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The acceleration of blockchain technology adoption in Taiwan

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ABSTRACT

This study explores the factors influencing the intention to adopt blockchain technology and the alignment between respondents' work characteristics and blockchain technology. It addresses the lack of attention from previous literature on these factors in the context of blockchain adoption, especially amidst the recent blockchain hype. By integrating Task-Technology Fit (TTF) and a modified version of the Unified Theory of Acceptance and Use of Technology (UTAUT), this study employs a questionnaire survey. The results demonstrate that the alignment between blockchain and work characteristics significantly impacts performance expectations and the recognition of opportunities, thereby influencing the intention to adopt blockchain. Furthermore, factors such as effort expectancy, social influence, facilitating conditions, and perceived policy uncertainty influence adoption intention by identifying opportunities. Exposure to blockchain-related knowledge reinforces the relationships mentioned above. Additionally, digital natives display greater confidence in blockchain's potential to enhance work performance than digital immigrants. These study findings offer valuable insights and strategies for blockchain technology providers and provide a comprehensive survey for individuals and professionals interested in embracing or understanding the dynamics of blockchain adoption.

1. Introduction

Since the introduction of blockchain technology in 2009, its best-known application has been Bitcoin, the world's most famous cryptocurrency. In the past, only a few tech enthusiasts engaged with it, and the general public associated it with speculation, high risk, and mystery [1]. The year 2021 marked a significant turning point for blockchain technology as it received increased attention. Due to the impact of the pandemic in 2021, people began shifting from physical activities to online ones, and virtual products, services, and applications like the Metaverse rapidly gained prominence. Blockchain, with its features of integrity, security, transparency, and traceability, not only enables people to record transactions and ownership of virtual items within the Metaverse but also assists in the real world in addressing the pandemic by improving the management of clinical trial data and streamlining communication between different sectors in the supply chain [2].

While blockchain technology has garnered significant attention, most people remain focused on its largest current application: cryptocurrencies, which they consider investment commodities. Nevertheless, the development of other blockchain applications is steadily increasing. For instance, in 2013, Vitalik Buterin founded Ethereum, a blockchain platform that can be used for payments and the development of various applications like smart contracts [3]. Furthermore, IBM announced its blockchain sector in 2021, offering blockchain solutions for various industries [4].

Not only has the industry started to pay attention to blockchain, but academia has also initiated related research. This study briefly

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categorizes current blockchain studies into three streams: financial technology and cryptocurrencies, business models and processes, and technical implementations. These three streams will be discussed in more detail in the literature review section. However, the factors influencing the adoption of blockchain from the perspective of job characteristics and their alignment with blockchain technology have rarely been studied. Additionally, some researchers have begun to discuss misconceptions and myths about blockchain as a panacea for all businesses [5–8]; that is, everyone is rushing to adopt blockchain, regardless of whether it is suitable for their business or not.

In light of the aforementioned context, this study aims to examine the alignment between respondents' work characteristics and the characteristics of blockchain technology, as well as the factors driving the adoption intention of blockchain technology from various perspectives, such as differences among age groups.

This examination is based on the combination of two theories: Task-Technology Fit (TTF) theory, which assesses whether respondents' task requirements match the characteristics of blockchain technology, and a modified version of the Unified Theory of Acceptance and Use of Technology (UTAUT) theory. The latter theory explores the factors influencing respondents' intention to adopt blockchain technology.

By testing whether the dependent variable of TTF, task-technology fit, has an effect on performance expectancy—an independent variable in UTAUT—as well as on respondents' opportunity recognition and their intention to adopt blockchain technology, this analysis aims to explore the relationships between respondents' perceptions of how well blockchain technology fits their work requirements and their intention to adopt blockchain technology, as mediated by performance expectancy and opportunity recognition. Furthermore, to account for the fact that many countries have yet to establish clear policies regarding the use of blockchain technology, this study includes 'perceived policy uncertainty' as one of the variables to examine its potential effects on respondents' intention to adopt blockchain technology. The research model is presented in Fig. 1.

The combination of the two theories mentioned above not only aims to address the research gap regarding whether respondents' assessment of the alignment between their own task requirements and blockchain technology characteristics affects their intention to use but also holds promise for providing insightful results in both academic and practical fields regarding blockchain technology adoption intentions.

To practically achieve the research objective, this study develops two research questions: (1) What are the factors that affect the intention to adopt blockchain technology following its recent surge in popularity? (2) How do personal characteristics influence the intention to adopt blockchain? This study believes that it's an opportune moment to expand our research scope and conduct additional studies to deepen our understanding of blockchain technology adoption and its potential in the post-pandemic era. Due to the novelty of blockchain technology and its sudden surge in popularity, this study posits that investigating this phenomenon not only contributes to understanding how respondents of different age groups perceive and intend to adopt blockchain technology but also assists existing businesses in assessing whether they can enhance their efficiency by adopting blockchain.

2. Research background and hypotheses

2.1. Blockchain research

Various applications based on blockchain technology have exploded in the last year, such as NFTs (Non-Fungible Tokens) and DeFi (Decentralized Finance). In the virtual world, where digital assets are easy to copy and distribute, an ideal mechanism for proving ownership has long been lacking; and even when one exists, the protective effect is often too weak. It is against this background that the applications of blockchain technology have evolved [9]. Due to the secure, immutable, and transparent nature of the blockchain [10–12], ownership of digital assets is recorded, and transactions are conducted via tokens.

