.925	0.754
	BI2	0.860	53.058			
	BI3	0.905	77.499			
	BI$	0.827	34.520			

The convergent validity is used to measure the amount of explanation of a hidden variable by its observable variables [26].

Discriminant validity means that the factors are not statistically correlated with each other [25]. Table 4 shows the mentioned comparisons. The bold numbers represent the square root of AVE for each factor. According to the presented results in this table, the discriminant validity of this study is also confirmed.

3. 4. Inner Model To evaluate the internal model, we need to calculate the beta, the corresponding t-statistic, R^2, f^2, and Q^2 [11, 26]. For this purpose, the Bootstrap procedure is applied with 5000 replicates. To test the hypotheses, the correlation coefficients of the path (beta) with the corresponding t-statistic should be checked. To support any of the hypotheses, the t-statistic is required to be higher than ±1.96 [11]. Obviously, hypotheses with statistics below this threshold value are rejected. As shown in Table 5, hypotheses 2 (EE -> BI), 7 (PV -> BI) and 8 (PR -> BI) are rejected.

According to Figure 5, the values of R^2 for the dependent factors behavioral intention to use and the performance expectancy is 0.631 and 0.168, respectively. In fact, about 63% of the variance associated with the behavioral intention to use m-marketing is attributable to performance expectancy factors, personal innovativeness, mobility, and perceived trust. Also, about 17% of the variance of performance expectancy depends on the effort expectancy.

According to Chavoshi and Hamidi [11], the values of R^2 equal to 0.25, 0.5 and 0.75 indicate that the model is weak, moderate and robust, respectively. Finally, given the value of R^2 for the tendency to use mobile marketing which is equal to 0.631, it can be concluded that the model presented in this study is robust and acceptable.

TABLE 4. Discriminant validates

	BI	EE	FC	HM	INN	MOB	PE	PR	PT	PV	SI
BI	**0.868**										
EE	0.388	**0.828**									
FC	0.547	0.585	**0.791**								
HM	0.588	0.315	0.395	**0.807**							
INN	0.679	0.422	0.531	0.538	**0.774**						
MOB	0.483	0.368	0.440	0.376	0.383	**0.828**					
PE	0.613	0.410	0.560	0.575	0.548	0.415	**0.815**				
PR	0.033	0.092	0.110	0.078	0.060	0.143	0.174	**0.878**			
PT	0.509	0.247	0.333	0.401	0.449	0.355	0.414	-0.066	**0.824**		
PV	0.446	0.391	0.443	0.410	0.458	0.356	0.473	0.100	0.342	**0.821**	
SI	0.599	0.416	0.549	0.518	0.522	0.327	0.581	0.093	0.484	0.462	**0.808**

TABLE 5. Inner model's hypotheses

Hypothesis	Path Coefficients	Standard deviations	t-statistics	Supported
PE -> BI	0.141	0.053	2.692	Yes
EE -> BI	0.021	0.043	0.482	No
EE -> PE	0.410	0.042	9.644	Yes
SI -> BI	0.153	0.048	3.194	Yes
FC -> BI	0.091	0.044	2.060	Yes
HM -> BI	0.143	0.047	3.066	Yes
PV -> BI	-0.000	0.037	0.013	No
PR -> BI	-0.057	0.047	1.220	No
PT -> BI	0.101	0.040	2.496	Yes
INN -> BI	0.314	0.047	6.613	Yes
MOB-> BI	0.147	0.039	3.791	Yes

