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Factors affecting the intention and behavior to adopt blockchain technology in Ho Chi Minh City, Viet Nam

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Abstract: This study investigates the factors influencing the intention and behavior toward the adoption of blockchain technology in Ho Chi Minh City, Vietnam, in the context of its growing importance in digital transformation and business model innovation. Based on survey data collected from 84 respondents and analyzed using the PLS-SEM approach, the research integrates two well-established theoretical models (TAM) and (UTAUT2) to provide a comprehensive evaluation of the determinants affecting blockchain adoption. The results indicate that effort expectancy (EE), facilitating conditions (FC), social influence (SI), trust in blockchain (BB), and blockchain transparency (BT) all have a positive impact on the intention to use blockchain, with effort expectancy (EE) emerging as the most influential factor. Furthermore, behavioral intention (BI) is found to significantly influence actual usage behavior (AU), whereas performance expectancy (PE) does not show statistically significant effects. This investigation represents one of the pioneering efforts to explore blockchain adoption in Vietnam and contributes to the development of blockchain-based enterprises through a conceptual framework for technology acceptance, particularly regarding individual employee behavior within organizations.

Keywords: *Behavioral intention, Blockchain transparency, Blockchain, Technology adoption.*

1. Introduction

The accelerated evolution of information technology continues to redefine organizational operations, management practices, and competitiveness across industries worldwide. Within the broader landscape of the Fourth Industrial Revolution (Industry 4.0), disruptive technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, and especially blockchain have emerged as critical enablers of digital innovation and transformation [1, 2]. Among these, blockchain is distinguished by its ability to decentralize, secure, and transparently validate digital records.

Blockchain applications are increasingly evident across domains including finance [3], healthcare [4], manufacturing [5], education [6], and logistics and supply chain operations [7]. Notably, the IBM–Maersk TradeLens platform exemplifies how blockchain can streamline global shipping processes, enhancing traceability and efficiency [8].

Despite its transformative promise, blockchain adoption in practice - particularly in emerging markets like Vietnam - faces substantial hurdles. Challenges such as limited user knowledge, technological and legal uncertainties, scalability issues, and trust concerns remain pervasive [5]. While both public and private sectors in Vietnam are showing increasing interest in blockchain applications, the academic literature remains fragmented, with few studies employing robust quantitative methods to explore user-level adoption behavior.

Existing research tends to focus on descriptive insights or small-scale qualitative case studies. For example, Luan-Thanh, et al. [9] applied the UTAUT2 model within the logistics sector in Ho Chi Minh City, but the findings lacked broader applicability. Furthermore, there is a notable gap in

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empirical studies that integrate established models such as TAM and UTAUT, which have shown explanatory power in global contexts. Addressing this void, the current study applies a combined UTAUT-TAM approach to examine the drivers of blockchain adoption intentions and behaviors among individuals and organizations in Ho Chi Minh City. The findings aim to contribute actionable insights for policy formulation, business planning, and the broader advancement of digital transformation in Vietnam's socio-economic landscape.

2. Literature Review

2.1. Blockchain Technology

Blockchain, commonly defined as a form of distributed ledger technology (DLT), is widely recognized for its capacity to ensure the integrity of financial transactions. In this system, a transaction is only recorded when all involved participants reach a consensus and provide explicit approval. Once validated, multiple transactions are aggregated into a single data block, which is then appended to a chronological chain of preceding blocks, forming an immutable ledger [10]. The decentralized consensus mechanism of blockchain ensures that every participant within the network remains informed of all transactions by maintaining a transparent and tamper-evident public record [11]. Due to its distributed architecture, the risk of data loss is virtually eliminated as long as at least one node within the network remains operational [12]. Notably, blockchain systems exhibit strong resilience against cyberattacks, as compromising individual nodes or subsets of nodes does not jeopardize the functionality of the overall network [13].