Not only has the industry started to pay attention to blockchain, but academia has also begun to conduct related research. This

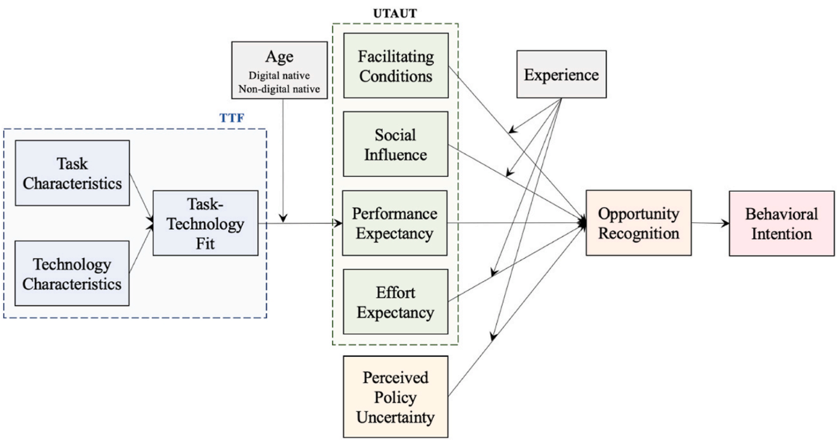

Fig. 1. Research model.

study briefly divides current blockchain studies into three streams:

(1) Financial technology (FinTech) and cryptocurrencies: Since blockchain is the underlying technology of cryptocurrencies that have recently gained popularity, many researchers want to learn more about this emerging industry and the opportunities of blockchain in finance. For example, Chuen et al. compared the characteristics of cryptocurrencies and traditional asset classes and suggested that cryptocurrencies can be a good alternative for portfolio enhancement. Moreover, the average daily return of almost all cryptocurrencies is higher than that of traditional assets [13]. Chang et al. studied cases of blockchain adoption in financial services and suggested that the most serious problem, knowledge concealment, can hinder blockchain adoption [14]. Fu et al. studied the risk of Ethereum's trading security and long-term development and developed a risk rating framework [15]. Akdoğu and Simsir investigated the M&A completion rates of the blockchain/cryptocurrency industry and found that the bitcoin price is an important determinant of the industry's deal completion rate [16].

(2) Business models and processes: Blockchain technology offers researchers and practitioners a significant opportunity to rethink the development of business models and the management of business processes. For example, Mendling et al. highlight the opportunities and challenges of blockchain for managing business processes and conclude that by using blockchain technology, even untrusted parties can establish trust through the use of smart contracts [17]. Queiroz and Wamba examine individual blockchain adoption behavior in logistics and supply chain in India and the U.S. and find differences in adoption behavior between professionals in India and the U.S [18]. Rimba et al. compare the cost of computing and storing the execution of business processes on the blockchain with that of cloud services and conclude that the cost of executing business processes on the Ethereum blockchain may currently be higher than on Amazon Simple Workflow Service [19]. Lee studies the possibilities of using blockchain for organizational collaboration and discusses the alignment between the characteristics of blockchain technology and democratic collaboration [20]. Calandra et al. examine the relationship between blockchain and sustainable business models, discussing how blockchain technology can be used for environmental management [21].

(3) Technical implementations: As an emerging technology, blockchain has attracted many technical experts to debate and discuss this topic. For example, Kumar et al. discuss the basic concepts of Hyperledger Fabric, one of the most mature blockchain implementations, and point out the main challenges for blockchain design and implementation [7]. Hardjono et al. design an interoperable blockchain architecture where common blockchain architecture components can be standardized by discussing a design philosophy for interoperable blockchain systems, resulting in lower development costs, better reusability, and higher levels of interoperability [22]. Rana et al. suggest using Layer 2 Polygon Blockchain smart contracts to safeguard digital evidence in legal proceedings in order to overcome issues of data alteration, unauthorized access, or flaws in centralized storage [23]. Selvarajan et al. propose the implementation of an Artificial Intelligence-based Lightweight Blockchain Security Model (AILBSM) to ensure the privacy and security of IIoT systems [24].

There are also research papers that examine the adoption of blockchain technology using various theories and models. For example, Vu et al. apply innovation adoption theory and develop a three-stage conceptual framework for implementing blockchain in food supply chains [25]. Kamble et al. utilize the Technology Acceptance Model (TAM) to assess intentions to adopt blockchain in the Indian supply chain [26]. Marikyan et al. employ the Protection Motivation Theory to study the cognitive factors underlying the decision to adopt blockchain [27]. However, there has been limited research on the factors influencing blockchain adoption from the perspective of the fit between job characteristics and blockchain technology.

In light of the aforementioned context and recent research that discusses misconceptions and myths about blockchain as a panacea for all businesses [5–8], this study focuses on the alignment between respondents' job characteristics and the features of blockchain technology, as well as the factors driving the intention to adopt blockchain technology from various perspectives, including differences among age groups.

2.2. *Task technology fit theory (TTF)*

Schneider et al. developed an analytical framework for companies to integrate blockchain technology into their business models [28]. However, this study reveals that many companies are currently drawn to blockchain solely due to its hype and novelty. For example, Esposito et al., Kumar et al., and Shahaab et al. have pointed out that businesses often consider blockchain a panacea without adequately assessing its appropriateness for their needs [5,7,8]. Therefore, this study includes the TTF model and focuses on examining the fit between respondents' work characteristics and the characteristics of blockchain technology, as well as their intention to adopt blockchain technology.

TTF was first introduced by Goodhue and Thompson in 1995 [29]. Their research aimed to demonstrate that a positive impact of technology requires a good fit with the task it is intended to support, leading to improved performance. Since its inception, TTF has been applied in various technological contexts and integrated with other models, such as TAM [30,31] and UTAUT [32,33]. Numerous studies have shown that TTF has an impact on performance expectancy [34]. For example, Kang et al. analyzed the factors influencing the acceptance of South Korea's smart home healthcare services, finding that task-technology fit significantly influenced performance expectancy [35]. Similarly, Faqih and Jaradat examined the adoption of augmented reality in education, and the results showed a positive effect of task-technology fit on performance expectancy [36].