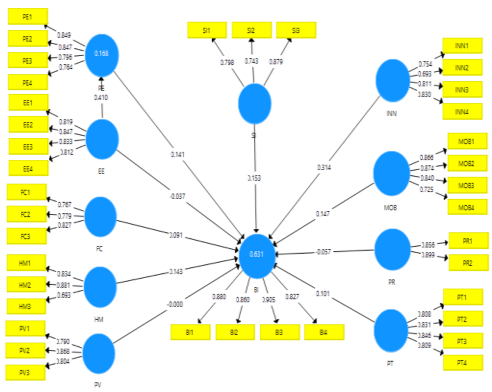

Figure 5. Obtained values of path correlations and R^2 through Smart PLS

Since the p-index is not a suitable criterion for measuring the impact of the independent variable on the dependent variable, a better index, f^2, should be used [29]. Given the values are shown in Table 6, perceived trust and facilitating conditions have low impact, performance expectancy, hedonic motivations, personal innovativeness, mobility, and social influence size have a moderate effect on behavioral intention to use, as well as, the effort expectancy has a significant impact on the performance expectancy.

Then we need to calculate the predictive relationship. For this purpose, the value of Q^2 must be calculated through the Blindfolding procedure. According to Hamidi and Chavoshi [26], for values above zero, the model has a predictive relationship, and if this value is 0.02, 0.15 and 0.35, it indicates a weak, moderate predictive relationship, respectively. The results of Table 7 show that the predictive relevance of the model presented in this study is a robust mobile marketing acceptance model.

3. 5. ANN Analysis The artificial neural network is "a machine that has been devised to model brain function for a specific task" [31]. In fact, the artificial neural network is a modeling of the human nervous system that enables the learning process to be simulated by the human brain. Due to the ANN's learning capability, this technique can improve its performance through learning process [39, 40].

TABLE 6. Effect size of independent variables

	Dependent variable	
Independent variable	**Behavioral intention**	**Performance Expectancy**
Performance Expectancy	0.025	-
Effort Expectancy	0.002	0.202
Social Influence	0.031	-
Facilitating Conditions	0.010	-
Hedonic Motivations	0.031	-
Price Value	0.000	-
Perceived Risk	0.008	-
Perceived Trust	0.018	-
Personal Innovativeness	0.139	-
Mobility	0.040	-

TABLE 7. Indicator of model's predictive relevance

Dependent Variable	Construct cross-validated redundancy
Performance Expectancy	0.102
Behavioral intention	0.433

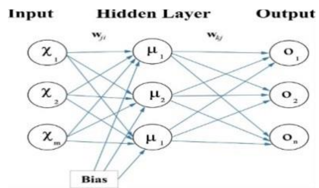

Figure 6. ANN Different Layers [12]

As noted in previous studies by Hamidi and Chavoshi [26], to evaluate the size of relative significance of independent variables for dependent variables the most common artificial neural network model, namely multi-layer perceptron, has been used. To this end, the confirmed factors in PLS analysis are given as input to the neural network. The proposed model of this study transformed into two artificial neural network models due to its two paths, which are shown in detail in Figure 7.

To avoid over-fitting, a 10-fold cross-validation procedure is used in which 90% of the data is considered as training data, and 10% is considered as test data [26]. The activation function in both the hidden and the output layers was sigmoid. The number of hidden layers and their associated neurons is also automatically calculated by the software to obtain the optimal state. Table 8 shows the Root Mean Square Errors (RMSE) values to measure model prediction for all 10 networks for both the training and the test modes.

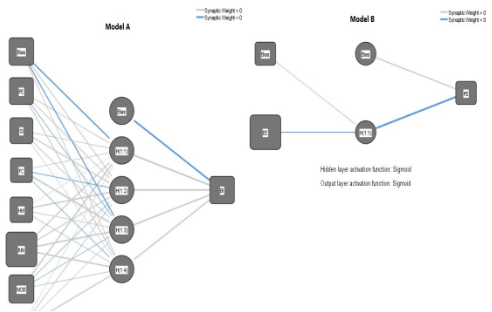

Figure 7. ANN Models

TABLE 8. RMSE values of ANN

Network	Model A Inputs: PE, SI, FC, HM, INN, MOB, and PT Output: BI		Model B Input: EE	
	Training	**Test**	**Training**	**Test**
1	0.0933	0.1019	0.1402	0.1091
2	0.0937	0.1	0.1440	0.1381
3	0.0869	0.0959	0.1404	0.906
4	0.0908	0.0570	0.1417	0.1136
5	0.0931	0.0764	0.1407	0.1255
6	0.0916	0.0915	0.1404	0.1328

