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Structural Equation Modeling and Machine Learning Models for Modeling Consumers' Adoption of Cryptocurrencies

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Abstract: This study examines the adoption of cryptocurrencies in restrictive regulatory environments, focusing on Jordan, and explores the factors influencing adoption using the model evaluates the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intention, alongside trust and multiple risk dimensions (financial, performance, privacy, and security). Data from 395 respondents were evaluated with structural equation modeling (SEM) and seven machine learning models to evaluate proposed hypotheses. The findings reveal that trust significantly drives behavioral intentions, while perceived risks, despite being acknowledged, do not deter adoption. Younger, tech-savvy users were less influenced by effort expectancy, highlighting demographic differences in adoption behavior. The integration of SEM and ML provides both theory-driven insights and predictive accuracy, revealing complementary perspectives on adoption dynamics. The study concludes that building trust, enhancing security and leveraging social influence are critical for wider cryptocurrency adoption, with implications for service providers and policymakers.

Keywords: Cryptocurrency, UTAUT, Trust, Risk, Machine Learning, Structural Equation Modeling

1 Introduction

Cryptocurrencies are a model of P2P electronic cash system suggested in 2008 by Nakamoto [1]. The system depended on both cryptography and blockchain technology to be independent from central banks hence the currency is digital. Such system saves money of banks overhead and time. The system utilizes the backbone of technology today which is the internet. The acceptance of the system was studied by many in different cultures and countries [2], [3], [4], [5], [6], [7], [8], [9], [10]. Still in Jordan the stance of the Central Bank of Jordan (CBJ) on cryptocurrencies and blockchain technology is not clear. Only one research paper [11] studied the adoption of cryptocurrency by Jordanians which was published in 2022. The global crypto adoption index ranks [12] Jordan 84th globally with index score 0.017 (out of 1) while the same index ranks India as number 1, and USA as number 4 and Nigeria at number 2. Other neighboring countries like the Kingdom of Saudi Arabia ranked 41, UAE ranked 56, Yemen 45 and Egypt 44 all ranked much higher than Jordan. Thus, this research aims to investigate the factors

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influencing individuals' adoption of cryptocurrencies among the residents of Jordan. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), trust, and perceived risk frameworks, the main objective of this study was to identify and analyze major factors that influence consumers' adoption of cryptocurrencies. This study will examine the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions from the UTAUT model on consumer behavior towards using cryptocurrencies according to trust, in the form of industry trust, vendor trust, and perceived risk, in the form of financial risk, performance risk, privacy risk, and security risk.

2 Literature Review

Nakamoto [1] Introduced a Peer-to-Peer electronic cash system in 2008 and presented the new concept of cryptocurrency. The key characteristics of cryptocurrency include decentralization, digital, cryptography, and blockchain. Hence, cryptocurrency exists in electronic form and operates independently of central banks and governments. Cryptography techniques are used to secure transactions and control the creation of new units in cryptocurrency. Transactions using cryptocurrency is recorded on a public, distributed ledger called blockchain [5], [13], [14], [15]. There are several reasons why people use cryptocurrency: Decentralization and autonomy, hence giving users more control over their financial transactions. Cryptocurrency provides Security by using different Cryptographic techniques to secure transactions and control the creation of new units, making it difficult for hackers to manipulate transactions [9], [13], [16]. Further, some cryptocurrencies offer a level of anonymity, allowing users to make transactions without revealing their identities [14]. Also, cryptocurrencies enable fast and borderless transactions, making it easier to send and receive money globally [10]. In addition, most cryptocurrencies have a limited supply, which can help prevent inflation and maintain the value of each unit [17]. Moreover, cryptocurrencies can be highly volatile, which means their value can fluctuate rapidly, potentially leading to high returns [14]. Then cryptocurrencies can provide a diversification opportunity for investors, allowing them to spread their risk across different asset classes. On the other hand, cryptocurrency investments also come with risks, such as volatility, regulatory uncertainty, and security risks [6], [18]. The Technology Acceptance Model (TAM) is considered one of the most frequently implemented frameworks for understanding cryptocurrency adoption. Several studies have confirmed the strong influence of perceived usefulness and ease of use on adoption intentions across different contexts. TAM has been applied to examine the intention to adopt cryptocurrency among Generation Z females in India [19], UAE residents [20], and citizens in Bangladesh [21]. Other TAM-based studies have investigated the intention to pay with cryptocurrency for tourism services by residents of Lithuania, Latvia, and Estonia [22] and explored Chinese and South Korean travelers' readiness to adopt cryptocurrency payments [23]. Namahoot et al. [24] examined consumers' intention to adopt cryptocurrency platforms in Thailand using TAM, while Shahzad et al. [25] conducted an extensive investigation into the adoption of cryptocurrency among a diverse population in Pakistan, including students, government employees, private sector employees, and business owners.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model [26] has been widely employed to capture the role of performance expectancy, effort expectancy, social influence, and facilitating conditions in cryptocurrency adoption. García-Monleón et al. [27] studied the factors driving the use of cryptocurrencies for value exchange among students and professors in Spain. Bozkurt and Akgül [28] investigated the role of social influence, perceived benefits, and facilitating conditions in shaping the intentions of individual investors in Turkey to adopt cryptocurrencies. Alomari and Abdullah [29] explored the predictors of cryptocurrency adoption among Saudi Arabian public university students. Researchers [30] also examined players' acceptance of cryptocurrency as a payment method in NFT games in Indonesia, while Facebook users' acceptance of cryptocurrency was studied in Hungary [31]. Furthermore, scholars investigated the factors influencing the adoption of cryptocurrencies for financial transactions among residents of Lebanon [32], Malaysia [33] and Spain [34].