2.2. Relevant Theories and Models

According to Davis [14] the Technology Acceptance Model (TAM) is among the most widely adopted theoretical frameworks for understanding user acceptance of technology. Within this model, actual system usage (AU) is directly influenced by behavioral intention (BI), which is in turn shaped by two primary perceptions: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the extent to which an individual believes that the use of a specific technology will enhance their job performance, while PEOU reflects the degree to which the technology is perceived as user-friendly and easy to operate. In the context of blockchain, when users perceive the system as both useful and easy to use, they are more likely to develop a positive intention toward its adoption, ultimately resulting in actual usage behavior [15]. TAM has been empirically validated across various technological contexts, supporting its applicability in studying blockchain adoption at the organizational level.

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh, et al. [16] synthesizes eight previous models of technology acceptance, including TAM, the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Innovation Diffusion Theory (IDT). UTAUT identifies four core constructs influencing technology acceptance: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). According to the model, BI is influenced by PE, EE, and SI, while AU is driven by both BI and FC. PE and EE are conceptually similar to PU and PEOU in TAM. In the context of blockchain, these constructs reflect users' belief that the technology can improve performance and is easy to adopt [15]. Although UTAUT originally included moderating variables such as gender, age, and experience, these are often omitted in empirical studies involving emerging technologies.

2.3. Factors Influencing The Intention and Use of Blockchain

This study adopts an extended theoretical framework by integrating constructs from both TAM and UTAUT to examine individual and organizational intentions and behaviors related to blockchain adoption. UTAUT [16] has been widely applied to explain user acceptance of new technologies through its core components: performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition, the study incorporates two blockchain-specific variables—

transparency and trust—to enhance the model's explanatory power in the specific context of blockchain [1, 17].

2.3.1. Performance Expectancy (PE)

Performance expectancy refers to the degree to which users believe that using blockchain will enhance their job performance [18]. Blockchain offers numerous benefits such as time savings, increased operational speed, improved security, and enhanced data integrity. These perceived benefits can positively influence users' adoption intentions. Prior studies have consistently shown a positive relationship between PE and BI [8, 17, 19, 20].

H_1: Performance expectancy positively influences the behavioral intention to use blockchain.

2.3.2. Effort Expectancy (EE)

Effort expectancy is defined as the degree of ease associated with the use of the system, aligning with the concept of perceived ease of use in TAM [15]. In the context of blockchain, EE reflects users' perceptions of the system's complexity and ease of operation. When users perceive blockchain as accessible and easy to learn, they are more likely to develop a favorable intention to adopt it [21]. Previous studies have confirmed the positive influence of EE on BI [8, 17, 18].

H_2: Effort expectancy positively influences the behavioral intention to use blockchain.

2.3.3. Social Influence (SI)

Social influence refers to the degree to which individuals perceive that important others (e.g., colleagues, supervisors, industry stakeholders) believe they should use the new technology [16]. In organizational settings, SI may stem from peer adoption or the need to keep up with technological trends. SI has been shown to play a significant role in encouraging individuals to adopt blockchain [18, 19, 22].

H_3: Social influence positively influences the behavioral intention to use blockchain.

2.3.4. Facilitating Conditions (FC)

Facilitating conditions refer to users' perceptions of the availability of resources and organizational support for implementing the technology [16]. In the blockchain context, this includes access to digital infrastructure, technical support, and cloud services. Blockchain reduces infrastructure burden through its decentralized structure and supports transparent data traceability [23]. Research has demonstrated a positive relationship between FC and blockchain usage intention [8, 20].

H_4: Facilitating conditions positively influence the behavioral intention to use blockchain.

2.3.5. Blockchain Transparency (BT)

Transparency refers to the blockchain system's ability to provide visibility and traceability of transactions across the supply chain [24, 25]. Blockchain increases auditability, open data sharing, immutability, and reduces reliance on intermediaries [26, 27]. This enhances trust and encourages technology adoption, particularly in logistics and public sector management [28, 29].

H_5: Blockchain transparency positively influences the intention to use blockchain.