7	0.0916	0.0820	0.1337	0.1687
8	0.0928	0.0665	0.1410	0.1340
9	0.0945	0.0748	0.1383	0.1445
10	0.0906	0.0885	0.1471	0.1217
Mean	0.0919	0.0834	0.1408	0.1278
Standard deviation	0.0020	0.0140	0.0032	0.0202

Sensitivity analysis is used to measure the sensitivity of the independent factors for the dependent factor. For this purpose, relative importance is shown by how much the predicted output value for the dependent factor varies with different inputs. Table 9 shows these values for both models.

Comparing the results of this table with Table 7, it can be concluded that there is a little difference in the order of importance of the factors influencing the adoption of mobile marketing use. For example, sensitivity analysis results indicate that the second most important factor is hedonic motivations, while effect size analysis results (f^2) believe that the second important factor is the mobility factor. This difference is due to varieties in the method of better analysis in artificial neural networks that detect nonlinear relationships in the model.

TABLE 9. ANN sensitivity analysis

Network	Model A							Model B
	PE	**SI**	**FC**	**HM**	**INN**	**MOB**	**PT**	**EE**
1	0.103	0.182	0.129	0.179	0.184	0.101	0.121	1.000
2	0.195	0.173	0.081	0.124	0.230	0.067	0.130	1.000
3	0.152	0.152	0.079	0.140	0.244	0.135	0.098	1.000
4	0.110	0.130	0.087	0.122	0.303	0.150	0.097	1.000
5	0.136	0.089	0.132	0.184	0.219	0.110	0.129	1.000
6	0.160	0.095	0.017	0.113	0.307	0.182	0.126	1.000
7	0.129	0.126	0.023	0.124	0.310	0.160	0.128	1.000
8	0.100	0.125	0.091	0.151	0.330	0.105	0.097	1.000
9	0.086	0.047	0.154	0.194	0.286	0.098	0.136	1.000
10	0.131	0.111	0.085	0.104	0.285	0.156	0.129	1.000
Average importance	0.130	0.123	0.088	0.144	0.270	0.126	0.119	1.000
Normalized importance (%)	48	45.5	32.5	53	100	47	44	100

4. CONCLUSION

The variables of this study include factors such as UTAUT2 technology adoption, perceived risk and trust and mobility were used to extend this model. These factors have been tested by some hypotheses. This test is performed by SEM, PLS, and ANN. The data required for this study were collected electronically and by paper. Here's a look at each of the UTAUT2 factors and the factors that extend it. Despite many efforts, this study is not without limitations. The first limitation of this study is that in academic research the statistical population is relatively small and has only studied the student population of a university in Iran. Although online polls were posted on popular social media websites among students of K. N. Toosi University of Technology, Iran, responses were very slow and resulted in a small sample size. Future studies could consider distributing this survey to consumers about specific products in the consumer community of a product for its mobile marketing. Secondly, the information collected here is from Iranian consumers and has not been considered by the international communities. Future studies could examine the acceptance of mobile marketing in two societies, a developed and one developing country.

