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Article

Continued Intention to Use of M-Banking in Jordan by Integrating UTAUT, TPB, TAM and Service Quality with ML

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Abstract: Mobile banking is a service provided by a bank that allows full remote control of customers' financial data and transactions with a variety of options to serve their needs. With m-banking, the banks can cut down on operational costs whilst maintaining client satisfaction. This research examined the most crucial factors that could predict the Jordanian customer's continued intention toward the use of m-banking. Following the proposed model, the research was conducted by using a self-conducted questionnaire and the responses were collected electronically from a convenience sample of 403 Jordanian customers of m-banking through social networks. The suggested model was adapted from the theory of planned behavior (TPB), the unified theory of acceptance and use of technology (UTAUT), and the technology acceptance model (TAM). The research model was further expanded by considering the factors of service quality and moderating factors (age, gender, educational level, and Internet experience). The collected data of customers were analyzed, validated, and verified by using a structural equation modeling (SME) approach including a confirmatory factor analysis (CFA), in addition to machine learning (ML) methods, artificial neural network (ANN), support vector machine (SMO), bagging reduced error pruning tree (RepTree), and random forest. Results showed that effort expectancy, performance expectancy, perceived risk, perceived trust, social influence, and service quality impacted behavioral intention, whereas facilitating conditions did not. Furthermore, behavioral intention impacted upon word of mouth and facilitating conditions (the latter regarding the continued intention to use m-banking), and had the highest coefficient value. Results also confirmed that all moderating factors affect the behavioral intention to continue using m-banking applications.

Keywords: unified theory of acceptance and use of technology; technology acceptance model; theory of planned behavior; mobile banking; m-bank applications

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1. Introduction

M-banking is short for mobile banking. M-banking is the use of an application that handles banking transactions when the application is linked to a bank account [1]. In this context, m-banking allows bank customers to administer financial transactions remotely and provides full remote control of customers' financial data and transactions with a variety of options to serve their needs, which include obtaining account balances and lists of recent transactions, digital bill payments, check deposits, peer-to-peer payments, and bank money transfer between users.

There is a shift toward "anytime, anywhere" banking according to [2], and as such, this research is a reflection of open-innovation dynamics. In fact, when the Japanese bank Jibun Bank conducted such a transformation, not only did the bank gain 500,000 new customers, but also, many banks in countries such as the USA, Germany, the UK, Spain [3], Sweden, and Austria followed suit. Understandably with regards to m-banking, the banks and financial institutions can cut down on operational costs whilst retaining client satisfaction, in view of its ease, flexibility, and speed of access. Nonetheless, [2] reports that 50% of smartphone owners admit that they do not use m-banking due to security, trust, and privacy concerns, as said by [4]. As this shows, many factors hinder the continued intention to use (CIU) m-banking; likewise, [4] listed several challenges that face m-banking, i.e., privacy, security, input mistakes, and use anxiety.

The continued intention to use (CIU) m-banking [5] is equally beneficial for both customers and banks. For banks and financial institutions, the gains are savings in overhead costs, increased availability, and an increase in the number of customers, whilst for customers, the benefits include time flexibility, convenience, 24/7 service accessibility, anonymity, security, avoiding in-person risks, health concerns (including but not limited to concerns related to pandemics), transaction cost [6] and effort, and optimizing money with features related to organizing digital expenditures versus savings. Whilst using m-banking has benefits and drawbacks, the question regarding CIU is whether the customer will continue to use such applications [7,8].

This pertains to Jordanians as much as the rest of the world. The research focuses on Jordanian behavior regarding the intention to continue using m-banking, in the view that Jordan holds a unique geopolitical position. Jordan, located in the heart of a volatile region, continues to serve as an anchor for regional stability and global public goods by hosting refugees and supporting cross-border collaboration and trade. Accordingly, a vast number of Jordanians are working abroad. Whilst there is no official government reported number, an estimated 786,000 Jordanian migrants are living abroad, that is, 10.5% of the country's total national population, who work in 70 different countries, with more than 2 billion dollars transferred. So, 79.5% of Jordanian expats are found in Gulf countries, 11% in the USA and Canada, 3.4% in Europe, and 3% in other countries, according to [9]. By the same token, expats living in Jordan represent 31% of the population (more than 2.5 million non-Jordanians) [10], most of whom are refugees, due to the regional conflict surrounding Jordan in Iraq, Syria, Israel, and Palestine. Simultaneously, Jordan is bestowed with an immense history, ancient monuments, nature reserves, and seaside resorts, coupled with a challenging economy and an aspirational quality of life. As such, Jordan recorded 5.3 million tourists in 2019 [11], ranking 66th worldwide.

M-banking use in Jordan is expected to be pivotal, since m-banking availability will ease financial transaction management regardless of location, emphasizing its convenience and 24/7 service accessibility. In this way, m-banking is becoming a worldwide cultural trend that provides tailored options accommodating customers' needs at their leisure. Intrinsically, different people with diverse needs and in constant mobility need to access their bank accounts "on the go". Taking into account the fact that Jordan has more than 15.3 million cellular subscriptions and that "the number of smartphone users is projected to reach 8.28 million by 2025" [12], there is an enabling environment for m-banking, and this provides the impetus to study the factors affecting Jordanian customers' behavioral intention to continue using m-banking. The suggested independent, intermediate, and moderating factors are based on the theory of planned behavior (TPB), the unified theory of acceptance and use of technology (UTAUT), and the technology acceptance model (TAM). The independent variables are perceived risk, effort expectancy, performance expectancy, social influence, perceived trust, and service quality. The intermediate factors are behavioral intention and word of mouth. The moderating factors are age, gender, educational level, and Internet experience.

The importance of this research stems from the open innovation dynamic model as shown in research [13,14] proposed by Chesbrough in 2003, which aimed to describe how innovation management processes need to evolve in order to survive.

A review of the literature is followed by a presentation of the suggested model for this research and hypothesis development. After that, the survey design and method will be presented. Then, results analysis and findings will be shown, followed by a conclusion and discussion. Finally, general findings with theoretical and practical implications will be shown.

2. M-Banking Literature Review

Several studies were conducted to find out if the customer would continue the use of m-banking. Some studies were conducted with the country as a major factor, such as in India [15,16] which we will discuss further in the next section, Jordan as we shall see in [17–20]. Oman in [21], Lebanon in [22,23], Zimbabwe in [24], Yemen in [25], Palestine in [26], Saudi Arabia in [6,27], Indonesia in [28], New Zealand in [29], Korea in [30], and Pakistan in [31]. Several studies concentrated on other aspects where political borders were ignored and concentrated on m-banking and e-banking. Next, some of these studies will be discussed.

As for Jordan, the study [17] investigated m-banking in Jordan using extended UTAUT2. The research [18] used part of TAM, namely, usefulness, perceived risk (PR), self-efficacy, and ease of use, and their influence on consumer's m-banking adoption. The third research [32], studied the impact of perceived usefulness (PU), trust, and self-efficacy telebanking adoption. The fourth research [19] studied e-banking using the UTAUT model. In addition, [20] studied e-banking and found that perceived ease of use (PEoU), PU, reasonable price, and security are barriers to intention to use. Hence, only two studies researched m-banking using UTAUT2 and part of TAM, whilst the other studies concentrated on telebanking, and e-banking.

Research [16] studied m-banking adoption and found that security, computer self-efficacy, PEoU, and perceived financial cost affect customers' intention of adopting m-banking in India. Moreover [15] studied m-banking by using the extended model UTAUT2, and found that emotional value, monetary value, quality value, trust, and effort expectancy (EE) have considerable influence on behavioral intention (BI), whilst performance expectancy (PE) and social value do not.

In Saudi Arabia, two studies [6,27] researched m-banking adoption. The first used TAM whilst intermixing with the task-technology fit (TTF) model. The second used joint UTAUT2 with the DeLone and McLean (D & M) IS Success Model.

In Lebanon, the research [22] studied the effects of ease of use, PU, trust, perceived credibility, trialability, normative pressure, compatibility, and self-efficacy on m-banking adoption. In addition, [23] studied Lebanese and British m-bank users. The study found that the age factor was a significant influence on the Lebanese regarding trust and easing conditions, whilst among the British respondents, the *age* factor was a significant influence on PE, EE, hedonic motivation, price value, and habit. It was also found that the *gender* factor was of influence among Lebanese respondents but not British respondents, on PE, EE, easing conditions, price value, and perceived security.

In Oman, research [21] studied m-commerce using the UTAUT2 model. In Zimbabwe, m-banking was researched by [24], studying social influence, relative advantage, PU, perceived self-efficacy, perceived compatibility, and PR, and their influence on m-banking adoption. In Yemen [25], Internet banking was studied using TRA, considering innovativeness, relative advantage, skepticism, mass media, PR, family's influence, and their influence on attitudes toward behavior, subjective norms, and technology readiness (TR), hence intention to use. The study [26] was conducted on Palestine m-banking adoption using technology organization environment (TOE). The research [31] used TPB and TAM to study the influence of gender on adopting m-banking in Pakistan.