Following the literature mentioned above, this study proposes two hypotheses to investigate the relationship between TTF and performance expectancy in the context of blockchain:

H1a. Task characteristics positively affect task-technology fit, which, in turn, affects performance expectancy in the context of blockchain.

H1b. Technology characteristics positively affect task-technology fit, which, in turn, affects performance expectancy in the context of blockchain.

2.3. Unified theory of acceptance and use of technology (UTAUT), policy uncertainty, and opportunity

The UTAUT is a technology acceptance model developed in 2003 by Venkatesh et al. [37]. The theory posits that there are four key constructs, namely effort expectancy, performance expectancy, facilitating conditions, and social influence, that determine usage intention and behavior. The theory also suggests that experience moderates the effects of effort expectancy, facilitating conditions, and social influence on usage intention and behavior.

There are few researchers using UTAUT to study the adoption of blockchain technology. Khazaei employs it to explain the use of blockchain by SMEs in Malaysia [38], and Tran and Nguyen utilize it to support the robustness of blockchain-enabled supply chain management [39]. However, considering the unusual hype around blockchain, which is heralded as the next paradigm shift in digital networks [40], this study suggests including specific variables presented in the following paragraphs of this section into the research model. This adaptation aims to address modern situations and comprehensively explore the intent of blockchain adoption.

The first suggested variable is perceived policy uncertainty. Policies and regulations are often seen as important determinants of the degree of innovation [41]. Particularly in the context of blockchain technology, policy uncertainty surrounding this radically new technology poses a significant challenge for both start-ups and large, established companies. Blockchain technology enables an entirely new architecture for payments, contract signing, property rights assertion, and information storage. This implies that current legal frameworks are not designed for this technology [42]. The relationship between policy uncertainty and opportunity recognition has been indicated in previous studies. For example, Khan et al.'s research suggests that policy uncertainty can influence investors' perspectives on the opportunities for research and development (R&D) investments [43].

Given the current state of blockchain policy, this study follows previous literature and integrates the concepts of policy uncertainty and opportunity recognition into the UTAUT to develop an extended model. Consequently, this study proposes the following hypotheses to investigate the intention of adopting blockchain technology in contemporary conditions:

H2. Effort expectancy affects opportunity recognition and, consequently, behavioral intention.

H3. Social influence affects opportunity recognition and, consequently, behavioral intention.

H4. Facilitating conditions affect opportunity recognition and, consequently, behavioral intention.

H5. Perceived policy uncertainty affects opportunity recognition and, consequently, behavioral intention.

To examine the comprehensive effects of task-technology fit and the extended UTAUT model in this study, we also propose a serial mediation hypothesis:

H6. Performance expectancy and opportunity recognition serially mediate the effects of task-technology fit on behavioral intention.

To further focus on blockchain adoption intention, this study follows previous research and sets experience as the moderator to test if the experience of using blockchain positively moderates the effects of three independent variables from UTAUT, namely effort expectancy, social influence, and facilitating conditions, as well as one independent variable added to make the research more suitable for the current environment and situation: perceived policy uncertainty, on opportunity recognition. Accordingly, the following hypotheses are proposed:

H7a. Experience moderates the effect of effort expectancy on opportunity recognition.

H7b. Experience moderates the effect of social influence on opportunity recognition.

H7c. Experience moderates the effect of facilitating conditions on opportunity recognition.

H7d. Experience moderates the effect of perceived policy uncertainty on opportunity recognition.

2.4. Digital natives and non-digital natives

In addition, the data reveals a significant age gap among individuals interested in blockchain, with younger age groups demonstrating a stronger inclination toward finding blockchain more useful. This inclination is likely linked to their upbringing. To categorize respondents in different age groups, this study classifies them into two types: digital natives and non-digital natives. Research indicates that digital natives, a term popularized by Prensky in 2001 to refer to individuals born after 1980 [44,45], have grown up in an almost fully digitized world. They exhibit a rapid ability to learn about and embrace new digital technologies, are more likely to invest in blockchain and cryptocurrencies, and perceive blockchain technology as useful compared to other generations.

Therefore, this study finds value in examining the influence of age in the research model within the context of blockchain. Drawing from the approach of Tam and Oliveira, who investigated the impact of age on the TTF model and discovered statistically significant differences within age subgroups [46], this study incorporates age as a moderator of the relationship between task technology fit and performance expectancy, resulting in the following hypothesis:

Table 1
Means, standard deviations, and correlations.