The use of UTAUT to study behavioral intention (BI) in the arena of cryptocurrency is seen in the following: In Hungry [35] investigate individuals' behavioral intentions to use cryptocurrencies and identify factors influencing technology adoption cryptocurrency in TAM, UTAUT, and IDT theories. Furthermore [36] studied the same among business travelers in Thailand using TAM, UTAUT. Again [37] studied the same in tourism in South Korea and China using TAM, UTAUT. [38] studied cryptocurrency adoption among tourism in Jeju Island, Korea using UTAUT. Additionally [39] studied metaverse commerce using UTAUT 2 and dual-factor theory. Also [40] studied performance expectancy, social influence, facilitating condition and price value of cryptocurrency in Malaysian. Moreover [41] studied social influence (SI), transparency (TR), price value (PV), traceability (TRA), and attitude (AT) was examined to identify customer satisfaction of cryptocurrency in Malaysian digital market. Similarly [42] studied Blockchain acceptance in the banking and finance sector using UTAUT and Trust. Likewise [43] studied blockchain-based sharing economy systems in Decentralising Airbnb using multigroup analysis (MGA). Researches [18], [44] contributed valuable insights into the complex landscape of cryptocurrency adoption, particularly in Spain. By applying the UTAUT framework and emphasizing the roles of performance expectancy and facilitating conditions, the authors provide understanding of consumer behavior towards cryptocurrencies. As for the trust and risk constructs many studies integrated trust and risk with UTAUT framework like [2], [3], [4], [5], [6], [7], [8], [9] and [10]. As explained next, Rahardja et al. [6] prove that trust significantly mediates the relationship between perceived benefits and BI, on the other hand, researchers found that perceived risk moderates this relationship negatively. Apaua and Lallie [4] also highlights the significance of trust in online transactions, which resonates with the broader context of cryptocurrency adoption. Understanding user perceptions of risk and trust is essential for fostering wider acceptance of digital currencies. McKnight and Chervany [7] argue that trust becomes especially critical in high-risk environments. Bulut [2] underscores the importance of consumer confidence in Bitcoin, linking trust to user participation and speculative opportunities. Campino and Yang [5] study the factors influencing the adoption of cryptocurrencies, focusing on perceived risk, trust, and user experience. The researchers argue that perceived risk is a significant barrier to cryptocurrency adoption, as consumers often associate cryptocurrencies with security risks. Financial literacy is also crucial for enhancing users' confidence and decision-making in cryptocurrency. Trust in blockchain-based applications significantly influences consumer intentions to engage with cryptocurrencies, aligning with the UTAUT framework. Perceived ease of use is a critical determinant of technology acceptance, and improving user experience through simplified interfaces and better educational resources can significantly enhance the likelihood of cryptocurrency adoption. Social factors also play a significant role in shaping consumer attitudes toward cryptocurrencies, suggesting that social networks can be leveraged to promote cryptocurrency usage. Also Walch [10] stated that Operational risks, including protocol vulnerabilities and scalability issues, further exacerbate perceived risks. On the other hand, users often become desensitized to perceived risks, focusing instead on the potential benefits of cryptocurrency adoption [3]. Huang et al. [44] stated that market volatility and frequent cyberattacks heighten financial risk, potentially deterring users. Legal risks, particularly in countries with restrictive regulatory frameworks like Jordan, amplify concerns about compliance and the absence of investor protections. Yu et al. [8] and Huang et al. [9] claimed that concerns about the security of personal information increased users' security risk, leading to increased apprehension. The only study conducted pertaining to Jordan with cryptocurrency was Almajali et al. [11]. The research examined the factors affecting the adoption of cryptocurrency in Jordan using the extended Theory of Reasoned Action (TRA) model. The research found that the intention to use cryptocurrency adoption in Jordan is positively influenced by several factors, including trust, perceived usefulness, perceived ease of use, and social influence, along with perceived risk and enjoyment. The literature highlights the importance of trust, perceived risk, and contextual variables in consumer behavior toward cryptocurrencies and provides valuable insights, but several gaps remain. First, limited studies focus on cryptocurrency adoption in countries like Jordan with restrictive regulatory environments. Second, the role of financial literacy in shaping adoption decisions remains underexplored. Also, service providers should foster trust and address perceived risks to enhance user engagement and adoption rates. This study addresses these gaps by applying the UTAUT framework alongside trust and perceived risk constructs to examine cryptocurrency adoption in Jordan. By incorporating structural equation modeling (SEM) and machine learning techniques, this research provides a comprehensive analysis of the factors influencing adoption, offering both theoretical and practical contributions. In this research, the unified theory of acceptance and use of technology (UTAUT) is used as a base theory and extended with perceived trust and perceived risk. Venkatesh et al. [26] identified four primary UTAUT constructs—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—as critical predictors of behavioral intention (BI). Performance expectancy, or the perceived benefits of using technology, consistently emerges as a strong determinant of adoption.

3 Theoretical Framework: Model and Hypothesis Development

The UTAUT model depends on the Technology Acceptance Model (TAM) to describe users' interests and attitudes toward technology [45]. The suggested model shown in Figure 1 is based on the UTAUT model in addition to financial risk, legal risk, security risk, operational risk, perceived risk, and perceived trust, as well as four regulating factors including response's Age, Gender, Internet Experience, and Education. The suggested model's hypotheses were developed based on several studies: [1], [2], [4], [6], [7], [8], [8], [9], [11], [12] , [14], [16], [18], [19], [20], [21], [22], [23], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39]. In the next section, the hypothesis about UTAUT will be examined and reinforced with literature. Next, the risk and trust, and the related hypothesis will be presented. Finally, the moderating hypothesis will be discussed and reinforced by related research. This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