2.3.6. Trust in Blockchain (BB)

Trust is a crucial factor in the adoption of new technologies. In blockchain, trust is built through decentralized consensus mechanisms and immutable data, which enable transparent, reliable, and tamper-proof transactions [19, 30]. Trust reassures users that the system operates securely and benefits them. Prior studies confirm the positive impact of trust on blockchain adoption intention [31, 32].

H_6: Trust in blockchain positively influences the behavioral intention to use blockchain.

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2.3.7. Behavioral Intention and Actual Usage

Behavioral intention (BI) is a key predictor of actual usage in both TAM and UTAUT models [16, 33]. It reflects an individual's willingness to engage in the behavior of using blockchain. The stronger the intention, the higher the likelihood of actual system use. This relationship has been validated by numerous studies in the blockchain context [18, 19].

H_7: Behavioral to use blockchain positively influences actual usage of blockchain.

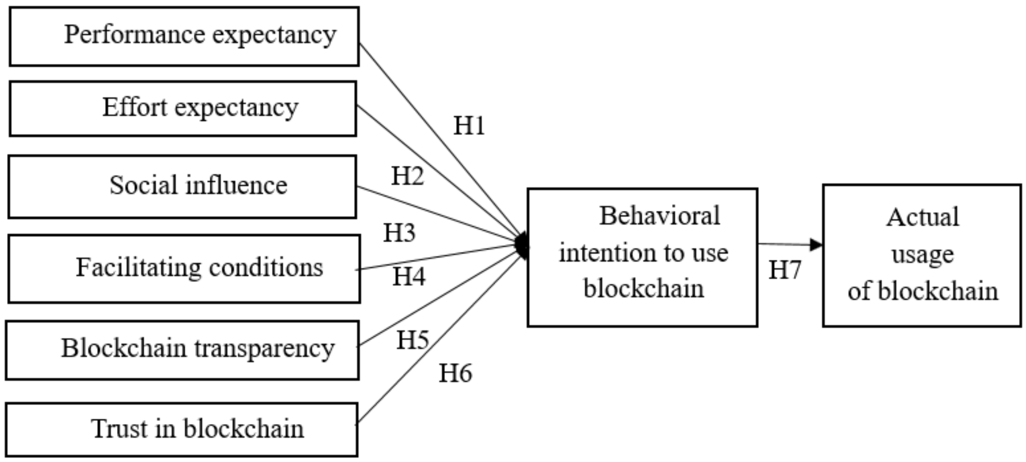

Figure 1.
Research Model.

3. Research Methodology

3.1. Data Collection

A paper-based survey was conducted targeting employees of enterprises that have implemented blockchain technology in Ho Chi Minh City, Vietnam. The survey ensured a high degree of reliability by utilizing the author's network of partners and clients for distribution. Among the 84 respondents, 38.10% were male and 61.90% were female. The age group with the highest response rate was 25 to under 30 years old, while the group with the fewest responses was under 25 years old. In terms of educational background, most respondents held either undergraduate (college/university) or postgraduate degrees. Regarding work experience, the largest proportion of respondents (61.90%) had worked at their current organization for 2 to 5 years. This was followed by those with 6 to 10 years of experience (22.62%), over 10 years (13.10%), and less than 1 year (2.38%). These figures indicate that the majority of respondents had mid-level tenure at their organizations, particularly between 2 and 5 years. In terms of industry sectors, the finance and banking sector accounted for the highest share of responses at 46.43%, followed by healthcare (23.81%), education (14.29%), other sectors (8.33%), and finally, supply chain management (7.14%). This distribution suggests that finance and banking is the most represented sector among blockchain users in the sample, while the supply chain sector had the lowest representation.

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Table 1.
Description of the Research Sample (n = 84).