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	VIF
1.Gender	1.38	.49	1																		1.10
2.Age	0.42	.49	.11*	1																	1.19
3.Education	1.87	.34	−.00	−.19**	1																1.15
4.Industry	11.73	3.87	−.10	−.04	.05	1															1.04
5.Major	5.87	2.37	.09	.13*	.00*	.07	1														1.11
6.Entrepreneurial experience	1.52	.50	.17**	−.02	−.10	.05	−.07	1													1.18
7.Entrepreneurial intention	1.34	.48	−.00	−.27**	.04	−.02	−.24**	.27**	1												1.30
8.Experience	3.43	1.05	−.09	.00	.09	.04	.06	−.20**	−.16**	1											1.99
9.Task characteristics	4.30	.54	−.02	−.01	.16**	.01	−.06	−.10	−.12*	.21**	1										1.52
10.Tech characteristics	3.95	.73	.04	.00	.04	−.05	.02	−.07	−.04	.05	.47**	1									1.96
11.Task-technology fit	3.31	.91	.04	−.07	.15**	.05	.02	−.07	−.15*	.26**	.38**	.54**	1								2.78
12.Effort expectancy	3.20	.87	−.14*	−.04	.13**	.02	−.02	−.19**	−.15*	.65**	.22**	.11*	.34**	1							2.12
13.Social influence	3.14	.92	−.02	.00	.04	−.00	.05	−.12*	−.16**	.49**	.33**	.28**	.50**	.51**	1						2.46
14.Performance expectancy	3.36	.85	.06	.03	.15**	−.02	.05	−.08	−.15**	.20**	.39**	.59**	.77**	.28**	.53**	1					3.12
15.Facilitating conditions	3.08	1.03	−.01	−.01	.03	.04	.04	−.12*	−.14**	.53**	.27**	.06	.29**	.56**	.66**	.29**	1				2.21
16.Perceived policy uncertainty	3.73	.87	−.10	−.01	.08	.03	−.02	−.05	−.11*	.18**	.23**	.09	.23**	.14*	.20**	.27**	.19**	1			1.15
17.Opportunity recognition	3.84	.69	.00	.10	.12*	.02	.05	−.18**	−.21**	.34**	.33**	.29**	.33**	.32**	.39**	.35**	.33**	.20**	1		1.40
18.Behavioral intention	3.28	.86	.05	.03	.10	−.01	.11*	−.10	−.20**	.41**	.36**	.49**	.58**	.38**	.58**	.63**	.52**	.30**	.41**	1	

N = 354 (two-tailed test). **: Statistically significant at $p < 0.01$; *: $P < 0.05$.

H8. Age moderates the effect of task-technology fit on performance expectancy.

3. Research method

3.1. Data collection

A questionnaire was used to collect data for hypothesis testing. The questionnaire contains seven single-select questions, namely age, gender, education, major, industry, entrepreneurial experience, and entrepreneurial intention. All other questions are measured on a five-point Likert scale from ‘strongly agree’ to ‘strongly disagree’ for the variables of task characteristics, technology characteristics, fit between task and technology, performance expectancy, social influence, effort expectancy, facilitating conditions, perceived policy uncertainty, opportunity recognition, experience, and behavioral intention. The measurement items of the questionnaire are summarized in Appendix A.

To understand the factors influencing participants’ behavioral intentions in adopting blockchain technology, we surveyed current students and alumni of the EMBA and MBA programs at National Taiwan University, the largest university in Taiwan by student enrollment. All the students and alumni from the mentioned programs are employed by companies or self-employed.

The questionnaire for this study was created using the online questionnaire platform SurveyCake, and the questionnaire link was sent to the study participants through online community groups on social media such as Facebook and communication software such as Line and Messenger. Using simple random sampling, the questionnaire link was sent to a population of 501, including 90 EMBA students, 216 EMBA alumni, and 195 MBA students. This study conducted a pilot test to identify any potential issues with the questionnaire that had been designed. The link to the online questionnaire was randomly distributed to students selected from National Taiwan University. Respondents were asked to pre-test all elements of the questionnaire, including its content, wording, format, layout, instructions, and question difficulty. After successfully passing the pilot test, this study finally obtained a total of 354 valid questionnaires, resulting in a response rate of 70.7 %. The data collection period was from July 30 to August 7, 2021. All participants voluntarily took part in the survey and consented to the use of their data for research purposes. The demographic composition of the respondents is presented in Appendix B.

3.2. Data analysis

In developing the aforementioned questionnaire, this study conducted a literature review to identify previously validated metrics, some of which were edited to suit the context of blockchain technology. Additionally, this study calculated Cronbach’s alpha coefficient for each factor to assess internal consistency and reliability. Following the recommendation of Pallant, this study removed factors with an α of <0.7, or <0.5 for fewer than ten items [47].

Drawing from Howard and Rose’s research on TTF [48] and Schlecht et al.’s and Viriyasitavat and Hoonsopon’s work on blockchain characteristics [12,49], this study adjusted two scales with seven items each to reflect task characteristics ($\alpha = 0.756$) and technology characteristics ($\alpha = 0.873$). Additionally, three items were adapted to represent task-technology fit ($\alpha = 0.944$). This study adapted items for effort expectancy ($\alpha = 0.908$), social influence ($\alpha = 0.879$), performance expectancy ($\alpha = 0.928$), facilitating conditions ($\alpha = 0.629$), behavioral intention ($\alpha = 0.929$), and experience ($\alpha = 0.752$) from Venkatesh et al.’s UTAUT model to reflect critical factors for blockchain technology adoption intention [37]. Items for perceived policy uncertainty ($\alpha = 0.841$) were adapted from Johnstone et al.’s research [50], and items for opportunity recognition ($\alpha = 0.664$) were adapted from Wang et al.’s study [51]. Finally, this study employed seven single-choice items to measure one of the moderators and six control variables: gender, industry, major, education, entrepreneurial experience, and entrepreneurial intention.

In addition to Cronbach’s alpha, variance inflation factors (VIFs) are also employed in this study to examine multicollinearity. VIFs indicate whether variables are correlated with each other, which can potentially affect the reliability of the results. Following the guideline set by Pallant [47], a VIF larger than 10 indicates a strong correlation. In Table 1, the VIFs range from 1.04 to 3.12, indicating the absence of multicollinearity. The table also presents the standard deviations, means, and correlations of all variables in this study.