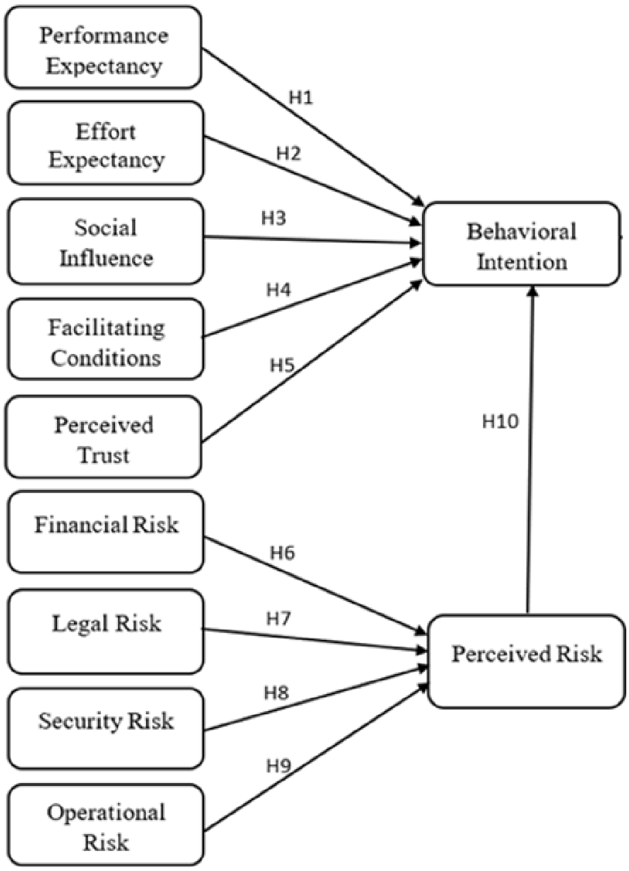

Fig. 1: The suggested research model

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

UTAUT was developed and presented by Venkatesh et al. [26]. The UTAUT model has four main ideas used in this research: PE, EE, SI, and FC. The four constructs influence BI, which is a measure of the strength of one's intention to perform a specified behavior as stated by Davis et al. [66]. Venkatesh et al. [26] defined Performance Expectancy (PE) as "the extent to which using a technology will provide benefits in performing certain activities.", researchers [3], [49], [50], [67], [68], [69] investigated the influence of the PE on the BI to invest in the cryptocurrency and found that higher PE leads to a stronger BI to adopt the cryptocurrency. on the other hand, Mahomed [67] claim that Performance expectancy has no significant effect on the behavioral intention to invest in cryptocurrency. Thus, the following hypothesis was developed: H1: Performance Expectancy positively influences Jordanians' Behavioral Intention (BI) to adopt cryptocurrency. According to Venkatesh et al. [26] Effort expectancy (EE) is "the degree of ease associated with the use of the system.", Several research projects investigated the relation between EE and the adoption of cryptocurrency [3], [49], [50], [67], [68], [69], Gupta et al. [49] stated that "Effort Expectancy is the least influencing factor considered by investors", on the other hand, Other studies have demonstrated that Higher effort expectancy will lead to a stronger behavioral intention to adopt and invest in cryptocurrency [3], [39], [51], [70]. On the other hand, Mahomed [67] claim that Performance expectancy has no significant effect on the behavioral intention to invest in cryptocurrency. Therefore, the following hypothesis was proposed: H2: Effort expectancy (EE) positively influences Jordanians' behavioral intention (BI) to adopt cryptocurrency. Mohd Thas Thaker et al. [52] defined that social influence (SI) as "the extent to which an individual believes that important others believe he or she should use the system.". Mahomed [67] stated that SI is the "Social pressure to use technology". Camilleri [71] and Venkatesh et al. [53] argue that SI is an important factor affecting an individual's decision to use technology where individuals are influenced by relatives, friends, and other important people in society. several scholars have examined the role of Social Influence in increasing individual behavioral intention to invest in cryptocurrency [49], [67], [72]. Gupta et al. [49] and Mahomed [67] argues that Social Influence is the most important factor encouraging investors to invest in cryptocurrency. while Kabir et al. [69] claim that the social influence on the behavioral intention to use blockchain technologies, such as cryptocurrency, is insignificant. which introduces the next hypothesis: H3: Social Influence (SI) positively influences Jordanians' Behavioral Intention (BI) to adopt cryptocurrency. Facilitating conditions (FC) are the extent to which an individual feels that the technological and organizational infrastructure exists to support system utilization [26]. Mahomed [67] stated that (FC) is the "Perception of resources and support available for the usage of the technology". Furthermore, studies have researched this factor, where researchers [3], [49], [50], [67], [68], [69] conclude that better-facilitating conditions will lead to a stronger behavioral intention to adopt cryptocurrency H4: Facilitating Conditions (FC) positively influence Jordanians' Behavioral Intention (BI) to adopt cryptocurrency." McKnight and Chervany [7] argue that trust is crucial in situations characterized by risk, uncertainty, and interdependence. Arli et al. [73] stated that the main factors contributing to consumers' trust in cryptocurrencies are knowledge of cryptocurrencies, trust in government, and the speed of transactions. researchers [6], [74], [75], [76], [77] provided insights on trust in Cryptocurrency technology, highlighting the importance of technological, social, interpersonal, and institutional trust. Based on the aforementioned, the researchers found that higher perceived trust will result in a higher behavioral intention to use cryptocurrencies. Accordingly, the following hypothesis was suggested: H5: Perceived Trust (PT) positively influences Jordanians' Behavioral Intention