Characteristics		Frequency	Percentage (%)
Gender	Male	32	38.10
	Female	52	61.90
Age	Under 25 years old	2	2.38
	25 – under 30 years old	52	61.90
	30 – 40 years old	18	21.43
	Over 40 years old	12	15.29
Educational Attainment	Undergraduate (College/University)	70	83.33
	Postgraduate	14	16.67
Years of Work Experience	Less than 1 year	2	2.38
	2 – 5 years	52	61.90
	6 – 10 years	19	22.62
	Over 10 years	11	13.10
Industry Sector	Supply Chain	6	7.14
	Finance and Banking	39	46.43
	Education	12	14.29
	Healthcare	20	23.81
	Other	7	8.33

3.2. Measurement Scales

The measurement items used in this study were adapted from previous validated research and modified to suit the context of the current study. Specifically, the performance expectancy (PE) construct includes 3 observed variables; effort expectancy (EE) includes 4 observed variables; social influence (SI) includes 3 observed variables; facilitating conditions (FC) includes 3 observed variables; blockchain transparency (BT) includes 3 observed variables; trust in blockchain (BB) includes 4 observed variables; behavioral intention to use blockchain (BI) includes 3 observed variables; and actual usage of blockchain (AU) includes 3 observed variables. All survey items were designed as closed-ended questions and measured using a five-point Likert scale, ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"), allowing respondents to indicate the extent to which they agreed with each statement.

3.3. Data Analysis

The proposed research model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The justification for selecting this method is as follows: (1) PLS-SEM analyzes data based on a composite model and is suitable for small to medium sample sizes, offering low bias in estimation [34]. (2) PLS-SEM is particularly appropriate in business research settings, where data driven decision making, “Let the data talk” is prioritized.

4. Results

4.1. Measurement Model

Table 2.
Reliability Analysis Results.

Construct	Indicator	Cronbach's Alpha (α)	Composite Reliability (CR)	Factor Loading	AVE	VIF
Actual Usage of blockchain (AU)	AU1	0.815	0.889	0.781	0.729	1.686
	AU2			0.918		2.338
	AU3			0.857		1.834
Trust in Blockchain (BB)	BB1	0.757	0.855	0.856	0.664	1.396
	BB2			0.824		1.748
	BB3			0.762		1.590
Behavioral Intention to use blockchain (BI)	BI1	0.884	0.928	0.908	0.812	2.596
	BI2			0.878		2.277
	BI3			0.916		2.742
Blockchain Transparency (BT)	BT1	0.711	0.838	0.730	0.634	1.190
	BT2			0.842		1.707
	BT3			0.814		1.763
Effort Expectancy (EE)	EE1	0.873	0.914	0.892	0.727	2.872
	EE2			0.889		2.688
	EE3			0.779		1.606
	EE4			0.845		2.290
Facilitating Conditions (FC)	FC1	0.793	0.880	0.857	0.709	1.958
	FC2			0.780		1.429
	FC3			0.886		2.147
Performance Expectancy (PE)	PE1	0.861	0.911	0.904	0.774	2.229
	PE2			0.897		2.065
	PE3			0.836		2.314
Social Influence (SI)	SI1	0.859	0.912	0.861	0.776	2.083
	SI2			0.919		2.202
	SI3			0.862		2.218

All indicator loadings exceeded the threshold of 0.7, indicating satisfactory individual item reliability Hair, et al. [34]. The evaluation of Cronbach's Alpha values also revealed that all constructs met the minimum threshold of 0.7 as recommended by Hair, et al. [34]. Among them, the BT construct (Cronbach's Alpha = 0.711; rho_C = 0.838) showed the lowest internal consistency, while the BI construct recorded the highest internal consistency (Cronbach's Alpha = 0.884; rho_C = 0.928). In conclusion, all constructs demonstrated high internal consistency reliability. The assessment of convergent validity (Table 2) further showed that the Average Variance Extracted (AVE) values for all constructs exceeded the recommended minimum of 0.50, confirming that all constructs exhibit good convergent validity.

4.2. Structural Model

4.2.1. Multicollinearity

All Variance Inflation Factor (VIF) values of the endogenous latent variables were below 3 (Table 2). Therefore, empirical evidence suggests that multicollinearity is not a serious concern in the structural model Hair, et al. [34].