Furthermore, this study utilizes factor analysis to assess the questionnaire’s validity. Firstly, this study evaluates the data’s suitability for factor analysis using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett’s sphericity test. A KMO value approaching 1 indicates the presence of common factors in the questionnaire, making it more suitable for factor analysis. Subsequently, a varimax rotation analysis is conducted to extract the factor loadings of each item within the major factors to assess convergent validity. According to Hair et al., factor loadings should converge under a common factor, with each item’s factor loading exceeding 0.5 [52]. When the cumulative explained variance surpasses 50 %, it signifies good convergent validity for the scale.

In this study, for Task Characteristics, the KMO value is 0.806, Bartlett’s sphericity test yields a significant result ($p < 0.001$), and item factor loadings range from 0.545 to 0.813, with a cumulative explained variance of 51.942 %. For Technology Characteristics, the KMO value is 0.876, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.653 to 0.851, with a cumulative explained variance of 64.130 %. For Task-Technology Fit, the KMO value is 0.746, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.925 to 0.965, with a cumulative explained variance of 89.926 %. For Effort Expectancy, the KMO value is 0.837, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.860 to 0.911, with a cumulative explained variance of 78.397 %. For Social Influence, the KMO value is 0.719, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.844 to 0.879, with a cumulative explained variance of 74.691 %. For Performance Expectancy, the KMO value is 0.844, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.837 to 0.940, with a cumulative explained variance of 82.384 %. For Facilitating Conditions, the KMO value is 0.724, Bartlett’s sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.855 to 0.888, with a cumulative explained variance of 76.098 %. For Perceived Policy Uncertainty, the KMO value is 0.500, Bartlett's sphericity test is significant ($p < 0.001$), and item factor loadings are 0.929, with a cumulative explained variance of 86.339 %. For Opportunity Recognition, the KMO value is 0.500, Bartlett's sphericity test is significant ($p < 0.001$), and item factor loadings are 0.866, with a cumulative explained variance of 75.028 %. For Experience, the KMO value is 0.500, Bartlett's sphericity test is significant ($p < 0.001$), and item factor loadings are 0.899, with a cumulative explained variance of 80.825 %. For Behavioral Intention, the KMO value is 0.841, Bartlett's sphericity test is significant ($p < 0.001$), and item factor loadings range from 0.624 to 0.804, with a cumulative explained variance of 73.957 %. The results of factor analysis are presented in Appendix C.

To examine the mediating effects of task-technology fit between two independent variables (task characteristics and technology characteristics) and the dependent variable (performance expectancy), as well as the mediating effects of opportunity recognition between four independent variables (facilitating conditions, social influence, effort expectancy, and perceived policy uncertainty) and the dependent variable (behavioral intention), this study employs the regression procedures recommended by Baron and Kenny [53]. Additionally, a bootstrap analysis is conducted following Hayes procedure to assess both single and serial mediation effects [54].

Furthermore, hierarchical multiple regression analysis is performed in SPSS to test the moderating effects of age on the relationship between task-technology fit and performance expectancy, as well as the effects of experience on the relationship between the five independent variables (effort expectancy, social influence, performance expectancy, facilitating conditions, and perceived policy uncertainty) and the dependent variable (opportunity recognition). Gender, industry, major, education, entrepreneurial experience, and entrepreneurial intention are included as control variables in all models.

4. Results

4.1. Single mediating effect

In this study, linear regression analyzes were conducted to test for mediating effects. Following Baron and Kenny [53], we first test for relationships between the independent variables and the dependent variable. The results of Models 1a and 1c in Table 2 show that the two independent variables, task characteristics and technology characteristics, are significantly related to the dependent variable, performance expectancy ($\beta = 0.577$, $p < 0.001$; $\beta = 0.676$, $p < 0.001$, respectively). Also, the results of Models 2a, 3a, 4a, and 5a in Table 3 show that the four independent variables of effort expectancy, social influence, facilitating conditions, and policy uncertainty are significantly related to the dependent variable of behavioral intention ($\beta = 0.362$, $p < 0.001$; $\beta = 0.524$, $p < 0.001$; $\beta = 0.426$, $p < 0.001$; $\beta = 0.278$, $p < 0.001$, respectively).

Second, we include mediators in the models. The mediator effect occurs when the effects of the independent variables on the dependent variables are attenuated by the addition of the mediator and the overall fit of the model is increased. It can be seen that in Models 1b and 1d (Table 2), the effects of task characteristics and technology characteristics are reduced when the mediator of task-technology fit is added. And the overall fit of the model is increased ($\Delta R^2 = 0.424$, 0.255, respectively). These results support H1a and H1b, which propose that task-technology fit mediates the effects of task characteristics and technology characteristics on performance expectancy. Also, Models 2b, 3b, 4b, and 5b in Table 3 show that the effects of effort expectancy, social influence, facilitating conditions, and policy uncertainty are reduced when the mediator of opportunity recognition is added. And the overall fit of the model is increased ($\Delta R^2 = 0.078$, 0.039, 0.052, 0.104, respectively).

In addition, Table 4 presents the bootstrap analysis with 5000 bootstrap samples of the mediation models. The indirect effects of the above mediation models are all supported because the confidence intervals of the bootstrap analysis do not include zero.

Table 2
Results of regression analysis for performance expectancy.

Variable	Model 1:			
	Performance expectancy			
	1a	1b	1c	1d
Gender	.107 (.088)	.036 (.061)	.056 (.076)	.023 (.059)
Industry	−.005 (.011)	−.012 (.008)	.001 (.009)	−.008 (.007)
Major	.015 (.018)	.014 (.013)	.002 (.016)	.009 (.012)
Education	.240 (.125)$^{+}$	.073 (.087)	.347 (.107)**	.139 (.083)$^{+}$
Entrepreneurial experience	−.025 (.088)	−.007 (.062)	.007 (.077)	.004 (.059)
Entrepreneurial intention	−.176 (.094)$^{+}$	−.044 (.066)	−.243 (.081)**	−.090 (.063)
Independent variables				
Task characteristics	.577 (.078)***	.189 (.058)**		
Technology characteristics			.676 (.050)***	.289 (.046)**
Mediator				
Task-technology fit		.666 (.035)***		.578 (.037)***
R^2	.182	.606	.381	.636
F value	10.989***	66.242***	30.366***	75.214***

N = 354 (two-tailed test). Standard errors in parentheses.
***: Statistically significant at $p < 0.001$; **: $p < 0.01$; *: $P < 0.05$; +: $p < 0.1$.