5. REFERENCES

1. Al-Louzi, B. and Iss, B., "Factors influencing customer acceptance of m-commerce services in jordan", ***Journal of Communication and Computer***, Vol. 9, No. 1, (2011), 1424-1436.
2. Al-Shihi, H., Sharma, S.K. and Sarrab, M., "Neural network approach to predict mobile learning acceptance", ***Education and Information Technologies***, Vol. 23, (2018), 1805-1824. https://doi.org/10.1007/s10639-018-9691-9
3. Alalwan, A.A., Baabdullah, A.M., Rana, N.P., Tamilmani, K. and Dwivedi, Y.K., "Examining adoption of mobile internet in saudi arabia: Extending tam with perceived enjoyment, innovativeness

and trust", ***Technology in Society***, Vol. 55, (2018), 100-110. https://doi.org/10.1016/j.techsoc.2018.06.007

4. Alalwan, A.A., Dwivedi, Y.K. and Rana, N.P., "Factors influencing adoption of mobile banking by jordanian bank customers: Extending UTAUT2 with trust", ***International Journal of Information Management***, Vol. 37, No. 3, (2017), 99-110. https://doi.org/10.1016/j.tele.2017.05.008
5. Alalwan, A.A., Rana, N.P., Dwivedi, Y.K. and Algharabat, R., "Social media in marketing: A review and analysis of the existing literature. ", ***Telematics and Informatics***, Vol. 34, (2017), 1177-1190. https://doi.org/10.1016/j.tele.2017.05.008
6. Alharbi, S. and Drew, S., "The role of self-efficacy in technology acceptance", in Proceedings of the Future Technologies Conference (FTC) 2018: Volume 1, Springer. (2019), 1142-1150.
7. Benbasat, I. and Barki, H., "Quo vadis tam?", ***Journal of the Association for Information Systems***, Vol. 8, No. 4, (2007), 7. https://doi.org/10.17705/1jais.00126
8. Brasel, S.A. and Gips, J., "Tablets, touchscreens, and touchpads: How varying touch interfaces trigger psychological ownership and endowment", ***Journal of Consumer Psychology***, Vol. 24, No. 2, (2014), 226-233.
9. Budiono, F., Lau, S. and Tibben, W., "Cloud computing adoption for e-commerce in developing countries: Contributing factors and its implication for indonesia", (2018).
10. Carlsson, C., Carlsson, J., Hyvonen, K., Puhakainen, J. and Walden, P., "Adoption of mobile devices/services-searching for answers with the utaut", in Proceedings of the 39th annual Hawaii international conference on system sciences (HICSS'06), IEEE. Vol. 6, (2006), 132a-132a.
11. Chavoshi, A. and Hamidi, H., "Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: A case from iran", ***Telematics and Informatics***, Vol. 38, (2019), 133-165. https://doi.org/10.1016/j.tele.2018.09.007
12. Chong, A.Y.-L., "Predicting m-commerce adoption determinants: A neural network approach", ***Expert Systems with Applications***, Vol. 40, No. 2, (2013), 523-530. https://doi.org/10.1016/j.eswa.2012.07.068
13. Chong, A.Y.-L., Chan, F.T. and Ooi, K.-B., "Predicting consumer decisions to adopt mobile commerce: Cross country empirical examination between china and malaysia", ***Decision Support Systems***, Vol. 53, No. 1, (2012), 34-43. https://doi.org/10.1016/j.dss.2011.12.001
14. Chong, A.Y.-L., Darmawan, N., Ooi, K.-B. and Lin, B., "Adoption of 3g services among malaysian consumers: An empirical analysis", ***International Journal of Mobile Communications***, Vol. 8, No. 2, (2010), 129-149. https://doi.org/10.1504/IJMC.2010.031444
15. Hamidi, H. and Seyed Lotfali, S., "Analysis of role of cloud computing in providing internet banking services: Case study bank melli iran", ***International Journal of Engineering, Transactions B: Applications***, Vol. 35, No. 5, (2022), 1082-1088. doi: 10.5829/ije.2022.35.05b.23.
16. Cohen, J., *Statistical power analysis for the behavioral sciences (revised ed.)*. 1977, New York: Academic Press.
17. Dai, H. and Palvi, P.C., "Mobile commerce adoption in china and the united states: A cross-cultural study", ACM SIGMIS Database: the DATABASE for Advances in Information Systems, Vol. 40, No. 4, (2009), 43-61. https://doi.org/10.1145/1644953.1644958