Other studies ignore political boundaries in favor of focusing on m-banking. The research [5,33] studied service quality and self-determination theory influence within continuous use intention. The research [30] studied m-banking using extended UTAUTs. The research [34] studied commitment, trust, and satisfaction; enjoyment; practicality; security/privacy; design/aesthetics; and sociality of service quality. The research [2] studied m-banking by investigating PU, PEoU, perceived enjoyment, consumer innovativeness, trust in the bank, perceived privacy, perceived reliability, attitudes, and intentions whilst influencing attitude and intention. Furthermore, [35] was conducted on migrant workers and studied PU, PEoU, PR, and perceived deterrents and their influence on attitude. The study also investigated the influence of subjective norms on PU and behavioral intention (BI).

Other studies also forewent political borders in favor of focusing on e-banking adoption intention. In [36], the researchers studied PU, PEoU, perceived security, and hedonic motivation. In [37], they used UTAUT and service quality. In [38] researchers based their work on bank transparency, the task technology fit (TTF) model, and technology continuance theory (TCT). The study aimed to discover the intention of use by investigating bank transparency, technology characteristics, task characteristics, expectation confirmation, PU, task technology fit, satisfaction, and attitude.

To reflect on the differences, a further 27 studies were reviewed, as shown in Table 1. Only 19 used established models, whilst 9 used different constructs, and 2 viewed only gender. In addition, 8 forewent the political borders and 19 did not. M-banking was studied in 19, whilst 9 studied e-banking and 1 studied telebanking, and another 1 studied banking as part of m-commerce.

Table 1. Summary of the studies conducted on m-banking using different factors and models.

Country	Model	Target	Reference
India	UTAUT2	m-banking	[15]
	Different constructs		[16]
Jordan	UTAUT2	m-banking	[17]
	TAM		[18]
	UTAUT	e-banking	[19]
	Different constructs		[20]
	Different constructs	telebanking	[32]
Oman	UTAUT2	m-commerce	[21]
Lebanon	Different constructs	m-banking	[22]
	Gender		[23]
Zimbabwe	Different constructs	m-banking	[24]
Yemen	TRA	internet banking	[25]
Palestine	TOE	m-banking	[26]
Saudi	TAM, TTF.	m-banking	[27]
	UTAUT2, (D& M) IS Success Model.		[6]
Indonesia	SRQ and Loyalty	m-banking	[28]
New Zealand	SRQ	m-banking	[29]
Korea	SRQ	m-banking	[30]
Pakistan	Gender	m-banking	[31].
No country	SRQ	m-banking	[33]
	SRQ		[5]
	UTAUT2		[39]
	Different constructs		[34]
	Different constructs		[35]
No country	Different constructs	e-banking	[36]

UTAUT	[37]
TTF and TCT	[38]

Thus, within the context of Jordan, there are a few studies that studied m-banking using UTAUT2 and TAM. However, no studies used UTAUT, TAM, TPB, service quality, behavioral intention, word of mouth, and their influence on continued intention to use, in addition to moderators (age, gender, educational level, Internet experience). Nor did any study confirm the results using machine learning methods.

3. Theoretical Framework: Model and Hypothesis Development

The suggested model revealed in Figure 1 is grounded on three models: UTAUT, TAM, and TPB, extended with service quality and four moderating factors. From UTAUT, the four major constructs were embraced by the model, namely PE, EE, SI, and FC. From TAM and TPB, the two constructs, PR and PT, were adopted as in [40], and the final construct was service quality (SRQ) [28]. The seven constructs/independent factors influence behavioral intention (BI) [40], which in turn influences word of mouth (WoM), which influences continued intention to use (CIU), as the model suggests. The proposed model and hypotheses were developed based on thirty-seven studies: [6–8,15,29,30,34,40–69].

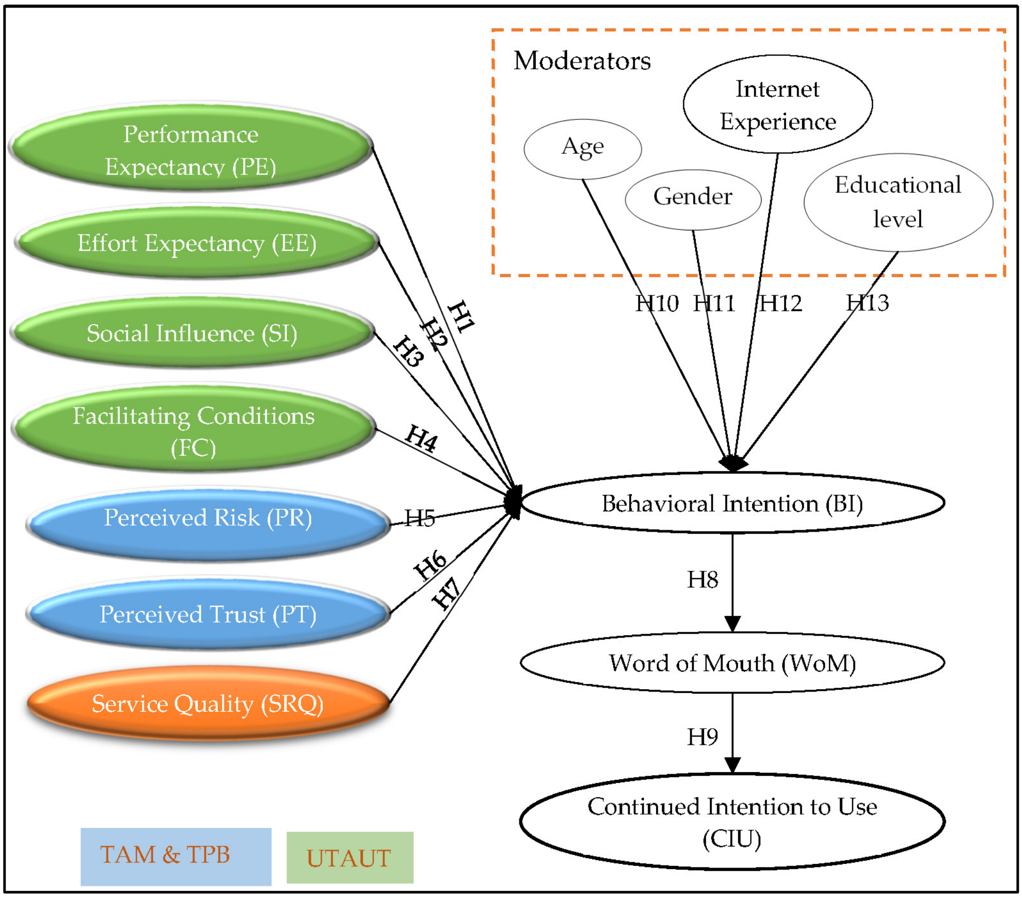

Figure 1. The proposed model of m-Banking continued intention to use.

In the sections that follow, the hypothesis related to UTAUT will be discussed and supported with literature. Next, the hypotheses related to TAM and TPB will be presented. Finally, the hypothesis related to service quality and moderating factors will be discussed and supported by related research.

3.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was introduced by [41] in 2003. UTAUT is based on the study of many other models according to [42]. UTAUT model has four major constructs since it was developed by Fred Davis and Richard. The four used in this research are: PE, EE, SI, and easing conditions. The factors influence BI, which is "a measure of the strength of one's intention to perform a specified behavior" according to [70].

PE is defined as "the extent to which using a technology will provide benefits in performing certain activities." [41]. PE was studied by [6,43], as well as [15,44–46], in m-banking applications. PE is a factor that influences BI, as the UTAUT suggests. Therefore, the following can be hypothesized:

H1: *Performance expectancy (PE) positively influences behavioral intention (BI) of customers to use m-banking services.*

Effort expectancy (EE) is "the degree of ease associated with the use of the system", according to [47], quoting [41]. Several research projects [6,15,44,45,48,49] showed that PE influences BI to use m-banking services. Even [44] noted the effortless use of m-banking applications. This led the researchers to state the following hypothesis:

H2: *Effort expectancy (EE) positively influences the behavioral intention (BI) of customers to use m-banking services.*

The definition of social influence (SI) is "the extent to which an individual believes that important others believe he or she should use the system." [48]. According to [71], social influence is a factor, drawn from several studies such as [6,15,44,48,72] and defined as the influence on an individual by relatives, friends, and others in the community to use technology. Prior research has extensively examined the role of SI in increasing customer intentions and the use of Internet banking [6,15,44,47,48,50]. This leads to the third hypothesis:

H3: *Social Influence (SI) positively influences the behavioral intention (BI) of customers to use m-banking services.*

The degree to which an individual believes that technical and organizational infrastructure exists to support system use is defined as facilitating conditions (FC) [41]. Furthermore, studies have researched this factor, such as [6,15,44,47,48,50]. This leads to the following hypothesis:

H4: *Facilitating conditions (FC) positively influences the behavioral intention (BI) of customers to use m-banking services.*

3.2. Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM)

Ref. [42] developed the theory of planned behavior (TPB) in 1991, which comprises an attitude that influences intention, which in turn influences behavior. TPB is classified into two types: original TPB and decomposed TPB.