4.2.2. R^2 (Coefficient of Determination) and f^2 (Effect Size)

Table 3.
R^2 và f^2

Construct	R^2 adjusted	Relationship	f^2
AU	0.600	BB → BI	0.073
BI	0.470	BI→ AU	0.077
		BT → BI	0.070
		EE → BI	0.141
		FC→ BI	0.102
		PE → BI	0.001
		SI→ BI	0.097

The adjusted R^2 value for Actual Use (AU) is 0.60, indicating that the independent variables in the model explain 60% of the variance in AU. Similarly, the adjusted R^2 value for Behavioral Intention (BI) is 0.47, suggesting that the model accounts for 47% of the variance in BI.

The effect size analysis reveals that Effort Expectancy (f^2 = 0.141) has a medium impact on BI. Meanwhile, Facilitating Conditions (f^2 = 0.102), Social Influence (f^2 = 0.097), Trust (f^2 = 0.073), and Transparency (f^2 = 0.070) exhibit small effects on BI. Additionally, BI exerts a small effect on AU (f^2 = 0.077 Hair, et al. [34].

4.2.3. Hypothesis Testing and Bootstrapping

The study employed bootstrapping techniques and further assessed the structural model using a resampling procedure with 5,000 subsamples (n = 5,000), based on the initial 84 observations. The results of the PLS analysis are illustrated in (Figure 2). As shown in (Figure 2) and (Table 4), the t-values for the hypotheses exceed 1.96, indicating statistical significance at the 5% level, except for H6, which was not supported. Under this context, the majority of the proposed hypotheses in the research model are empirically validated.

Table 4.
Hypothesis Testing Results.

Hypothesis	Relationship	Path Coefficient (O)	Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P values	Conclusion
H1	BB -> BI	0.220	0.209	0.111	1.981	0.048	Supported
H2	BI -> AU	0.267	0.280	0.108	2.471	0.014	Supported
H3	BT -> BI	0.189	0.192	0.082	2.315	0.021	Supported
H4	EE -> BI	0.365	0.366	0.103	3.542	0.000	Supported
H5	FC -> BI	0.306	0.298	0.114	2.677	0.007	Supported
H6	PE -> BI	-0.019	-0.035	0.090	0.209	0.835	Not Supported
H7	SI -> BI	0.221	0.223	0.091	2.441	0.015	Supported