Table 3
Results of regression analysis for behavioral intention.

Variable	Model 2–6: Behavioral intention									
	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
Gender	.154 (.090)$^{+}$	.123 (.085)	.090 (.079)	.079 (.076)	.074 (.082)	.063 (.079)	.083 (.091)	.067 (.086)	.029 (.079)	.013 (.073)
Industry	−.005 (.011)	−.007 (.010)	−.003 (.010)	−.005 (.009)	−.009 (.010)	−.010 (.010)	−.006 (.011)	−.007 (.011)	−.010 (.010)	−.006 (.009)
Major	.030 (.018)	.029 (.018)	.020 (.016)	.021 (.016)	.023 (.017)	.024 (.016)	.028 (.019)	.028 (.018)	.029 (.016)$^{+}$	.025 (.015)
Education	.133 (.126)	.072 (.120)	.188 (.110)*	.133 (.108)	.222 (.115)$^{+}$	.153 (.111)	.189 (.129)	.102 (.121)	.035 (.112)	−.042 (.103)
Entrepreneurial experience	.007 (.090)	.055 (.086)	−.001 (.079)	.038 (.077)	.012 (.083)	.054 (.080)	−.061 (.092)	.010 (.087)	−.040 (.080)	.005 (.074)
Entrepreneurial intention	−.239 (.095)*	−.157 (.092)$^{+}$	−.186 (.084)*	−.130 (.083)	−.220 (.087)*	−.151 (.085)$^{+}$	−.264 (.098)**	−.162 (.093)$^{+}$	−.173 (.085)*	−.098 (.079)
Independent variables										
Effort expectancy	.362 (.050)***	.277 (.050)***								
Social influence			.524 (.041)***	.459 (.042)***						
Performance expectancy										.397 (.064)***
Facilitating conditions					.426 (.038)***	.365 (.039)***				
Policy uncertainty							.278 (.050)***	.221 (.048)***		
Mediator										
Task-technology fit									.528 (.042)***	.195 (.059)**
Opportunity recognition		.383 (.063)***		.274 (.058)***		.314 (.059)***		.430 (.063)***		.244 (.055)***
R^2	.181	.259	.362	.401	.307	.359	.136	.240	.353	.460
F value	10.898***	15.077***	28.002***	28.819***	21.857***	24.139***	7.784***	13.645***	27.012***	32.620***

N = 354 (two-tailed test). ***: Statistically significant at $p < 0.001$; **: $p < 0.01$; *: $P < 0.05$; +: $p < 0.1$. Standard errors in parentheses.

These results support H2, H3, H4, and H5, which propose that opportunity recognition mediates the effects of effort expectancy, social influence, facilitating conditions, and policy uncertainty on behavioral intention.

4.2. Serial mediating effect

In addition to the single mediating effects, this study examines the serial mediating effect with two serial mediators following the procedure described by Hayes [54]. In this section, we examined whether performance expectancy and opportunity recognition sequentially mediate the effects of task-technology fit on behavioral intention. Furthermore, a bootstrap analysis with 5000 bootstrap samples is used to estimate the effects of the serial mediation model. According to Hayes, if the confidence intervals of the bootstrap analysis do not include zero, an indirect effect is supported [54].

Fig. 2 shows the serial mediation with performance expectancy and opportunity recognition as mediators of task-technology fit effects on behavioral intention (Model 6a and 6b in Table 3). Table 4 shows the result that performance expectancy and opportunity recognition partially mediate the relationship between task-technology fit and behavioral intention (total indirect effect = 0.333, 90 % CI = [0.213, 0.470]; direct effect = 0.195, 90 % CI = [0.097, 0.292]).

The above results partially support H6, which states that performance expectancy and opportunity recognition serially mediate the effects of task-technology fit on behavioral intention.

4.3. Moderating effect

In this study, hierarchical multiple regression analysis was used to test for moderating effects. Models 7a, 7b, 7c, and 7d in Table 5 show the interaction effect of experience on the effects of effort expectancy, social influence, facilitating conditions, and policy uncertainty on behavioral intention. The results reveal that the interaction effects of experience between three of the four independent variables—effort expectancy, social influence, and facilitating conditions—and the dependent variable, behavioral intention, are positive and statistically significant ($\beta = 0.080$, $p < 0.01$; $\beta = 0.123$, $p < 0.001$; $\beta = 0.082$, $p < 0.05$, respectively). These results support H7a, H7b, and H7c, which propose that experience positively moderates the effects of effort expectancy, social influence, and facilitating conditions on behavioral intention. However, the interaction effect of experience between one of the independent variables, policy uncertainty, and the dependent variable, behavioral intention, is not significant ($\beta = 0.027$, $p = 0.367$). Therefore, H7d, which proposes that experience positively moderates the effect of policy uncertainty on behavioral intention, is not supported.

Model 8 in Table 5 shows the interaction effect of age on the relationship between task-technology fit and performance expectancy. The results show that the interaction between age and task-technology fit is statistically significant ($\beta = -0.247$, $p < 0.001$). This result supports H9, which states that age moderates the effect of task technology fit on performance expectancy.