18. Davis, F.D., "Perceived usefulness, perceived ease of use, and user acceptance of information technology", ***MIS Quarterly***, (1989), 319-340. https://doi.org/10.2307/249008
19. Davis, R., "Conceptualising fun in mobile commerce environments", ***International Journal of Mobile Communications***, Vol. 8, No. 1, (2010), 21-40. https://doi.org/10.1504/IJMC.2010.030518
20. Torabi, A., Hamidi, H. and Safaie, N., "Effect of sensory experience on customer word-of-mouth intention, considering the roles of customer emotions, satisfaction, and loyalty", ***International Journal of Engineering, Transactions C: Aspects***, Vol. 34, No. 3, (2021), 682-699. doi: 10.5829/ije.2021.34.03c.13.
21. Duarte, P. and Pinho, J.C., "A mixed methods UTAUT2-based approach to assess mobile health adoption", ***Journal of Business Research***, Vol. 102, (2019), 140-150. https://doi.org/10.1016/j.jbusres.2019.05.022
22. Dwivedi, Y.K., Shareef, M.A., Simintiras, A.C., Lal, B. and Weerakkody, V., "A generalised adoption model for services: A cross-country comparison of mobile health (m-health)", ***Government Information Quarterly***, Vol. 33, No. 1, (2016), 174-187. https://doi.org/10.1016/j.giq.2015.06.003
23. Faqih, K.M. and Jaradat, M.-I.R.M., "Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: Tam3 perspective", ***Journal of Retailing and Consumer Services***, Vol. 22, (2015), 37-52. https://doi.org/10.1016/j.jretconser.2014.09.006
24. Gao, T.T., Rohm, A.J., Sultan, F. and Pagani, M., "Consumers un-tethered: A three-market empirical study of consumers' mobile marketing acceptance", ***Journal of Business Research***, Vol. 66, No. 12, (2013), 2536-2544. https://doi.org/10.1016/j.jbusres.2013.05.046
25. Guo, X., Zhao, Y., Jin, Y. and Zhang, N., "Two-sided adoption of mobile marketing platforms: Towards an integrated conceptual model", in 2010 Ninth International Conference on Mobile Business and 2010 Ninth Global Mobility Roundtable (ICMB-GMR), IEEE., (2010), 474-480.
26. Hamidi, H. and Chavoshi, A., "Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the university of technology", ***Telematics and Informatics***, Vol. 35, No. 4, (2018), 1053-1070. https://doi.org/10.1016/j.tele.2017.09.016
27. Herrero, Á. and San Martín, H., "Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2", ***Computers in Human Behavior***, Vol. 71, (2017), 209-217. https://doi.org/10.1016/j.chb.2017.02.007
28. Hew, J.-J., Badaruddin, M.N.B.A. and Moorthy, M.K., "Crafting a smartphone repurchase decision making process: Do brand attachment and gender matter?", ***Telematics and Informatics***, Vol. 34, No. 4, (2017), 34-56. https://doi.org/10.1016/j.tele.2016.12.009
29. Hew, T.-S., Leong, L.-Y., Ooi, K.-B. and Chong, A.Y.-L., "Predicting drivers of mobile entertainment adoption: A two-stage sem-artificial-neural-network analysis", ***Journal of Computer Information Systems***, Vol. 56, No. 4, (2016), 352-370. https://doi.org/10.1080/08874417.2016.1164497
30. Hirschman, E.C., "Innovativeness, novelty seeking, and consumer creativity", ***Journal of Consumer Research***, Vol. 7, No. 3, (1980), 283-295. https://doi.org/10.1086/208816
31. Hsu, C.-I., Shih, M.-L., Huang, B.-W., Lin, B.-Y. and Lin, C.-N., "Predicting tourism loyalty using an integrated bayesian network mechanism", ***Expert Systems with Applications***, Vol. 36, No. 9, (2009), 11760-11763. https://doi.org/10.1016/j.eswa.2009.04.010
32. Huang, L., Mou, J., See-To, E.W. and Kim, J., "Consumer perceived value preferences for mobile marketing in china: A mixed method approach", ***Journal of Retailing and Consumer Services***, Vol. 48, (2019), 70-86. https://doi.org/10.1016/j.jretconser.2019.02.007
33. Huang, T.-L. and Liao, S.-L., "Creating e-shopping multisensory flow experience through augmented-reality interactive

technology", ***Internet Research***, (2017). https://doi.org/10.1108/IntR-11-2015-0321