(BI) to adopt cryptocurrency. Cox [54] Stated that ”financial risk refers to the extent to which the product value cannot match the cost of payment”, Huang et al. [9] and Chen [13] argue that cryptocurrency’s value and transaction prices fluctuate significantly, constituting investment and exchange risks. In addition to the possible financial risk related to the repeated attacks on the cryptocurrency by hackers, where over 1.7 billion US Dollar in cryptocurrency was stolen in 2023 [78]. Hence, cryptocurrency investment involves financial risk and potential financial losses for cryptocurrency users [9], [13], [78], [80]. Therefore, the following hypothesis was proposed: H6: Financial risk (FR) positively influences Jordanians’ perceived risk of cryptocurrency. Huang et al. [9] defined the Legal risk as ”the imperfect legislation and regulations related to the cryptocurrency”. Cryptocurrencies are legal and acknowledged in different countries, where they are treated as assets, like in the USA [81], [82], [83]. On the other hand, in many countries such as China, Egypt, Iraq, Bolivia, and Jordan, cryptocurrencies have been banned, and the mining and exchange of cryptocurrencies are prohibited, where it is either illegal or lacks official regulation [9], [81], [83], [84]. moreover, because Cryptocurrencies are digital virtual assets, and currently, no central authority or government agency regulates them, this may involve different risks such as price volatility, trading platform shutdowns, and money laundering [83], [85], [86]. Accordingly, Cryptocurrencies do not provide any exclusive legal protection or compensation, and any investments or transactions are less protected by financial supervisory legislation and rules [9], [87], [88], In cases of loss or fraud, the investor may not be compensated [89], [90]. Hence, stating the following hypothesis: H7: Legal risk (LR) positively influences Jordanians’ perceived risk of cryptocurrency. Security risk refers to ”the exposure of the personal information of a cryptocurrency user.” [9], Liebermann and Stashevsky [55] investigated the security issues related to online virtual transactions, and the researchers found that concerns about the security of personal information increased users’ perceived risk and reduced their willingness to use online e-commerce systems. Scholars [9], [15], [56], [91] stated that the confidentiality of using cryptocurrency can’t be guaranteed due to several serious security risks, for instance, the wallets’ safety, and cyberattacks. These risks also make users perceive greater risk when trading cryptocurrency. Therefore, security risks may lead cryptocurrency adopters to stop using it [8], [17], [91]. Hence, the following hypothesis was proposed: H8: Security risk (SR) positively influences Jordanians’ perceived risk of cryptocurrency Huang et al. [9] characterized the operational risk as ”the potential vulnerabilities in the protocol and mechanical design of the cryptocurrency”. scholars [14], [92], [93] investigated the characteristics of risk management in cryptocurrency operations, researchers stated that ”the cryptocurrency system’s processes are still under construction”, and claimed its resilience is lacking in long-term assessment and validity, where operator infractions, losses, and control failures can increase operational risks. Operational risks may include cryptocurrency’s technological infrastructure failures, scalability challenges, private key management, data and transaction integrity, human operational mistakes, and dependence on third-party services. [9], [44], [56], [57], [94], [95]. Walch [10] found that the operational risks of cryptocurrency include decentralization challenges, governance complexities, software vulnerabilities, and the need for skilled and expert developers to manage the evolving financial market infrastructure. According to the studies mentioned, researchers concluded that higher operational risk increases the perceived risk related to cryptocurrency adoption. Thus, the following hypothesis was anticipated: H9: Operational risk (OR) positively influences Jordanians’ perceived risk of cryptocurrency Scholars [18], [96], [97] concluded that perceived risk negatively influences the intention to adopt information technology and systems. Huang et al. [9] stated that ”perceived risk can increase users’ discontinuance usage intention to cryptocurrency”. Huang et al. [9] suggested that perceived risk represents “an individual’s belief that using cryptocurrencies might result in unknown, negative, and undesirable results”. Where higher perceived risk adversely influences behavioral intention to invest in cryptocurrencies, researchers [9] investigated the four potential risks that affect perceived risk, and found that legal, operational, and financial risks are critical to increase users’ perceived risk. Accordingly, hypotheses H6-H9 were suggested, and propose the following hypothesis: H10: Perceived Risk (PR) negatively influences Jordanians’ behavioral intention (BI) to adopt cryptocurrency.

4 Data Analysis and Results

In this study, we combined Structural Equation Modeling (SEM) and Machine Learning (ML) to capture both the theoretical and predictive dimensions of cryptocurrency adoption [48], [61], [98]. SEM was selected because it allows us to test complex relationships between constructs, such as Effort expectancy, Perceived trust, and Perceived Risk, while also accounting for measurement errors [99], [100], [101]. These constructs are not directly measurable, so SEM’s ability to handle latent variables makes it well suited for validating our conceptual model, which is grounded in established adoption theories. This ensures that our results are both statistically sound and theoretically meaningful. At the same time, we recognized that SEM, while powerful for theory testing, is not primarily designed for high predictive accuracy, especially when the data may involve nonlinear relationships or subtle interactions between variables. This is where ML adds value [102], [103], [104], [105], [106]. By applying ML models, we can uncover hidden patterns in the data and improve our ability to predict user adoption behavior beyond what the theoretical model specifies. By bringing these two approaches together, we benefit from the strengths of each: SEM provides robust, theory-driven insights, and ML offers flexible, data-driven predictions. This combination reflects a growing trend in information systems research, where blending explanatory and predictive methods produces richer, more actionable findings. This section will present research demography analysis, descriptive statistics, measurement model, and structural model.

4.1 Participants and Procedure

A web-based survey questionnaire was developed in Google Docs in both Arabic and English, a five-point Likert scale employed ranging from strongly disagree (1) to strongly agree (5). The questionnaire was reviewed by a panel of 10 academicians, and their feedback was incorporated to refine the survey's content. The survey link was distributed through groups and pages targeting university students, researchers, and Jordanian residents on the most popular social networking platforms in Jordan; Facebook, LinkedIn, and WhatsApp. Participation was voluntary, with no financial incentives offered. A convenience sampling method was employed in this study. Data from 395 respondents were evaluated with structural equation modeling (SEM) and seven machine learning models to evaluate proposed hypotheses.

4.2 Demographic Analysis

According to Backhaus et al. data table [107] , a minimum of 384 application users was required to achieve the optimum statistical sample size for this research. The survey was conducted from 6 February 2025 to 12 April 2025, and after removing the deficient surveys, 395 applications remained. The respondents' demographic data are presented in Table 1. Four variables were included: age, gender, educational level, and internet experience. Age was categorized into five groups, gender into two groups, educational level into five groups, and internet experience into three groups.

As shown, the respondents' demographic data showed that the participants almost equal regarding relatives (i.e., "males and females"), the age of most of them lays between 18 and 28, and the education level of most of them is bachelor's degree, they had good and excellent knowledge of using the internet.

4.3 Descriptive Analysis

To analyze the respondents' answers in the survey, the mean and standard deviation were calculated. The mean indicates the central tendency of the data, while the standard deviation measures the dispersion, showing the variability in the data [108], [109]. A small standard deviation means values are close to the mean; a large one indicates greater spread. Each item's level was determined using the formula: (5-1)/5 = 0.80, where 1-1.80 = very low,1.81-2.60 = low, 2.61-3.40 = moderate, 3.41-4.20= high, and 4.21-5 =very high. The items were then ordered by their means. Table 2 presents the results.