The first modified TAM was developed in 1989, according to [42]. The final TAM was developed in 1996. In 1989, the research [73] suggested that attitude (ATT) influences the continued intention to use (CIU). The same model, TAM, also suggested that CIU influences the intention to recommend or the actual use. The study [27] researched m-banking adoption in the Kingdom of Saudi Arabia by using TAM whilst intermixing with the TTF model. In addition, references [52,53] studied the influence of attitude on the CIU. In the research [52], the researchers studied customers' continued mobile app use in the service industry, whilst in [53], a study was conducted to discover the positive predictors of continued intention to use digital ticketing. Furthermore, studies [7,8] researched continued use intention among the elderly of wearable health technologies. Built on the previous literature, the following hypotheses (H5–H9) were developed.

Perceived risk (PR) "will have a negative effect on attitudes towards reusing e-government services" [74]. In addition, PR as a factor was researched by [40,54] in different realms but with the same idea of influencing the use of computer web applications, whilst [54] included under PR several types of PR, including social risk, performance risk, financial risk, time risk, and security risk. On the other hand, ref. [55] included financial, performance, time, social, privacy, psychological, and overall risks. The following hypothesis is drawn from the above literature review:

H5: *Perceived risk (PR) negatively influences the behavioral intention (BI) of customers to use m-banking services*.

Perceived trust (PT) was investigated by [15,40] among others. Trust is a positive belief about reliability, according to [34,40], quoting [56,57], who defined trust as "consumer confidence in a retailer's reliability and integrity". The study [15] found trust has significant influence on intention behavior. Furthermore, ref. [34] found that trust has an influence on satisfaction and commitment. Hence, the following hypothesis was developed:

H6: *Perceived trust (PT) positively influences customers' behavioral intentions (BI) to use m-banking services*.

According to [75], service quality (SRQ) is "the result of an evaluation process in which customers compare their expectations with the service they have received", and service quality has many standards that can be classified into five dimensions: "tangibles, reliability, responsiveness, assurance, and empathy". According to [46], several studies were conducted to examine SRQ. Authors in [33] discussed service quality from within self-determination theory in mobile banking. Authors in [58] examined the antecedents and consequences of perceived SRQ in the hotel industry, whilst [76] studied consumption value of m-banking services. In addition, [77] studied system and service qualities with customer satisfaction. The study [59] questioned whether perceived service quality can predict the performance of retail service. SRQ and service quality assurance regarding m-banking was discussed in [6] with regards to three aspects: the bank, the Internet provider, and the browser. The researcher of [6] depended on several researchers, such as [30,78], to reach such conclusions. Studies such as [29] in New Zealand and [30] in Korea also stressed the value of SRQ in m-banking. Hence, based on the previously mentioned research, the following hypothesis was developed.

H7: *Service quality (SRQ) positively influences the behavioral intention (BI) of customers to use m-banking services*.

Behavioral intention (BI) is the tendency of person to recognize technology [44]. In addition, the same source stated that BI affects the acceptance of technology, as [44] referenced [60–62] to prove the importance and influence of BI towards technology acceptance.

Word of mouth (WoM) is "people communicating informally about specific products or services with others." as stated by [43], quoting several researchers like [63,64]. WoM is becoming more important as social networks are growing. The influence of behavioral intention (BI) over word of mouth (WoM) was discussed by [43,65], leading to the development of the following hypothesis:

H8: *Behavioral intention (BI) positively influences m-banking user word of mouth (WoM)*.

Continued intention to use (CIU) was confirmed by many studies [66,67,69], as cited by [5,79]. Several studies [65,79,80] investigated the role of WoM over continues intention to use (CIU). As stated previously, WoM is getting stronger since it can reach more audiences because of social networks. Hence, based on the previous research, the following hypothesis was developed:

H9: *Word of mouth (WoM) positively influences continued intention to use (CIU) of m-bank application.*

This research suggested four moderating factors: educational level, gender, age, and Internet experience. The suggestion is based on several published papers, and the next section presents the hypotheses related to moderating factors along with their respective literature.

3.3. Moderating Factors Hypotheses

The study includes four moderating factors in addition to the seven main factors. The moderating factors as suggested in the model are age, gender, education level, and Internet experience. The development of hypotheses on moderation factors are based on [7,15,31,44,50,72,81–87].

3.3.1. Hypothesis Related to Age

With two opposing points of view, age is an important moderating factor. The first point of view contends that greater age means worse sight and worse movement and comprehension for m-bank application. Hence, such a factor has a negative effect on the use of m-banking. On the other hand, greater age means less mobility; hence, older customers will have the ability to reach the bank from the comfort of their homes. Many studies looked for age as a moderator factor, i.e., [7,50,72,82–86]. Hence, the subsequent hypothesis was formulated.

H10: *Age has a significant moderating effect on consumers' m-banking behavioral intention.*

3.3.2. Hypothesis Related to Gender

Gender is another moderating factor investigated by this study. Gender is suggested in UTAUT and was conducted as a moderator in [15,31,44,82,84,87]. As with the demography of the population of the study, the researchers wanted to investigate the influence of gender, age, education, and Internet experience on the behavioral intention intermediate variable as suggested in the UTAUT original model [72], hence the next hypothesis were formulated:

H11: *Gender has a significant moderating effect on consumers' m-banking behavioral intention (BI).*

3.3.3. Hypothesis Related to Internet Experience

Internet experience refers to the amount of practice a person has in using Internet technologies [44,84]. Based on the previously mentioned research the following hypothesis is postulated.

H12: *Internet experience has a significant moderating effect on consumers' m-banking behavioral intention (BI).*

3.3.4. Hypothesis Related to Educational Level

Many studies were conducted on this moderator variable. Education level influences the perspective of the Internet use of applications in general, hence the moderator factor has influence on the use of m-banking as stated by [84]. Educational level affects people's acceptance of modern technologies (at the least, those with a higher level will have an educated guess about the topic). Hence, the following hypothesis is assumed.

H13: *Educational level has a significant moderating effect on consumers' m-banking behavioral intention (BI)*.

4. Survey Design/Methods

The goal of this research is to study the continued intention to use (CIU) regarding m-banking applications in Jordan. Since research on this issue was limited, the researchers developed a model shown in Figure 1, and in turn, developed the hypothesis above. A questionnaire was developed and tested, then from a sample of convenience the data was collected. The next three sections (research context, measurement items, and participants and procedure) will explain in detail the survey design and method of this research.

4.1. Research Context

As the world shifts towards a greater social distance due to the COVID-19 pandemic [88], m-banking is becoming the new ATM, and there is a genuine need to study whether the m-banking customer will continue to use m-bank applications. This study examines which factors will influence such intention. As stated previously, although customers install m-bank applications on their mobile, not all customers go on to use the application. Hence, this study was conducted as follows.

4.2. Measurement Items

A questionnaire survey was created to test the research model proposed for this study. The survey items were created based on previous research. There are fourteen variables (independent, mediating, and moderating) in the model. Each variable was measured as follows:

Age into five groups, gender into two groups, educational level into four groups, and Internet experience into three groups, seen in Table A1. The constructs effort expectancy (EE) and performance expectancy (PE), each measured by four items derived from [6] cited from [72]. Social influence (SI) measured by three items derived from [6] cited from [72]. Facilitating conditions (FC) measured by four items derived from [6] cited from [72]. Perceived risk (PR) measured by four items derived from [40]. Perceived trust (PT) measured by four items derived from [40]. Service quality (SRQ) was measured by three items derived from [6]. Behavioral intention (BI) measured by three items derived from [40]. Word of mouth (WoM) measured by four items derived from [80]. Continued intention to use (CIU) measured by six items derived from [85]. All measurements are shown in Table A1. Next participants and collection procedure are presented.

4.3. Participants and Procedure

Using Google docs, a web-based, survey questionnaire was prepared in both Arabic and English, using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The survey was reviewed by a panel of 11 academicians. Feedback was collected and the questionnaire was rectified accordingly. Consequently, the survey was piloted on 25 m-bank users in Jordan to test the understandability of the questions. Revisions were made to the survey.