Table 4
Bootstrap analysis to test significance of mediation effects.

Path/effect	Bootstrap estimate			
	B	SE	LLCI	ULCI
Total	.577	.078	.423	.731
Direct	.189	.058	.075	.303
Ind: Task characteristics→Task-technology fit→Performance expectancy	.388	.070	.260	.536
Total	.676	.050	.578	.775
Direct	.289	.046	.199	.379
Ind: Technology characteristics→Task-technology fit→Performance expectancy	.387	.051	.291	.488
Total	.362	.050	.263	.461
Direct	.277	.050	.179	.375
Ind: Effort expectancy→Opportunity recognition→Behavioral intention	.085	.024	.043	.134
Total	.524	.041	.444	.605
Direct	.459	.042	.377	.542
Ind: Social influence→Opportunity recognition→Behavioral intention	.065	.018	.032	.104
Total	.426	.038	.350	.501
Direct	.365	.039	.289	.441
Ind: Facilitating conditions→Opportunity recognition→Behavioral intention	.061	.017	.031	.099
Total	.278	.050	.180	.377
Direct	.221	.048	.127	.315
Ind: Perceived policy uncertainty→Opportunity recognition→Behavioral intention	.057	.021	.019	.103
Total	.528	.042	.459	.597
Direct	.195	.059	.097	.292
Indirect (total)	.333	.078	.213	.470
Ind1: Task-technology fit→Performance expectancy→Behavioral intention	.280	.073	.167	.407
Ind2: Task-technology fit→Opportunity recognition→Behavioral intention	.024	.018	.001	.058
Ind3: Task-technology fit→Performance expectancy→Opportunity recognition→Behavioral intention	.030	.014	.008	.054

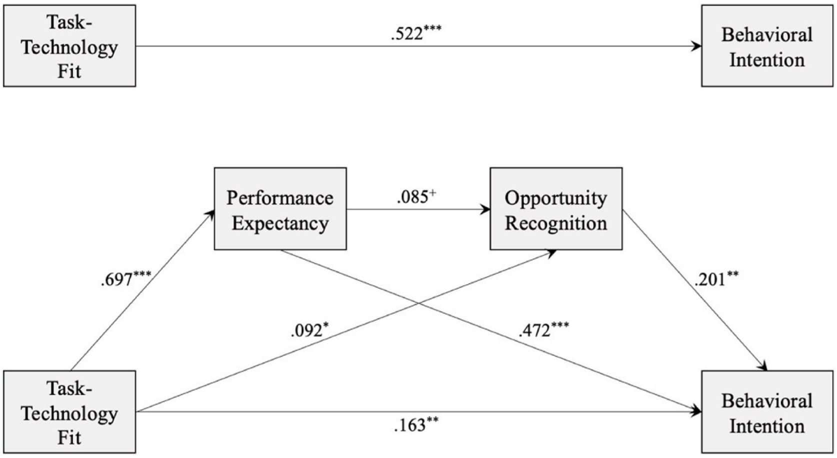

Fig. 2. Serial mediation model with performance expectancy and opportunity recognition as mediators of task-technology fit on behavioral intention.

Table 5
Results of hierarchical regression analysis for opportunity recognition.

Variable	Model 7: Opportunity recognition			Model 8: Performance expectancy	
	7a	7b	7c	7d	8
Gender	.098 (.071)	.047 (.069)	.070 (.070)	.063 (.071)	.031 (.061)
Industry	.005 (.009)	.006 (.008)	.003 (.009)	.003 (.009)	−.011 (.007)
Major	−.008 (.015)	−.010 (.014)	−.007 (.014)	−.003 (.015)	.005 (.012)
Education	.151 (.100)	.177 (.096)+	.184 (.098)+	.170 (.100)+	.185 (.087)*
Entrepreneurial experience	−.099 (.072)	−.109 (.070)	−.116 (.071)	−.116 (.072)	−.023 (.061)
Entrepreneurial intention	−.203 (.075)**	−.196 (.073)**	−.181 (.075)*	−.199 (.076)*	.009 (.067)
Independent variables					
Effort expectancy	.099 (.052)+				
Social influence		.164 (.040)***			
Performance expectancy					
Facilitating conditions			.111 (.039)**		
Policy uncertainty				.099 (.039)*	
Experience	.156 (.043)***	.133 (.036)***	.141 (.038)***	.183 (.034)***	
Occupation					
Task-technology fit					.839 (.046)***
Age					.166 (.062)**
Interaction variables					
Experience* Effort expectancy	.080 (.030)**				
Experience* Social influence		.123 (.031)***			
Experience* Performance expectancy					
Experience* Facilitating conditions			.082 (.032)*		
Experience* Policy uncertainty				.027 (.030)	
Age* Task-technology fit					−.247 (.058)***
R^2	.190	.237	.201	.177	.617
F value	8.941***	11.892***	9.621***	8.240***	61.673***

N = 354 (two-tailed test). ***: Statistically significant at p < 0.001; **: p < 0.01; *: P < 0.05; +: p < 0.1. Standard errors in parentheses.

The moderators' conditional effects are presented in Table 6 and Fig. 3 to better understand the moderating effects in this study. In this study, age is divided into digital native and non-digital native. The results in Table 6 show that the effect of task-technology fit on performance expectancy is positively strengthened by both digital natives and non-digital natives (90 % CI = [0.749, 0.929]; 90 % CI = [0.503, 0.680], respectively), with digital natives having a greater influence than non-digital natives (Fig. 3).

Table 6
Conditional effects of the focal predictors at values of the moderator.