Table 1. Respondents' Demographic Profiles.

Category	Category	Frequency	Percentage
Gender	Male	198	50.1
	Female	197	49.9
Age (Year)	18 to less than 28	367	92.9
	28 to less than 38	13	3.3
	38 to less than 48	12	3.0
	48 to less than 58	3	0.8
	58 and over	0	0.0
Educational level	High school and less	17	4.3
	Diploma	4	1.0
	Bachelor	363	91.9
	Master	11	2.8
	PhD	0	0.0
Internet Experience	Low	17	4.3
	Good	224	56.7
	Excellent	154	39.0

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Kurtosis	Skewness
Behavioral Intention (BI)	3.101	0.919	0.086	-0.326
Effort Expectancy (EE)	3.249	0.882	0.030	-0.420
Facilitating Condition (FC)	3.123	0.820	0.185	-0.407
Financial Risk (FR)	3.493	0.867	0.575	-0.480
Legal Risk (LR)	3.247	0.845	0.213	-0.192
Operational Risk (OR)	3.418	0.840	0.234	-0.377
Performance Expectancy (PE)	3.125	0.933	0.244	-0.349
Perceived Risk (PR)	3.312	0.822	0.212	-0.241
Perceived Trust (PT)	3.002	0.879	-0.091	-0.289
Subjective Influence (SI)	2.776	0.833	-0.177	-0.096
Security Risk (SR)	3.317	0.880	0.134	-0.427

4.4 Measurement Model

This research followed the suggestions of Hair et al. [110], Kock [101] and Kock et al. [100] to test the validity using the loadings and the average variance extracted (AVE) and composite reliability for testing the consistency or reliability of the answers. As suggested by Becker et al. [99] the loadings should be greater than 0.7, the AVE should be greater than 0.5 and the CR should be greater than 0.7. As shown in Table 3, all the loadings are greater than 0.7 except for UB4, all the AVE were greater than 0.5 and the CR were all higher than 0.7 thus confirming the items are valid and reliable [111] The discriminant validity was assessed using the HTMT ratio developed by Henseler et al. [112]. Franke and Sarstedt [113] suggested that if the HTMT ratios are lower than 0.85 then the discriminant validity was established. As presented in Table 4, all the HTMT ratios were lower than 0.85, thus confirming that the respondents that they were distinct constructs.

Table 3. Measurement Model

Variable	Items	Loadings	CR	AVE
Behavioral Intention	BI1	0.921	0.953	0.834
	BI2	0.890		
	BI3	0.929		
	BI4	0.913		
Effort Expectancy	EE1	0.828	0.928	0.763
	EE2	0.883		
	EE3	0.883		
	EE4	0.897		
Facilitating Condition	FC1	0.823	0.872	0.631
	FC2	0.780		
	FC3	0.794		
	FC4	0.779		
Financial Risk	FR1	0.887	0.929	0.813
	FR2	0.906		
	FR3	0.911		
Legal Risk	LR1	0.872	0.931	0.772
	LR2	0.887		
	LR3	0.860		
	LR4	0.894		
Operational Risk	OP1	0.902	0.918	0.788
	OP2	0.892		
	OP3	0.869		
Performance Expectancy	PE1	0.932	0.944	0.848
	PE2	0.928		
	PE3	0.902		
Perceived Risk	PR1	0.920	0.890	0.732
	PR2	0.908		
	PR3	0.725		
Perceived Trust	PT1	0.866	0.929	0.767
	PT2	0.874		
	PT3	0.872		
	PT4	0.891		
Subjective Influence	SI1	0.868	0.923	0.751
	SI2	0.860		
	SI3	0.870		
	SI4	0.868		
Security Risk	SR1	0.883	0.920	0.794
	SR2	0.890		
	SR3	0.899		

Table 4. Discriminant Validity (HTMT ratio)

Variable	BI	EE	FC	FR	LR	OP	PE	PR	PT	SI	SR
Behavioral Intention (BI)											
Effort Expectancy (EE)	0.511										
Facilitating Condition (FC)	0.628	0.796									
Financial Risk (FR)	0.142	0.280	0.357								
Legal Risk (LR)	0.204	0.204	0.316	0.595							
Operational Risk (OR)	0.246	0.267	0.393	0.690	0.712						
Performance Expectancy (PE)	0.596	0.571	0.609	0.236	0.223	0.237					
Perceived Risk (PR)	0.146	0.218	0.327	0.786	0.600	0.830	0.189				
Perceived Trust (PT)	0.672	0.560	0.674	0.075	0.203	0.124	0.638	0.042			
Subjective Influence (SI)	0.516	0.510	0.645	0.165	0.312	0.238	0.560	0.210	0.549		
Security Risk (SR)	0.103	0.192	0.278	0.652	0.567	0.651	0.131	0.779	0.064	0.196	

Table 5. Hypotheses Testing

Hypothesis	Relationship	Std. Beta	Std. Dev.	t-value	p-value	BCI LL	BCI UL	f2
H1	PE → BI	0.196	0.067	2.921	0.002	0.083	0.303	0.04
H2	EE → BI	0.031	0.062	0.502	0.308	-0.067	0.137	0.00
H3	SI → BI	0.106	0.054	1.980	0.024	0.014	0.192	0.02
H4	FC → BI	0.170	0.063	2.677	0.004	0.061	0.268	0.02
H5	PT → BI	0.342	0.066	5.142	p< .001	0.229	0.449	0.12
H6	FR → PR	0.283	0.051	5.527	p< .001	0.200	0.367	0.12
H7	LR → PR	-0.016	0.050	0.322	0.374	-0.100	0.063	0.00
H8	OP → PR	0.376	0.052	7.280	p< .001	0.292	0.462	0.18
H9	SR → PR	0.288	0.057	5.083	p< .001	0.192	0.379	0.13
H10	PR → BI	0.021	0.056	0.376	0.353	-0.065	0.118	0.00