The survey link was distributed via groups and pages of university students, researchers, and Jordan residents in Facebook, LinkedIn, and through WhatsApp groups, the most popular network platforms in Jordan. The convenience sampling method was applied in this study. Participants were voluntary, and no financial incentive was offered. In addition, the researchers approached m-banking application users, such as students, where universities demand e-payments through m-banking applications.

According to Morgan Table data, 384 applications users should be reached for the optimum size of the statistical sample of this research [89]. The survey was conducted from 15 December 2021 to 3 January 2022, and after removing the deficient surveys, 403 m-bank applications users remained, as shown in Table 2. The demographic profile of the respondents for this study revealed that they are mostly women between the ages of 18 and 34, have a bachelor's degree, and have extensive Internet experience. The population of Jordan is educated with a literacy rate for adult male population of 98.12% (3,464,009 persons) and a literacy rate for adult female population of 95.16% (3,282,251 persons). Almost 50% of the population of is below 30 years old, reflecting the demography of the sample.

Table 2. Demographic of the respondents.

Category	Category	Frequency	Percentage%
Gender	Male	187	46.4
	Female	216	53.6
	Total	**403**	**100**
Age (year)	18 to less than 34	257	63.8
	34 to less than 44	61	15.1
	44 to less than 54	42	10.4
	54 to less than 64	37	9.2
	64 and over	6	1.5
	Total	**403**	**100**
Education level	High school and less	21	5.2
	Diploma	59	14.6
	Bachelor	290	72.0
	Postgraduate	33	8.2
	Total	**403**	**100**
Internet experience	Low	19	4.7
	Good	174	43.2
	Excellent	210	52.1
	Total	**403**	**100**

5. Data Analysis and Results

The analysis of data for this study included: firstly, a descriptive analysis to measure respondent's attitudes; secondly, a structural equation model (SEM) (which included a confirmatory factor analysis (CFA) and then structural equation modeling (SEM) using Amos 20, performed to test the study hypotheses); thirdly, the moderating effects; and finally, validation of this research using machine learning (ML). SEM and CFA verified the hypotheses and analyzed the results whilst ML validated and predicted mean square error and correlation coefficient (R^2), similar to the work of [90–96], since other researchers suggested the use of triangulation of mixed methods [97], which is an effective tool to understand and explore in depth the findings of the study at hand. This research employed triangulation by using multiple data collection and analysis.

5.1. Descriptive Analysis

One way to measure the respondent's attitude is to calculate the mean and standard deviation for each question asked to each respondent. The mean is the central tendency of the data, and standard deviation is dispersion which offers an index of the spread or variability in the data [87,98]. The level of each item was decided by (1)

$$level = \frac{highest\ point\ in\ Likert\ scale - lowest\ point\ in\ Likert\ scale}{number\ of\ levels\ used} = \frac{5-1}{5} = 0.8 \quad (1)$$

Hence the level (0.80), where (1–1.80) was considered to be "very low", (1.81–2.60) considered to be "low", (2.61–3.40) considered to be "moderate", (3.41–4.20) considered to be "high", and (4.21–5) considered to be "very high". Then, the items were ordered based on their means. Tables 3 and 4 present the results.

Table 3. Overall mean and standard deviation of the study's variables.

Type of Variable	Variables	Mean	Standard Deviation	Level	Order
Independent variables	Performance expectancy (PE)	4.1309	0.78073	High	1
	Effort expectancy (EE)	4.0955	0.75734	High	3
	Social influence (SI)	3.8222	0.88572	High	6
	Facilitating conditions (FC)	4.0918	0.77082	High	4
	Perceived risk (PR)	3.1340	1.09869	Moderate	7
	Perceived trust (PT)	4.1098	0.80781	High	2
	Service quality (SRQ)	3.8768	0.85614	High	5
Mediating variable	Behavioral intention (BI)	4.1489	0.83946	High	2
	Word of mouth (WoM)	3.9479	0.84167	High	1
Dependent variable	Continued intention to use (CU)	3.9715	0.81866	High	-

As shown in Table 3, data analysis results have indicated that all research variables are applied to prominent levels, whilst respondent's attributes of PR do exist moderately, with a mean of 3.1340. Table 4 shows the mean, standard deviation, level, and order scores for items for each variable.

Table 4. Mean and standard deviation of the study's variables.

Performance Expectancy (PE)	Mean	SD	Level	Order
PE1	4.16	0.833	High	2
PE2	4.15	0.831	High	3
PE3	4.20	0.819	High	1
PE4	4.02	0.872	High	4
Effort expectancy (EE)	**Mean**	**SD**	**Level**	**Order**
EE1	4.10	0.843	High	2
EE2	4.08	0.822	High	3
EE3	4.08	0.834	High	3
EE4	4.12	0.780	High	1
Social influence (SI)	**Mean**	**SD**	**Level**	**Order**
SI1	3.84	0.923	High	1
SI2	3.79	0.936	High	3
SI3	3.83	0.933	High	2
Facilitating conditions (FC)	**Mean**	**SD**	**Level**	**Order**
FC1	4.15	0.840	High	1
FC2	4.12	0.858	High	2
FC3	4.11	0.836	High	3
FC4	3.98	0.904	High	4

Perceived risk (PR)	Mean	SD	Level	Order
PR1	3.14	1.150	Moderate	2
PR2	3.10	1.167	Moderate	4
PR3	3.12	1.158	Moderate	3
PR4	3.17	1.189	Moderate	1
Perceived trust (PT)	**Mean**	**SD**	**Level**	**Order**
PT1	3.98	0.958	High	4
PT2	4.02	0.914	High	3
PT3	4.37	0.846	Very high	1
PT4	4.07	0.906	High	2
Service quality (SRQ)	**Mean**	**SD**	**Level**	**Order**
SRQ1	3.90	0.898	High	1
SRQ2	3.88	0.894	High	2
SRQ3	3.85	0.909	High	3
Behavioral intention (BI)	**Mean**	**SD**	**Level**	**Order**
BI1	4.21	0.863	Very high	1
BI2	4.19	0.856	High	2
BI3	4.04	0.969	High	3
Word of mouth (WoM)	**Mean**	**SD**	**Level**	**Order**
WoM1	3.89	0.926	High	4
WoM2	3.93	0.901	High	3
WoM3	3.97	0.868	High	2
WoM4	4.00	0.875	High	1
Continued intention to use (CIU)	**Mean**	**SD**	**Level**	**Order**
CIU1	4.04	0.838	High	2
CIU2	3.97	0.880	High	4
CIU3	3.97	0.904	High	4
CIU4	3.78	0.989	High	5
CIU5	4.05	0.899	High	1
CIU6	4.01	0.881	High	3

5.2. SEM Analysis

In this study the SEM analysis was used to test the research hypotheses in two steps. First, CFA was conducted, then SEM using Amos 20 was presented to test the study hypotheses.

5.2.1. Measurement Model

CFA was performed to verify the attributes of the instrument items. The measurement model reveals how latent variables or hypothetical constructs are assessed in terms of observed variables and embodies the validity and reliability of the observed variables' responses to the latent variables [99–102]. Table 5 reveals the Average Variance Extracted (AVE) for the variables, composite reliability, Cronbach alpha, and the factor loadings. All the indicators of factor loadings exceeded 0.50, indicating convergent validity [99,103]. Furthermore, because all the factor loadings went above 0.50, the measurement reached convergent validity at the item level. In addition, to show a high level of internal consistency for the latent variables, the composite reliability values exceeded 0.60. Furthermore, the convergent validity was proved because each value of AVE exceeded 0.50 [89,99].

Table 5. Properties of the final measurement model.