34. Im, S., Bayus, B.L. and Mason, C.H., "An empirical study of innate consumer innovativeness, personal characteristics, and new-product adoption behavior", ***Journal of the Academy of Marketing Science***, Vol. 31, No. 1, (2003), 61-73. https://doi.org/10.1177/0092070302238602
35. Imtiaz, S., "The studies of unified theory of acceptance and use of technology (utaut) in m-commerce context", ***International Journal of Information Communication Technology and Digital Convergence***, Vol. 3, No. 1, (2018), 42-56.
36. Jaradat, M.-I.R.M. and Faqih, K.M., "Investigating the moderating effects of gender and self-efficacy in the context of mobile payment adoption: A developing country perspective", ***International Journal of Business and Management***, Vol. 9, No. 11, (2014), 147. https://doi.org/10.5539/ijbm.v9n11p147
37. Kalinic, Z. and Marinkovic, V., "Determinants of users' intention to adopt m-commerce: An empirical analysis", ***Information Systems and e-Business Management***, Vol. 14, (2016), 367-387. https://doi.org/10.1007/s10257-015-0287-2
38. Khalifa, M. and Ning Shen, K., "Explaining the adoption of transactional B2C mobile commerce", ***Journal of enterprise Information Management***, Vol. 21, No. 2, (2008), 110-124. https://doi.org/10.1108/17410390810851372
39. Kim, C., Mirusmonov, M. and Lee, I., "An empirical examination of factors influencing the intention to use mobile payment", ***Computers in Human Behavior***, Vol. 26, No. 3, (2010), 310-322. https://doi.org/10.1016/j.chb.2009.10.013
40. Kim, H.-W., Chan, H.C. and Gupta, S., "Value-based adoption of mobile internet: An empirical investigation", ***Decision Support Systems***, Vol. 43, No. 1, (2007), 111-126. https://doi.org/10.1016/j.dss.2005.05.009

Persian Abstract

چکیده

این مطالعه تئوری یکپارچه پذیرش و استفاده از فناوری (UTAUT) را برای بررسی عوامل پیش‌بینی کننده پذیرش بازاریابی تلفن همراه توسعه داد. متغیرهایی مانند نوآوری شخصی، انگیزه های لذت جویانه، انتظار عملکرد، تحرک و نفوذ اجتماعی برای پذیرش بازاریابی تلفن همراه مورد مطالعه قرار گرفتند. برای ارزیابی داده‌ها از رویکرد شبکه‌های عصبی مصنوعی پیش‌بینی‌شده (ANN) استفاده شد و از نتایج داده‌ها برای مقایسه با تحلیل مسیر استفاده شد. مدل ANN توسط مدل آماری خطی از ریل خارج شد و توانست اهمیت همه پیش‌بینی‌کننده‌هایی را که با مدل تحلیل مسیر قابل شناسایی نبود، نشان دهد. نتایج نشان می‌دهد که نوآوری شخصی مؤثرترین عامل در پذیرش بازاریابی تلفن همراه است. پس از آن، انگیزه های لذت جویانه، انتظار عملکرد، تحرک، نفوذ اجتماعی، اعتماد و شرایط تسهیل کننده نقش حیاتی ایفا می کنند. علاوه بر این، نتایج نشان می‌دهد که ارزش قیمت، ریسک درک شده و انتظار تلاش موثر نبودند.