4.5 Structural Model

The research assessed multivariate skewness and kurtosis, following Cain et al. [114]. The results indicated the data was not multivariate normal, with Mardia's multivariate skewness $\beta = 18.523$, $p < .01$) and kurtosis ($\beta = 235.215$, $p < 0.01$). As suggested by Becker et al. [99], path quantities were calculated, standard errors, t-values, and p-values for the structural model using a 10,000-sample bias-corrected bootstrapping. Table 5 summarizes the criteria used to test the hypotheses. The $\mathbb{R}^2$ for Perceived Risk was 0.633, for Intention was 0.482 which indicates that all the predictors together can explain 63.3% of the Perceived Risk, 48.2% of Behavioral Intention. As presented in Table 5, PE ($\beta = 0.196$, $p < 0.01$), SI ($\beta = 0.106$, $p < 0.05$), FC ($\beta = 0.170$, $p < 0.01$) and PT ($\beta =$

Table 6. PLS-Predict

MV	Q²predict	PLS-SEM_RMSE	IA_RMSE	PLS-IA_RMSE
BI1	0.344	0.823	1.016	-0.193
BI2	0.341	0.779	0.960	-0.181
BI3	0.358	0.857	1.070	-0.213
BI4	0.421	0.751	0.987	-0.236

0.342, $p < 0.01$) were positively related to Behavioral Intention while PR ($\beta = 0.021$, $p > 0.05$) was not significant. Thus, H1, H3, H4, H5 were supported while H2 and H6 were not supported. As for the predictors of PR it shows that FR ($\beta = 0.283$, $p < 0.01$), OP ($\beta = 0.376$, $p < 0.01$) and SR ($\beta = 0.288$, $p < 0.01$) were all positively related to PR while LR ($\beta = -0.016$, $p > 0.05$) was not significant. Thus, H8, H9, and H10 were supported while H7 was not supported.

Finally, predictive power was tested using the PLS-Predict [115] with a 10-fold procedure and as shown in Table 6, all the errors of the PLS model were lower than the benchmark models of AI model thus, one may conclude that the suggested model has a strong predictive power.

5 Machine Learning Analysis

Model 1 is designed to study and investigate the factors affecting the Behavioral Intention to adopt cryptocurrency, incorporating six independent features derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, with additional constructs for trust and risk perceptions. The features include Performance Expectancy (PE), which reflects the belief that using cryptocurrency will enhance transactional efficiency and outcomes, and Effort Expectancy (EE), that evaluates the seeming comfort of using cryptocurrency platforms. Social Influence (SI) captures the degree to which individuals believe that significant others expect them to adopt and use cryptocurrency, while Facilitating Conditions (FC) measure the availability of support systems and resources necessary for effective use, such as access to devices and customer service. Perceived Trust (PT) evaluates confidence in the security, transparency, and reliability of cryptocurrency systems, while Perceived Risk (PR) considers the potential for negative outcomes, such as financial loss, privacy breaches, or market volatility. The target variable, Behavioral Intention (BI), represents an individual's willingness or likelihood to adopt cryptocurrency for transactions. By analyzing these features, Model 1 aims to identify the key determinants of BI, providing insights into the drivers and barriers of cryptocurrency adoption. However, the Table 1 presents a comparative analysis of the performance metrics of seven different machine learning models—Linear Regression, k-Nearest Neighbors (kNN), Support Vector Machines (SVM), AdaBoost, Neural Network, Gradient Boosting, Random Forest, and Decision Tree—evaluated using MSE, RMSE, MAE, MAPE, and $\mathbb{R}^2$ [101], [102], [103], [104], [105]. Among these, Linear Regression emerges as the best-performing model, achieving the lowest error metrics (MSE: 0.472, RMSE: 0.687, MAE: 0.483, and MAPE: 0.196) and the highest $\mathbb{R}^2$ (0.444), indicating its effectiveness in explaining 44.4% of the variance in the target variable. Both kNN and SVM display comparable performance, with slightly higher error values and an $\mathbb{R}^2$ of 0.403, making them competitive alternatives. On the other hand, AdaBoost performs moderately well ($\mathbb{R}^2$: 0.367), while Gradient Boosting ($\mathbb{R}^2$: 0.329) and Neural Networks ($\mathbb{R}^2$: 0.360) underperform, potentially due to overfitting or dataset limitations. Random Forest ($\mathbb{R}^2$: 0.282) and Decision Tree ($\mathbb{R}^2$: 0.003) show poor performance, with Decision Tree demonstrating particularly high error metrics. These results suggest that simpler models like Linear Regression are better suited for this dataset, likely due to the linear relationships between features and the target variable. The relatively low $\mathbb{R}^2$ values across all models highlight the need for additional features or alternative approaches to improve predictive accuracy. This analysis underscores the importance of balancing model complexity and performance when predicting Behavioral Intention.

Table 7. Model- 1 results

Model	MSE	RMSE	MAE	MAPE	R²
Linear Regression	0.472	0.687	0.483	0.196	0.444
kNN	0.507	0.712	0.514	0.207	0.403
SVM	0.507	0.712	0.512	0.224	0.402
AdaBoost	0.537	0.733	0.479	0.203	0.367
Neural Network	0.543	0.737	0.537	0.219	0.360
Gradient Boosting	0.569	0.754	0.499	0.200	0.329
Random Forest	0.609	0.781	0.581	0.259	0.282
Tree	0.845	0.919	0.634	0.244	0.003