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach Alpha	Composite Reliability *	AVE **
Performance expectancy (PE)					0.948	0.96	0.97
PE1	0.920	***	0.846	0.107			
PE2	0.943	0.043	0.889	0.076			
PE3	0.943	0.042	0.890	0.074			
PE4	0.830	0.041	0.689	0.236			
Effort expectancy (EE)					0.943	0.96	0.96
EE1	0.877	***	0.770	0.163			
EE2	0.907	0.037	0.823	0.120			
EE3	0.934	0.037	0.873	0.088			
EE4	0.875	0.037	0.766	0.142			
Social influence (SI)					0.948	0.95	0.87
SI1	0.938	***	0.881	0.101			
SI2	0.931	0.029	0.867	0.116			
SI3	0.912	0.030	0.832	0.146			
Facilitating conditions (FC)					0.918	0.94	0.95
FC1	0.911	***	0.829	0.120			
FC2	0.915	0.034	0.837	0.120			
FC3	0.914	0.033	0.835	0.115			
FC4	0.720	0.047	0.519	0.393			
Perceived risk (PR)					0.958	0.94	0.95
PR1	0.931	***	0.867	0.175			
PR2	0.953	0.035	0.909	0.124			
PR3	0.926	0.035	0.857	0.191			
PR4	0.879	0.036	0.772	0.321			
Perceived trust (PT)					0.913	0.95	0.96
PT1	0.881	***	0.776	0.107			
PT2	0.907	0.037	0.822	0.076			
PT3	0.711	0.041	0.505	0.074			
PT4	0.925	0.035	0.855	0.236			
Service quality (SRQ)					0.947	0.95	0.88
SRQ1	0.875	***	0.766	0.188			
SRQ2	0.958	0.036	0.918	0.066			
SRQ3	0.945	0.037	0.893	0.088			
Behavioral intention (BI)					0.928	0.94	0.84
BI1	0.911	***	0.829	0.127			
BI2	0.934	0.032	0.872	0.094			
BI3	0.873	0.040	0.762	0.223			
Word of mouth (WoM)					0.958	0.96	0.97
WoM1	0.892	***	0.796	0.174			
WoM2	0.932	0.033	0.869	0.106			
WoM3	0.944	0.031	0.892	0.081			
WoM4	0.925	0.033	0.855	0.111			
Continued intention to use (CU)					0.958	0.96	0.97
CIU1	0.918	***	0.843	0.110			
CIU2	0.932	0.033	0.869	0.101			

CIU3	0.938	0.034	0.879	0.098
CIU4	0.802	0.034	0.644	0.348
CIU5	0.877	0.046	0.769	0.187
CIU6	0.894	0.038	0.800	0.155

* Utilizing [104] formula of composite reliability and **average variance extracted (AVE).

Also, as observed from Table 6, all the intercorrelations between pairs of constructs were less than the square root of the AVE estimates of the two constructs, providing discriminant validity [100]. Consequently, the measurement results showed that this study had adequate levels of convergent and discriminant validity.

Table 6. Correlations of constructs.

Constructs	PE	EE	SI	FC	PR	PT	SRQ	BI	WoM	CIU
PE	0.98									
EE	0.799	0.97								
SI	0.702	0.615	0.93							
FC	0.833	0.842	0.651	0.97						
PR	0.096	0.035	0.070	0.070	0.97					
PT	0.708	0.711	0.547	0.713	0.115	0.97				
SRQ	0.695	0.681	0.596	0.656	0.047	0.658	0.93			
BI	0.775	0.734	0.597	0.741	0.131	0.850	0.690	0.91		
WoM	0.758	0.740	0.686	0.759	0.067	0.675	0.657	0.727	0.98	
CIU	0.763	0.747	0.654	0.782	0.094	0.696	0.648	0.757	0.925	0.98

Note: Diagonal elements are square roots of the average variance extracted for each of the ten constructs. Off diagonal elements are the correlations between constructs.

5.2.2. Structural Model

Structural equation modeling (SEM) using Amos 20 was performed to test the study hypotheses. SEM allows simultaneous testing of all hypotheses including direct and indirect effects. The results of the direct effects show that social influence (SI), performance expectancy (PE), perceived risk (PR), effort expectancy (EE), perceived trust (PT), and service quality (SRQ) are positively and significantly affected by behavioral intention (BI). As a result, H1-H3 and H5-H7 were supported; whilst *facilitating conditions* (H4) did not have influences on *behavioral intention (BI)* with (β= 0.038); consequently, H4 was rejected. In addition, *behavioral intention (BI)* is positively and significantly affected *word of mouth (WoM)*, and the latter on *continued intention to use (CIU)*; therefore, H8, and H9 were supported.

Furthermore, coefficient of determination (R^2) for the research intrinsic variables for *BI*, *WoM*, and *CIU* were 0.504, 0.343 and 0.741, respectively, which shows that the model does account for the variation of the proposed model. Table 7 below provides a summary of the tested hypotheses.

Table 7. Summary of proposed results for the theoretical model.

Research Proposed Paths	Coefficient Value	t-Value	*p*-Value	Empirical Evidence
H1: PE → BI	0.209	7.381	0.000	Supported
H2: EE → BI	0.095	3.264	0.001	Supported
H3: SI → BI	0.066	2.634	0.008	Supported
H4: FC → BI	0.038	1.318	0.188	Not supported
H5: PR → BI	−0.045	−2.237	0.025	Supported
H6: PT → BI	0.482	17.592	0.000	Supported

H7: SRQ → BI	0.114	4.422	0.000	Supported
H8: BI → WoM	0.696	14.491	0.000	Supported
H9: WoM → CIU	0.861	33.941	0.000	Supported

Furthermore, whether they have the facilitating condition or not, m-bank users would have the intention to use m-bank applications, according to this finding. On the other hand, FC, according to [6], did have an influence on actual use. Figure 2 reflects the model with coefficient values. One can draw the following conclusions regarding the constructs: The WoM has the highest coefficient value, influencing the CIU of m-banking applications. Hence, the coefficient value of BI is the second highest. Hence, BI influences WoM the most. The third highest coefficient value is PT's influence on BI, whilst PE is the fourth coefficient value. The fifth coefficient value is SQR, which influences BI, whilst the sixth and seventh places of coefficient value are EE and SI, respectively. The negative influence of PR is obvious but not very high with (−0.045) and the least is the FC influence using the coefficient value.

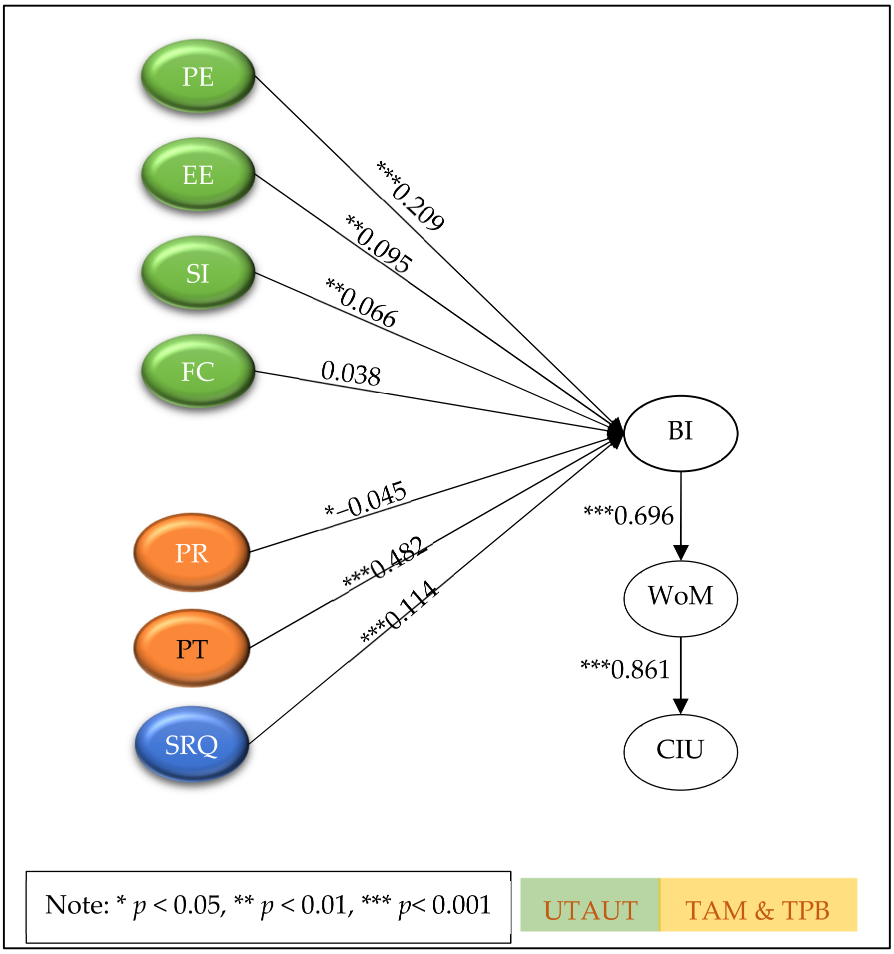

Figure 2. Proposed model with results of coefficient value.

5.3. Moderation Effects

Hypotheses H10, H11, H12, and H13 argued that there is a significant difference in the respondent behavioral intention due to gender, age, educational level, and Internet experience. Independent samples *t*-test was employed to investigate if there are any significant differences in the respondent behavioral intention that can be attributed to gender. In addition, ANOVA test was employed to examine if there are any significant differences in the respondent behavioral intention that can be attributed to gender, age, education, and Internet experience. The results of *t*-test, shown in Table 8, showed that there is a significant difference in the *behavioral intention (BI)* that can be attributed to *gender* (*t-value* = 2.799, $p \leq 0.05$), that refers to men rather than women.

Table 8. *t*-test of the respondents' behavioral intention attributed to gender.