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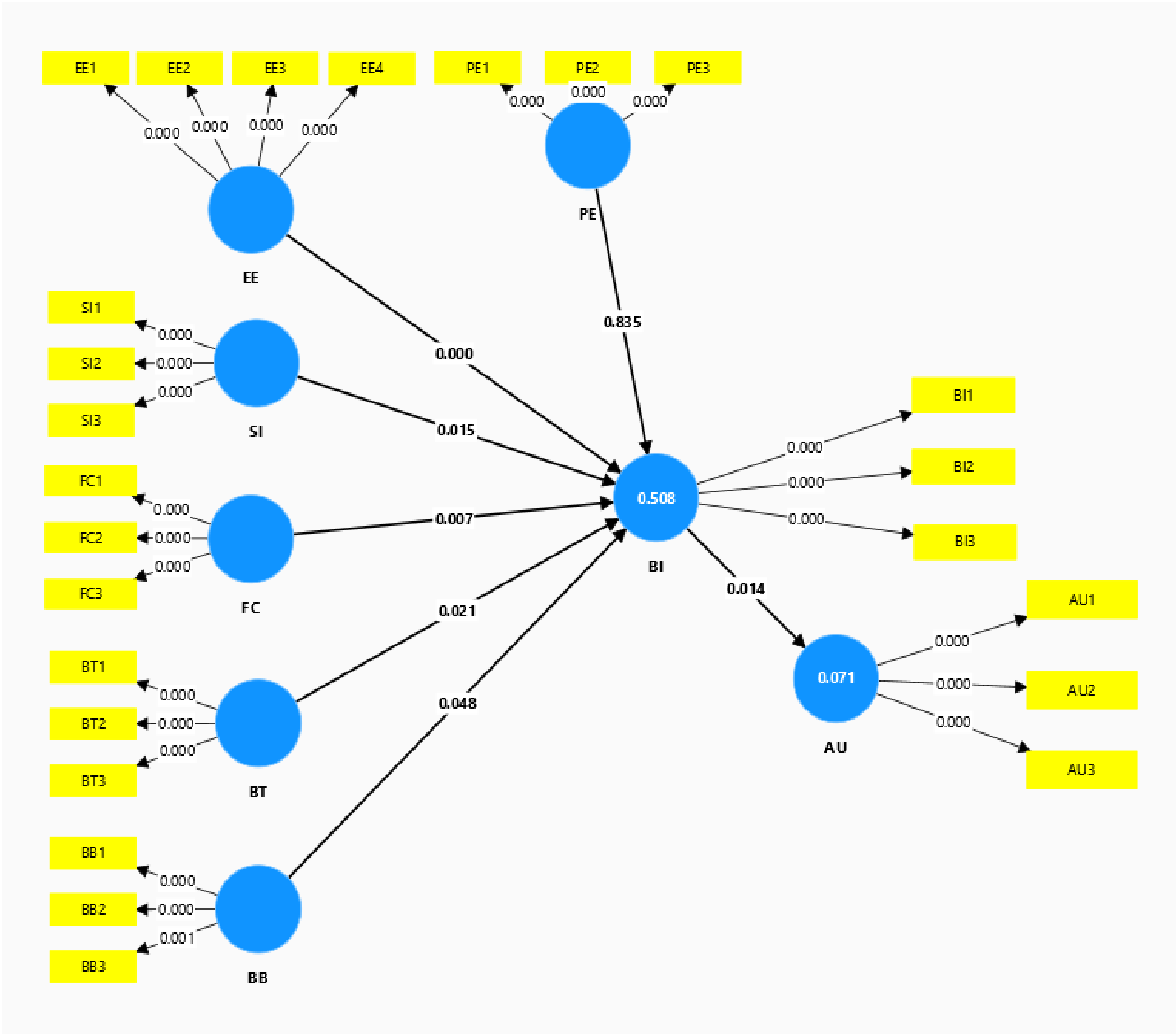

Figure 2.
PLS-SEM Model Evaluation Results.

5. Discussion

This study proposed an integrated research model that combines key constructs from existing theories, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Blockchain Transparency (BT), Trust in Blockchain (BB), Behavioral Intention (BI), and Actual Usage (AU), to examine the relationships among these variables. Based on data collected from 84 survey respondents in Ho Chi Minh City and analyzed using the PLS-SEM approach, the results indicate that EE has the strongest positive impact on BI ($\beta = 0.365$, $t = 3.542$). This finding aligns with prior studies Park [8] and Queiroz, et al. [20] although it contrasts with the findings of Kapnissis, et al. [19]. Additionally, FC ($\beta = 0.306$, $t = 2.667$), SI ($\beta = 0.221$, $t = 2.441$), BB ($\beta = 0.220$, $t = 1.981$), and BT ($\beta = 0.189$, $t = 2.441$) also positively influence BI. Notably, PE does not have a statistically significant effect on BI, which is consistent with previous research by Kapnissis, et al. [19]; Queiroz, et al. [20] and Wong, et al. [17] Lastly, BI has a significant positive impact on AU ($\beta = 0.267$, $t = 2.471$), supporting the research hypothesis and in line with findings reported by Wong, et al. [15].

6. Implications and Limitations

6.1. Theoretical Implications

The findings of this study contribute to extending the theoretical understanding of blockchain adoption behavior in organizational contexts, particularly within developing economies. By integrating constructs from the UTAUT model with extended factors such as trust and blockchain transparency, the study provides a more comprehensive view of the motivational drivers behind individuals' intentions and behaviors toward emerging technologies. The research confirms the significant roles of effort expectancy, facilitating conditions, and social influence, while also emphasizing the importance of intrinsic technological attributes such as transparency and trustworthiness in shaping adoption intentions. The non-significant effect of performance expectancy challenges the universal assumptions embedded in traditional technology acceptance models when applied to novel technologies like blockchain. Therefore, the study suggests that technology adoption behavior in organizations should be examined through a holistic lens that considers human, organizational, and technological factors.