Model 2 is designed to predict Perceived Risk (PR) as the target variable by analyzing four key features that capture the multidimensional nature of risk associated with cryptocurrency usage. Financial Risk represents the potential for monetary loss due to market volatility, investment fluctuations, or value depreciation of cryptocurrencies. Legal Risk reflects uncertainties related to the regulatory and legal status of digital currencies, including concerns about compliance, legal disputes, or potential regulatory changes. Security Risk encompasses fears of cybersecurity threats such as hacking, data breaches, theft of private keys, and other vulnerabilities in cryptocurrency platforms. Operational Risk focuses on the risk of system failures, transaction errors, technical glitches, or delays in processing payments, all of which could disrupt the user experience. Together, these features provide a comprehensive framework for understanding the factors that shape users' perceptions of risk, enabling Model 2 to offer insights into how such concerns influence the adoption of cryptocurrencies and highlight areas where improvements can build user trust. However, Table 2 compares the performance of several machine learning models in predicting the target variable (Perceived Risk) using five evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination ($\mathbb{R}^2$). Among the models, Linear Regression outperforms others, achieving the lowest error values (MSE: 0.254, RMSE: 0.504, MAE: 0.365, and MAPE: 0.123) and the highest $\mathbb{R}^2$ (0.617), that it explains 61.7% of the difference in Perceived Risk. Support Vector Machines (SVM) also performs well, with slightly higher error metrics (MSE: 0.282, RMSE: 0.531, MAE: 0.388, and MAPE: 0.137) and an $\mathbb{R}^2$ of 0.576, suggesting it is a competitive alternative. Other models, such as k-Nearest Neighbors (kNN) and Neural Networks, demonstrate moderate performance, with kNN achieving an $\mathbb{R}^2$ of 0.515 and Neural Networks an $\mathbb{R}^2$ of 0.495, though both exhibit higher error metrics compared to Linear Regression and SVM. Ensemble models like AdaBoost and Gradient Boosting, along with Random Forest and Decision Tree, perform comparatively poorly, indicated by $\mathbb{R}^2$ values that are ranging from 0.402 to 0.388 and higher error metrics, likely due to overfitting or the inability to effectively capture the underlying relationships in the data. These results suggest that simpler models, particularly Linear Regression, are more effective for this task, highlighting the importance of model selection in relation to the complexity of the data and the nature of the target variable.

While a variety of machine learning models were implemented to validate and complement our SEM findings, our analysis revealed that Linear Regression outperformed Neural Networks or Gradient Boosting, which are considered more complex alternatives. This result can be attributed to several factors. First, the modest sample size may have constrained the training capacity of high-dimensional models, making them more prone to overfitting. Second, the relationships between

Table 8. Model- 2 results

Model	MSE	RMSE	MAE	MAPE	R^2
Linear Regression	0.254	0.504	0.365	0.123	0.617
SVM	0.282	0.531	0.388	0.137	0.576
kNN	0.322	0.567	0.407	0.133	0.515
Neural Network	0.335	0.579	0.433	0.143	0.495
AdaBoost	0.394	0.628	0.484	0.157	0.406
Gradient Boosting	0.397	0.630	0.436	0.144	0.402
Random Forest	0.403	0.635	0.472	0.178	0.392
Tree	0.406	0.637	0.452	0.147	0.388

features and the target variable (Behavioral Intention and Perceived Risk) appear to be largely linear, as evidenced by the superior $\mathbb{R}^2$ performance of the Linear Regression model (0.444 for BI, 0.617 for PR). Additionally, Linear Regression offers higher interpretability, allowing a clearer understanding of feature contributions. These findings underscore the importance of matching model complexity to the data structure and highlight that advanced models do not always yield better predictive performance, especially when data is limited or linear patterns dominate.

6 Discussion

This section explores the study's findings using the UTAUT model, perceived risk, and trust frameworks. The section highlights theoretical contributions, practical implications, limitations, and recommendations for future research.

6.1 Theoretical Contributions

The results confirm that performance expectancy (PE), social influence (SI), facilitating conditions (FC), and perceived trust (PT) are all highly affect the behavioral intention (BI) to adopt cryptocurrencies. Among these, PT had the highest impact (β = 0.342, p <0.01), underlining the crucial role of trust, this aligns with prior studies emphasizing that trust is essential in environments involving risk and uncertainty, such as cryptocurrency adoption, where trust serves as a mechanism to counteract users' concerns about fraud, security, and system reliability. Similarly, the results show that the significance of SI (β = 0.106, p <0.05) approves the role of social approval in determining user behavior, which agrees with Gupta et al. [49] findings that recommendations from peers and family members influence the adoption of new technologies. Interestingly, effort expectancy (EE) did not significantly affect BI (β = 0.031, p >0.05), where the lack of significance might reflect the demographic characteristics of the respondents' sample, which was overwhelmingly young (over 90% under 28) and highly educated. This group is generally more digitally fluent and familiar with navigating technology platforms, including cryptocurrency applications. For these users, ease of use may not represent a barrier to adoption, as they are already comfortable with similar technologies. Thus, effort expectancy loses predictive value when digital comfort is assumed. The findings for perceived risk (PR) are particularly useful. While financial risk (FR), security risk (SR), and operational risk (OR) significantly contributed to PR, legal risk (LR) did not. The insignificant effect of LR (β = -0.016, p $>$0.05) could be due to the Jordanian's laws and regulations that banned the cryptocurrency where cryptocurrency trading is prohibited under the laws of Jordan. Moreover, PR did not significantly influence BI (β = 0.021, p $>$0.05). This suggests that while users recognize the risks associated with cryptocurrencies, these concerns are not enough to deter their intention to adopt. This finding aligns with Arias-Oliva et al. [3] who claimed that users may become desensitized to perceived risks over time. According to SEM and ML results, we found that the two approaches complemented each other well. SEM confirmed our hypothesized relationships, showing which factors in the model had significant effects and in what direction. ML, on the other hand, was less about testing theory and more about making accurate predictions. It not only achieved higher predictive accuracy but also uncovered some nonlinear interactions between predictors that the SEM framework did not explicitly capture. In short, SEM gave us a clear, theory-based picture of how the variables are connected, while ML added a predictive edge and revealed patterns that might otherwise have gone unnoticed. Using both methods together gave us a richer and more well-rounded understanding of cryptocurrency adoption than either could have provided on its own.