Variable	Male			Female			*t*	df	Sig.
	Std. Dev.	**Mean**	**N**	**Std. Dev.**	**Mean**	**N**			
Behavioral intention	0.79041	4.2727	187	0.8673	4.0417	216	2.797	399.932	0.005

Also, results of ANOVA test, shown in Table 9, showed that there is significant difference in the respondent *behavioral intention (BI)* in favor of *age* ($p \leq 0.05$), *education level* ($p \leq 0.05$), and *Internet experience* ($p \leq 0.05$), as also reported in [4]

Table 9. ANOVA Analysis of respondents' BI attributed to age, educational level, and Internet experience.

Variable		Sum of Squares	Df	Mean Square	F	Sig.
BI attributed to *age.*	Between groups	12.123	4	3.031	4.448	0.002
	Within groups	271.166	398	0.681		
	Total	**283.289**	**402**			
BI attributed to *educational level.*	Between groups	10.249	3	3.416	4.992	0.002
	Within groups	273.04	399	0.684		
	Total	**283.289**	**402**			
BI attributed to *Internet experience.*	Between groups	8.798	2	4.399	6.411	0.002
	Within groups	274.491	400	0.686		
	Total	**283.289**	**402**			

Table 10 provides the statistical significance of the differences between each pair of groups for *age*. As noticed in Table 3, the five groups (i.e., from 18 to less than 34, from 34 to less than 44, from 44 to less than 54, from 54 to less than 64, and 64 and over) were statistically different from one another, whilst noting that the mean difference is significant at the 0.05 level.

Table 10. Multiple comparisons analysis of the behavioral intention attributed to age.

(I) Age	(J) Age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	**Upper Bound**
18 to less than 34	34 to less than 44	−0.25422	0.11756	0.196	−0.5764	0.0679
	44 to less than 54	−0.18279	0.13738	0.672	−0.5592	0.1937
	54 to less than 64	−0.29025	0.14514	0.268	−0.688	0.1075
	64 and over	0.96801 *	0.34089	0.038	0.0339	1.9022
34 to less than 44	18 to less than 34	0.25422	0.11756	0.196	−0.0679	0.5764
	44 to less than 54	0.07143	0.1655	0.993	−0.3821	0.525
	54 to less than 64	−0.03604	0.172	1	−0.5074	0.4353
	64 and over	1.22222 *	0.35316	0.005	0.2544	2.19
44 to less than 54	18 to less than 34	0.18279	0.13738	0.672	−0.1937	0.5592
	34 to less than 44	−0.07143	0.1655	0.993	−0.525	0.3821
	54 to less than 64	−0.10746	0.18611	0.978	−0.6175	0.4025
	64 and over	1.15079 *	0.36024	0.013	0.1636	2.138
54 to less than 64	18 to less than 34	0.29025	0.14514	0.268	−0.1075	0.688
	34 to less than 44	0.03604	0.172	1	−0.4353	0.5074
	44 to less than 54	0.10746	0.18611	0.978	−0.4025	0.6175

	64 and over	1.25826 *	0.36327	0.005	0.2628	2.2537
64 and over	18 to less than 34	−0.96801 *	0.34089	0.038	−1.9022	−0.0339
	34 to less than 44	−1.22222 *	0.35316	0.005	−2.19	−0.2544
	44 to less than 54	−1.15079 *	0.36024	0.013	−2.138	−0.1636
	54 to less than 64	−1.25826 *	0.36327	0.005	−2.2537	−0.2628

* $p < 0.05$.

Table 11 shows the statistical significance of the differences between each pair of groups for education. The four groups (i.e., high school and less, diploma, bachelor, and postgraduate) were statistically different from each other. The mean difference is significant at the 0.05 level.

Table 11. Multiple comparisons analysis of the behavioral intention attributed to education.

(I) Educational Level	(J) Educational Level	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
High school and less	Diploma	−0.81060 *	0.21020	0.001	−1.3529	−0.2683
	Bachelor	−0.60744 *	0.18694	0.007	−1.0897	−0.1252
	Postgraduate	−0.65224 *	0.23092	0.026	−1.2480	−0.0565
Diploma	High school and less	0.81060 *	0.21020	0.001	0.2683	1.3529
	Bachelor	0.20316	0.11814	0.315	−0.1016	0.5080
	Postgraduate	0.15836	0.17982	0.815	−0.3056	0.6223
Bachelor	High school and less	0.60744 *	0.18694	0.007	0.1252	1.0897
	Diploma	−0.20316	0.11814	0.315	−0.5080	0.1016
	Postgraduate	−0.04479	0.15198	0.991	0-.4369	0.3473
Postgraduate	High school and less	0.65224 *	0.23092	0.026	0.0565	1.2480
	Diploma	−0.15836	0.17982	0.815	−0.6223	0.3056
	Bachelor	0.04479	0.15198	0.991	−0.3473	0.4369

* $p < 0.05$.

Table 12 provides the statistical significance of the differences between each pair of groups for *Internet experience*. The three groups (i.e., low, good, and excellent) were statistically different from one another. The mean difference is significant at the 0.05 level.

Table 12. Multiple comparisons analysis of the behavioral intention attributed to Internet experience.

(I) Internet Experience	(J) Internet Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Low	Good	−0.23735	0.20015	0.462	−0.7082	0.2335
	Excellent	−0.49307 *	0.19846	0.036	−0.9599	−0.0262
Good	Low	0.23735	0.20015	0.462	−0.2335	0.7082
	Excellent	−0.25572 *	0.08492	0.008	−0.4555	−0.0559
Excellent	Low	0.49307 *	0.19846	0.036	0.0262	0.9599
	Good	0.25572 *	0.08492	0.008	0.0559	0.4555

* $p < 0.05$.

5.4. Artificial Intelligence Validation and Prediction

The study evaluates five machine learning (ML) classification models whilst the classification ML techniques map the inputs to desired outputs in a well-formed manner of variant patterns [105]. The five models are: artificial neural network (ANN) [106], Linear regression [107], sequential minimal optimization algorithm for support vector machine (SMO) [108], bagging with the REFTree model [109], and random forest [110]. The ANN is a graph of weighted edges and computational nodes that connects the target output to the inputs by updating the weights of the graph through a process known as a back-propagation algorithm. This algorithm reduces the error of the predicted and target output values. The linear regression is a model of polynomial functions that has independent variables with weighted coefficients and a target-dependent output. The training phase in iterations of the process adjusts the coefficients of the linear function from the training dataset. The SMO technique updates the weighted vectors of the SVM model using the sequential minimal optimization algorithm. In the bagging technique, several REFTree models are built from a random sample of the instances and features of the training set, and the average value of the trees is the final predicted value. The random forest is a model of decision trees (DT) that is built up of a random sampling of training data points and random subsets of features. The result of the model is the average value of the DT trees.

Customers' proclivity to use the m-banking system is discussed in this study. Using this technology or promoting it to others is influenced by several factors. The essential value is to connect the factors to the customers' proclivity in well-formed patterns summarizing the data of plenty of customers. However, ML field provides techniques to build models of various forms that, in a classification concept, relates independent variables to dependent variables. This study confirms three models: the impacts of

UTAUT, TAM and TPB, and SRQ factors to the BI as a dependent variable, the BI as an independent factor to WoM variable, and WoM factor to CIU variable. Figure 3 depicts the results of five ML algorithms applied on three models. The x-axes are the models, whilst y-axes provide the R^2 and mean square error (MSE) values. The R^2 stands for how variation is the dependent variable (target) that is expected from the independent values. The MSE stands for how much is the average distance between the predicted and actual values of a model's output. As shown in Figure 3 of the R^2 values to the target values, the linear regression and SMO ML models obtain reasonable results compared to other ML techniques of the three models. This shows that the linear coefficients of the built models are more correlated to the target labels. Model 1 uses linear regression and SMO models to obtain the power to predict the BI variable from the independent variables with an efficient coefficient for each of independent variables compared to the dependent variables (i.e., the BI to WoM variables). The ML models can predict the CIU variable from the WoM variable due to the strong relationship between the two factors.