6.2. Practical Implications

The study identifies effort expectancy as the strongest predictor of blockchain adoption intention. This implies that when employees perceive blockchain as easy to learn and use with minimal effort, their likelihood of accepting the technology increases. From a managerial perspective, organizations should invest in hands-on and visual training programs to facilitate user engagement. Simple instructional materials, virtual assistants, and tutorial videos can help reduce cognitive load. Internal communication should also highlight the ease of use and benefits of blockchain to eliminate psychological resistance. Technology implementation should be carried out in phased trials, incorporating user feedback before a full-scale rollout, to foster a sense of control and mitigate change resistance.

Facilitating conditions emerged as the second most influential factor, suggesting that infrastructural support, legal frameworks, and organizational capacity are crucial. Organizations should ensure that their IT infrastructure can effectively integrate blockchain. Updating and communicating relevant regulations can reassure employees about legal compliance. Collaboration with regulatory bodies to pilot blockchain solutions under a secure legal environment is also advised. Moreover, investing in specialized talent and enhancing employees' digital skills will improve adaptability and resilience to technological changes.

The positive relationship between intention and actual blockchain usage supports existing models like UTAUT and TAM. In practice, this underscores the importance of nurturing a supportive environment that cultivates favorable intentions from the outset. Managers should create an innovation-friendly culture where employees are encouraged to explore new technologies without fear of failure. Policies that reward pioneering behaviors, such as recognizing teams that successfully implement blockchain, can help reinforce this culture and translate intentions into real-world application.

Social influence was also found to significantly affect behavioral intention, highlighting the role of business communities, partners, customers, and leadership in shaping perceptions and decisions regarding new technology adoption. Practically, companies should avoid isolated adoption and instead build strategic alliances with stakeholders throughout the value chain. Hosting joint training sessions, forums, and workshops can foster consensus and knowledge sharing. Additionally, assessing the technological readiness of partners and offering technical support can help build a more integrated blockchain ecosystem.

While not the strongest driver, trust still plays a meaningful role in shaping adoption intentions. From a management perspective, this indicates the need for enhancing internal knowledge of blockchain systems. Choosing the appropriate type of blockchain (public, private, or consortium) should align with industry characteristics and required security levels. Investing in a technically proficient workforce and offering reskilling opportunities for existing employees will improve understanding and mitigate uncertainty. Organizations that possess realistic expectations and a clear grasp of blockchain's risks and benefits are better positioned for successful implementation.

Blockchain transparency is the final factor confirmed to have a positive effect on adoption intention. This highlights that the system's clarity, auditability, and traceability are highly valued by users. In practice, organizations should increase internal awareness of blockchain's role in operational transparency. Case studies from peer companies can be used as compelling examples to build trust and motivation. Furthermore, blockchain solution providers should actively support organizations by offering technology demos, workshops, and consulting especially for companies with limited experience in distributed technologies.

6.3. Limitations and Future Research

Despite successfully achieving the research objectives, several limitations must be acknowledged. First, the scarcity of domestic literature on blockchain and its relatively low adoption rate in Ho Chi Minh City restrict the comparative and generalizability potential of the findings. Second, although the small sample size did not compromise quantitative analysis, it may limit the broader interpretation and generalization of the results. Third, the non-significant impact of performance expectancy contradicts theoretical expectations, warranting further investigation. Lastly, this study considered a limited number of constructs, focusing primarily on an integrated TAM–UTAUT framework with trust and transparency as extensions. Future research is recommended to explore the competitive advantages brought by blockchain implementation through in-depth empirical studies. Larger sample sizes and broader coverage are encouraged to enhance robustness. Additionally, future studies should investigate why performance expectancy does not significantly influence intention. Lastly, extending the current model by incorporating frameworks like TOE–TTF–UTAUT by Wong, et al. [15] is suggested for a more holistic analysis.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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