6.2 Practical Implications

The study provides several actionable insights for service providers, policymakers, and other stakeholders. The strong influence of PT on BI underscores the importance of building trust in cryptocurrency platforms. Service providers should prioritize transparency, security, and reliability to address user concerns. Measures such as guaranteeing secure transactions, offering fraud prevention mechanisms, and maintaining robust privacy policies can strengthen user trust. Security improvements are especially critical given the significant contribution of SR to PR. Users are concerned about possible breaches or unauthorized access to their personal and financial information, which may reduce their willingness to adopt cryptocurrencies. Companies can alleviate these concerns by investing in advanced encryption technologies and educating users about safe practices. Also, the insignificance of legal risk may be attributed to cryptocurrency's outright ban in Jordan; this regulatory rigidity might desensitize users or exclude them from considering legal concerns in their risk assessment altogether, aligning with the notion of 'risk normalization' in forbidden markets. The significant role of SI highlights the value of leveraging social networks and communities. Awareness campaigns can focus on social network influencers and peer recommendations to enhance the perceived social endorsement of cryptocurrencies. Additionally, promoting success stories or testimonials from satisfied users can help create a positive social image. While EE was not significant in this study, simplifying the user experience is still essential for reaching less tech-savvy demographics in Jordan. Although legal risk (LR) is considered conceptually critical in restrictive environments like Jordan, LR did not show a significant influence on perceived risk or behavioral intention in our model. This counterintuitive result may reflect the psychological normalization of legal ambiguity, where consumers, aware of the prohibition, mentally discount legal consequences or avoid legal reflection altogether due to the absence of regulatory enforcement. According to the practical implications mentioned, policymakers and other stakeholders should consider controlled regulatory sandboxes to experiment with crypto applications in a legally safe environment. Simultaneously, public campaigns focusing on trust and safety may ease public skepticism without breaching legal constraints.

6.3 Limitations

This study has several limitations. First, the sample is predominantly young and educated, with 92.9% of respondents aged under 28 and 91.9% holding at least a bachelor's degree. These demographics may not represent the broader population, particularly older or less educated individuals who may face different barriers to cryptocurrency adoption. Future studies should consider more diverse samples to provide a holistic understanding. Second, because the cryptocurrencies are prohibited in Jordan, this may have caused respondents, particularly those involved in cryptocurrency transactions, to experience some apprehension and reserved when answering the questionnaire. Third, the study focused on the Jordanian context. While the findings offer valuable insights, they may not be generalizable to countries with different regulatory environments, cultural attitudes, or levels of technological infrastructure. Comparative studies across regions would provide a more comprehensive perspective.

6.4 Future Directions

Based on the findings, several areas for future research emerge. First, exploring the role of financial knowledge in cryptocurrency adoption could provide deeper insights. Users with higher financial knowledge may perceive risks differently or trust cryptocurrencies more readily. Incorporating financial knowledge as a variable in future models could yield valuable results. Second, further investigation into the effects of legal frameworks is needed. While LR was insignificant in this study, its impact might be more pronounced in countries with different regulations. Researchers could explore how varying regulatory environments influence adoption across regions. Lastly, future studies should investigate other potential moderators, such as income levels, cultural differences, or technological infrastructure. Also, the study's sample was skewed toward younger and highly educated individuals (over 90% under 28 years and with a bachelor's degree or higher), which may limit generalizability to older or less-educated populations. However, this sample profile aligns with national demographics, as about 60% of Jordan's population is under the age of 30 (Jordan Department of Statistics, 2024). Future studies should adopt stratified sampling approaches to ensure the inclusion of older age groups and individuals with more diverse educational and socioeconomic backgrounds. Also, the modest R^2 values indicate the need to incorporate variables like financial literacy, income level, and cultural dimensions to better model cryptocurrency adoption behavior. Moreover, due to the legal prohibition of cryptocurrencies in Jordan, participants may have underreported usage or intent, introducing social desirability bias, accordingly, future research could adopt anonymous qualitative methods or indirect questioning to mitigate such effects. Also, future research should examine EE in populations with lower digital literacy, such as older adults or individuals with limited access to technology, to explore whether EE becomes a more salient predictor in those contexts. Furthermore, future research should conduct cross-country comparisons to examine how varying regulatory environments influence cryptocurrency adoption. Such comparisons can provide valuable insights into how legal, cultural, and institutional factors interact with individual-level determinants of adoption, thereby enriching the theoretical generalizability and policy relevance of cryptocurrency adoption models. Also, Future research should explore trust as a multidimensional construct by distinguishing between institutional and interpersonal trust, which can offer deeper insights into how different forms of trust influence adoption under varying regulatory conditions. These factors may provide a richer understanding of how demographic and contextual variables influence cryptocurrency adoption.

7 Conclusions

This study examined the factors influencing the adoption of cryptocurrencies among Jordanians using the UTAUT framework, perceived trust, and perceived risk. The findings reveal several important insights that contribute to both theory and practice. Key predictors of behavioral intention (BI) include performance expectancy (PE), social influence (SI), facilitating conditions (FC), and perceived trust (PT). Among these, PT arose as the most significant factor, highlighting the vital role of trust in driving cryptocurrency adoption. These results align with existing literature, emphasizing that fostering trust in technology is essential, especially in environments characterized by uncertainty. Perceived risk (PR) presented mixed results. While financial, security, and operational risks significantly influenced PR, legal risk did not. Additionally, PR itself did not significantly affect BI, suggesting that users recognize the risks but continue to use cryptocurrencies. This finding contributes to the ongoing debate on how perceived risk shapes technology adoption, particularly in emerging markets. The insignificant effect of effort expectancy (EE) highlights the readiness of the younger, tech-savvy population in Jordan to adopt digital technologies. However, this result may not generalize to older or less experienced groups, underscoring the need for further investigation. The study highlights the importance of building trust, improving security, and leveraging social influence to promote cryptocurrency adoption. Furthermore, legal issues and enhanced user experiences can further address barriers and foster wider acceptance. Despite its contributions, the study has limitations. It focuses on a specific demographic and geographic context, which may limit the generalizability of its findings. Future research should explore diverse populations, regulatory environments, and long-term adoption patterns to build a more comprehensive understanding of cryptocurrency adoption. Also, future research could extend this work by applying the combined SEM–ML approach in different contexts using larger and more diverse samples. This would help validate the generalizability of the findings and explore whether similar patterns hold across cultures, industries, and emerging markets.

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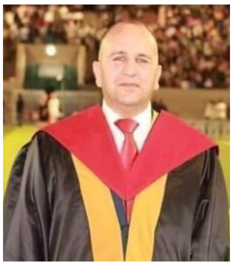

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