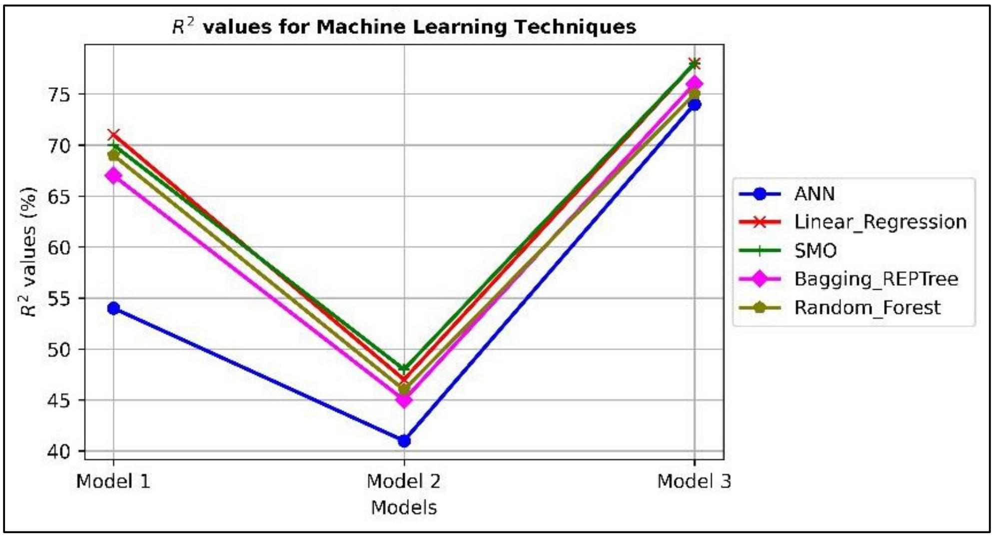

Figure 3. Machine learning techniques R^2.

Furthermore, Figure 4 ensures the effectiveness of the SMO model that achieves a low MSE value between the target and the actual values of the model.

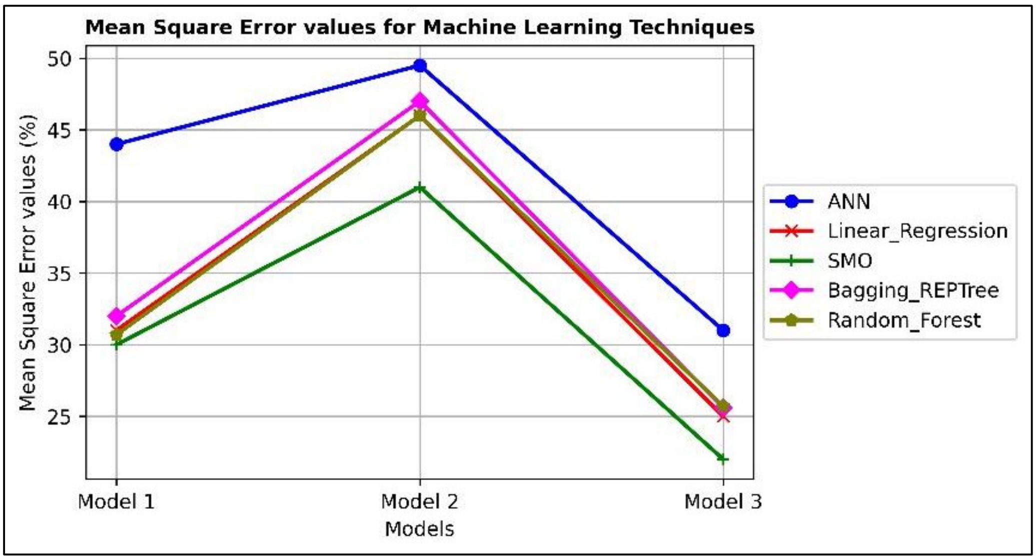

Figure 4. ML techniques mean square error.

6. Discussion and Conclusions

The analysis produces the subsequent conclusions with respect to the basis of analysis, starting with analysis of correlation, where *PE* and *EE* correlate the most with *FC* (0.833, 0.842), and the least with *SRQ* (0.695, 0.681) as seen in Table 5. Hence, all three factors must be considered in the design and development of m-banking software. *PR* correlates the least with *all variables*, as the numbers show in the correlation Table 5. *PR* also affected the other factors negatively, since *PR* is translated into *lack of trust* and later reflects negatively on m-banking users. *Word of Mouth* correlated the most with *continued intention to use (CIU)* of m-banking applications (0.925), seconded by *perceived trust (PT)*. *Behavioral intention (BI)* correlated the most among all (0.850), as seen in Table 5. Hence, *word of mouth* can be considered a very important factor regarding the *CIU* of m-banking, which entails that the reputation of m-banking applications is an instigating factor in attracting future bank customers. *Perceived trust (PT)* and *behavioral intention (BI)* are both very important factors and must be considered in m-banking application design and development.

The results of the direct effects show that performance expectancy (PE), effort expectancy (EE), social influence (SI), perceived risk (PR), perceived trust (PT), and service quality (SRQ) positively and significantly affected behavioral intention (BI). On the other hand, facilitating conditions (FC) did not influence behavioral intention (BI). Hence, such factors must be considered and weighed heavily with regards to m-banking applications.

Hypothesis H1, which pertains to PE positive influence on BI, was supported in this research and in studies such as [6,43–46]. On the other hand, the Indian study [15] refuted such results. In addition, the study [22] conducted in Lebanon found that age as a moderator influenced PE among British responders, whilst gender influenced PE among Lebanese responders.

Hypothesis H2, which pertains to EE positive influence on BI, was supported in this research and studies such as [6,15,44,45,48,49]. In addition, the study [22] conducted in Lebanon found age to be moderator influence EE among British responders, whilst gender influenced EE among Lebanese responders.

Hypothesis H3, which pertains to SI positive influence on BI, was supported in this research and studies such as [6,15,44,47,48]. The findings of the Zimbabwe study [24] also agreed with this research finding.

Hypothesis H4, which pertains to FC positive influence on BI, was not supported in this research and studies such as [6,15,44,47,48,50].

The hypothesis H5 pertains to the negative influence of PR on BI, which was supported in this research and was suggested by [40,54], and [55]. Likewise, this finding agreed with [17], which studied m-banking in Jordan as previously stated. Studies [18] from Jordan, [24] from Zimbabwe, and [25] from Yemen reached the same result. Furthermore, [35] which was conducted on migrant workers also reached the same conclusion.

Hypothesis H6, which pertains to influence of PT's positive influence on BI, was supported by this research and agreed with the findings of [2,34,40]. Furthermore, studies [32] from Jordan and [15] from India agreed with this result. On the other hand, in study [22], the age factor was of significance among Lebanese regarding trust.

The hypothesis H7, concerned with SRQ's positive influence on BI, was supported by this study and agreed with the finding of [29] in New Zealand study and [30] in Korea. The studies [5,33,37] also reached the same conclusion.

Hypothesis H8, pertaining to BI's positive influence on WoM, was supported and agreed with the findings of [43,63–65]. The hypothesis H9 pertaining to the influence of WoM on CUI was supported and, as such, agreed with previous studies [5,33,63,66,67,69,79,80]. Furthermore, when discussing the coefficient value of the nine constructs as shown in Figure 2 and Table 7, the WoM had the highest coefficient value, which is an indicator that respondents do value WoM more than anything, in laymen's terms. Hence, banks should be aware of dissatisfied customers, as the study indicates that people tend to believe and change their attitudes according to a fellow human rather than a banker or professional.

The gender factor was presented in H11 and used as a moderator in studies [15,22,23,44,82,84,87]. In [22], a study conducted in Lebanon found that gender is an influencing factor among Lebanese respondents on PE and EE. On the other hand, age was an influencing factor on PE and EE among British respondents. The gender aspect has an impact on the behavioral intention (BI) regarding the CIU of m-banking, thereby suggesting that male customers would be more inclined to continue using m-banking applications more than female customers. This is a unique finding worth further investigation on the grounds of such an inclination. Furthermore, such a discovery could be made with advanced training and familiarity with m-banking applications for women, or as an initiating factor that must be considered in m-banking application design and development, to focus on attracting genderism into m-banking.

Age, educational level, and Internet experience attributes were presented in H10, H12, and H13 and were previously used in [4,7,23,44,50,51,72,82–86]. Age, educational level, and Internet experience can be attributed to *behavioral intention (BI)*. Younger groups, with higher education and better Internet experience, are more inclined to use m-banking. Hence, banks can target such groups for marketing and bridge the gap by enhancing their outreach.

6.1. Theoretical Implications

Many studies have been conducted on m-banking, as stated previously, and listed in the above sections, such as [6,15–22,24–26,29–33]. Although such studies covered many countries with many models, this study is the only study that covered Jordan with the suggested model in Figure 1. Accordingly, this research will further enrich the literature on m-banking not only for Jordan but also be used as a baseline case-study for other countries.

Also, this study is the only one that used SEM, CFA, and machine learning (ML) methods to confirm the results to predict CIU. The use of such methods is dupped from the idea of triangulation of mixed methods [97], similar to the work of [90–96]. Furthermore, the ML validated the findings that WoM can predict CIU, and BI can predict WoM as shown previously.

In addition, the study reveals the influence of seven factors on the behavioral intention of m-banking users, which in turn influences the WoM factor. The WoM gives credibility to the m-banking application, which entails influence of the WoM influence on CIU for the m-banking application. Hence, the study can predict the future use of m-banking applications for banks and customers and may be used as an incentive for the government for future laws and regulations.

In retrospect, the study investigated the moderating factors such as age, gender, education, and Internet experience as well as their influences on the previously mentioned seven factors. Such an approach was not handled explicitly in other studies that only considered gender [15,87] whilst neglecting age, education, and Internet experience.

The study introduced the moderating variable Internet experience, which was not included in any of the previously mentioned studies. Hence, we have named such groups for further targeting and bridging the gap between such groups.

6.2. Managerial Implications

M-banking is no longer a luxury; it is a pivotal service that allows consumers to conduct financial transactions remotely and provides full remote control of customers' financial data and transactions with a variety of options to serve their needs. There is a shift from e-banking and regular banking with branch banks and branchless banking to m-banking. With m-banking, banks and financial institutions can cut down on operational costs whilst maintaining client satisfaction as well as attract new customers. The ease of use, flexibility, and speed of access to data inevitably indicate the constant use of mobile banking.

The results verified the following factors as influences on the Jordanian customers' behavioral intentions to continue using mobile banking applications: effort expectancy, performance expectancy, perceived risk, social influence, perceived trust, and service quality. However, the results confirmed that the following moderating factors mildly affect behavioral intention to continue using mobile banking applications: age, gender, Internet experience, and educational level. However, facilitating conditions did not affect behavioral intention. The research also recognized a real need for banks to consider focusing particular issues in the design of m-banking applications, including, security, privacy, trust, ease of use, and interface languages, as well as further targeting groups based on age, gender, educational level, and Internet experience.

Considering that m-banking use is expected to be pivotal since m-banking availability will facilitate financial transaction management regardless of location (emphasizing convenience and 24/7 service accessibility), m-banking is becoming a worldwide cultural trend that provides tailored options to accommodate customers' needs at their leisure. Intrinsically, different people with diverse needs and in constant mobility have a need to access their bank accounts "on the go". As such, m-banking needs inter-agency cooperation (whether that may be banks, financial institutions, regulating bodies, or governments) to ease the hurdles of handling the money exchange issue across borders; governments can do this by issuing more adaptable laws and regulations, and banks by developing much needed and state-of-the-art m-applications.

The customer must be aware of m-banking applications and their different offers and techniques. Hence, banks are highly encouraged to invest in customers' awareness as well as to focus on the savings that customers can reap from taking advantage of the different offers from different banks. Subsequently, banks should focus on their respective m-banking applications. M-bank applications are the ATMs of the future; therefore, banks need to rethink their policies and service levels to be intuitive and adaptable to their customers' needs.

Bank policy should accommodate the coming change. Many banks in Jordan still think that m-banking is just a fad or unnecessary hassle, yet m-banking becoming a necessity and a major part of banking. Hence, banks must develop their banking policy and accommodate such demand. Furthermore, such change should be reflected in the information technology department by the application installed on the smartphone of the customer. Such action is reflected in innovation dynamics model, which immerses banks in the information technology realm.

Governments in different countries must pay attention to regulations and laws as technology progresses. Governments must issue the right regulations to protect their citizens, banks, and currencies without limiting their opportunities. As technologies pave the way to new frontiers, governments should be alert so as not to deprive their citizens and banks of such opportunities. Burying their heads in the sand will not change the facts. Hence, governments should issue laws and regulations to handle modern technologies as suggested by [1].

6.3. Limitations and Future Research

During the conduct of the research and the resulting study, many challenges faced the researchers, starting with time constraints. In view of the fact that most of the people who were approached to answer the questionnaire expressed their lack of available time to complete the questionnaire, the researchers had difficulties in finding m-banking customers who would be available to complete the questionnaire.

This study was conducted during the COVID-19 epidemic, which limited the mobility of the research team, although the pandemic-related measures of movement restrictions did enhance the use of m-banking applications. Hence, the research team relied on electronic means of communication, whether in distributing the questionnaire or conducting interviews.

Lack of access to information about bank customers, which is governed by the privacy laws in the banks, and the prevention of disclosure of customers' information to third parties, hindered obtaining statistical information related to the study of factors affecting the continuation intention to use m-banking.

As for future research, many constructs were not included in this study such as information language, income level, traveling frequency, and sense of achievement. We believe such factors should be covered in future research. More detailed study that can concentrate on the m-bank application attributes can be conducted to explore further the factors influencing adopting m-bank applications and the influence of m-bank applications.

Another idea of future research is to conduct an experiment where the application users are virtually followed and their interaction with the m-banking application is registered in detail. Furthermore, banks should listen to their customer and their dissatisfied customers since WoM has the highest coefficient value.

6.4. Conclusions

To conclude, this study aimed to discover and examine crucial factors that could predict continued intention toward the use of m-banking. The model of the research was based on well-known theories and models theory of planned behavior (TPB), unified theory of acceptance and use of technology (UTAUT), and technology acceptance model (TAM). A survey was conducted using sample of convenience on 403 m-bank application users. The researchers used SEM, CFA, and five machine learning methods to validate and verify the outcome and model, along with the hypotheses. Outcomes showed that effort expectancy, performance expectancy, perceived risk, perceived trust, social influence, and service quality impacted behavioral intention, whereas facilitating conditions did not. Furthermore, behavioral intention impacted upon word of mouth and facilitating conditions (the latter regarding continued intention to use). Outcomes also confirmed that all moderating factors affect the behavioral intention to continue using m-banking applications. Performance expectancy had ranked as highest in influence, and word of mouth had the highest coefficient value.

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Appendix A

Table A1. The constructs and their measures with each original source.

Constructs	ID: Items/Measure	Adopted from
Demographic information	Gender 1. Male 2. Female	[15]
	Age (years) 1: 18 to less than 34 years old. 2: 34 to less than 44 years old. 3: 44 to less than 54 years old. 4: 54 to less than 64 years old. 5: 64 and over.	[7]
	Educational level 1: High school and less. 2: Diploma. 3: Bachelor. 4: Postgraduate	[84]
	Internet experience 1: Low. 2: Good. 3: Excellent.	[44]
Perceived trust (PT)	• PT1: I believe that using mobile banking to transfer money is always safe. • PT2: I believe mobile banking is a safe way to transfer money. • PT3: My bank notifies me immediately if anything goes wrong with any of my transactions. • PT4: Based on my experience, I believe that using mobile banking is safe.	[40]
Behavioral intention (BI)	• BI1: I intend to use the mobile banking system if I have access to it. • BI2: For my banking needs, I would use mobile banking. • BI3: If I have access to the mobile banking system, I want to make the most of it.	[40]
Perceived risk (PR)	• PR1: Using mobile banking services exposes my bank account to the risk of fraud. • PR2: Using mobile banking services puts my bank account at risk. • PR3: I believe that using mobile banking services jeopardizes my privacy. • PR4: If I use mobile banking services, hackers may gain access to my bank account.	[40]
Service quality (SRQ)	• SRQ1: The service quality I receive from mobile banking is excellent. • SRQ2: I am very pleased with the service I receive from Mobile Banking. • SRQ3: Mobile banking provides high-quality service.	[6]
Effort expectancy (EE)	• EE1: I find it simple to learn how to use mobile banking. • EE2: My interaction with Mobile Banking is simple and easy to grasp. • EE3: Internet Mobile Banking is simple to use for me. • EE4: It is simple for me to learn how to use mobile banking.	[6]
Performance expectancy (PE)	• PE1: I use mobile banking in my daily life. • PE2: Using mobile banking increases my chances of completing important tasks. • PE3: Mobile banking allows me to complete tasks more quickly. • PE4: I am more productive when I use mobile banking.	[6]

Social influence (SI)	• SI1: Important people in my life believe that I should use mobile banking. • SI2: People who have an impact on my behavior believe that I should use mobile banking. • SI3: People whose opinions I respect prefer that I use mobile banking.	[6]
Facilitating conditions (FC)	• FC1: I have the necessary resources to use mobile banking. • FC2: I have the knowledge necessary to use mobile banking. • FC3: Mobile banking works with the other technologies I use. • FC4: I can seek assistance from others if I am having difficulty using mobile banking.	[6]
Word of mouth	• WoM1: I'd like to introduce others to mobile banking. • WoM2: I'm happy to recommend mobile banking to others. • WoM3: I will recommend mobile banking to others. • WoM4: I will tell others about the benefits of mobile banking.	[80]
Continued intention to use (CIU)	• CIU1: I tell other people how much I like mobile banking. • CIU2: Those who seek my advice on such matters should consider mobile banking. • CIU3: I would recommend mobile banking to friends and family. • CIU4: On some Internet message boards, I would post positive messages about the mobile banking service I use. • CIU5: I intend to keep doing business with the current mobile banking system. • CIU6: I plan to do more business with the current mobile banking system.	[111]

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