Performance expectancy	Non-digital native				Digital native			
	B	SE	LLCI	ULCI	B	SE	LLCI	ULCI
Task-technology fit	.839	.046	.749	.929	.592	.045	.503	.680

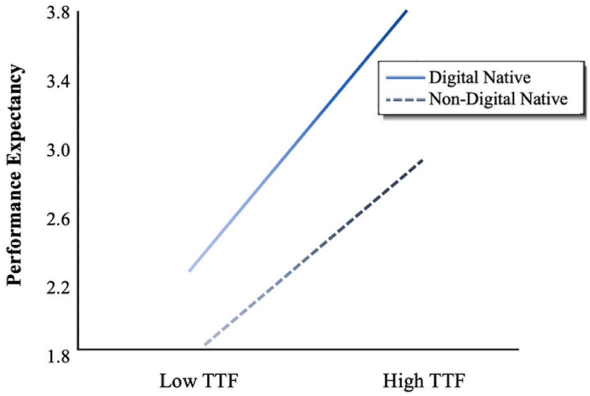

Fig. 3. Moderation of age on task-technology fit and performance expectancy.

5. Discussion

Blockchain has garnered significant attention from both the industry and academia in recent years. However, there has been limited research on the factors influencing the adoption of blockchain, especially from the perspective of job characteristics and their alignment with blockchain technology. Furthermore, some researchers have begun discussing misconceptions and myths surrounding blockchain, often portraying it as a universal solution for all businesses [5–8].

With this in mind, this study aims to fill the research gap by examining the alignment between respondents' work characteristics and the characteristics of blockchain technology. It also explores the factors driving the adoption intention of blockchain technology from various perspectives, including differences among age groups. To accomplish this, this study combines the TTF and UTAUT frameworks and proposes the following 12 hypotheses. The verification of these hypotheses holds the promise of providing valuable insights in both academic and practical fields regarding blockchain technology adoption intentions.

H1a. Task characteristics positively affect task-technology fit, which, in turn, affects performance expectancy in the context of blockchain.

H1b. Technology characteristics positively affect task-technology fit, which, in turn, affects performance expectancy in the context of blockchain.

H2. Effort expectancy affects opportunity recognition and, consequently, behavioral intention.

H3. Social influence affects opportunity recognition and, consequently, behavioral intention.

H4. Facilitating conditions affect opportunity recognition and, consequently, behavioral intention.

H5. Perceived policy uncertainty affects opportunity recognition and, consequently, behavioral intention.

H6. Performance expectancy and opportunity recognition serially mediate the effects of task-technology fit on behavioral intention.

H7a. Experience moderates the effect of effort expectancy on opportunity recognition.

H7b. Experience moderates the effect of social influence on opportunity recognition.

H7c. Experience moderates the effect of facilitating conditions on opportunity recognition.

H7d. Experience moderates the effect of perceived policy uncertainty on opportunity recognition.

H8. Age moderates the effect of task-technology fit on performance expectancy.

All the hypotheses mentioned above are supported except H7d. The verification results of the hypotheses show that:

(1) The fit between blockchain technology characteristics and job characteristics affects performance expectations for blockchain technology and also influences opportunity recognition, which, in turn, affects the intention to use blockchain.
(2) In addition to the factors mentioned above, the expected effort required to use blockchain, the social support for blockchain, the conditions facilitating blockchain technology, and the perception of blockchain regulations also influence the intention to adopt blockchain by identifying opportunities.
(3) For individuals who have been exposed to blockchain-related knowledge or products, the influences of expected effort to use blockchain, support for blockchain in the social environment, and conditions facilitating blockchain technology on opportunity recognition are stronger.
(4) The effect of task-technology fit on performance expectancy is stronger for digital natives. In addition, for digital natives, the alignment between blockchain and work characteristics does not influence their expectations of the benefits blockchain can

bring to work performance as much as it does for digital immigrants. Digital natives believe that blockchain can improve work performance even when blockchain and work characteristics are not well-aligned, while non-digital natives do not.

The results answer the questions raised and provide theoretical and practical implications listed below. These findings help practitioners and researchers interested in blockchain gain a better understanding of the perspectives held by professionals of different age groups regarding this emerging technology and the factors influencing their willingness to adopt it.

5.1. Factors influencing the intention to adopt blockchain

First, this study demonstrates that social influence, effort expectancy, facilitating conditions, and perceived policy uncertainty influence opportunity recognition and, consequently, the intention to adopt blockchain. This suggests that individuals who perceive blockchain technology as easy to use, have social influences recommending blockchain, possess technical infrastructure supporting blockchain use, or perceive policy uncertainty are more likely to see it as an opportunity and, consequently, have a higher intention to adopt blockchain. These results align partially with Venkatesh et al.'s research, which identifies factors driving the intention to use new technologies, including effort expectancy, social influence, and facilitating conditions [37]. However, in the context of blockchain, this study also reveals that perceived policy uncertainty affects the willingness of professionals to adopt blockchain, and their opportunity perceptions are influenced before their intention to adopt.

Second, the results of this study demonstrate that the alignment between tasks and blockchain technology influences performance expectancy, subsequently affecting opportunity recognition, which, in turn, influences the intention to adopt blockchain. This suggests that an individual who believes that blockchain technology will support specific tasks, such as gaining customer or partner trust, conducting rapid fundraising, improving process efficiency, accurately recording specific information or data, identifying content or product authenticity, enhancing customer or partner privacy, and fostering innovation, is more likely to perceive job performance benefits from blockchain. This perception then enhances opportunity recognition and, consequently, increases the intention to adopt blockchain.

Building on the research findings of Goodhue and Thompson [29], this study confirms that professionals who believe that the characteristics of blockchain align with their work are more inclined to consider blockchain as an asset to their performance.

In addition, it is worth noting that the demographics of the population in this study show that the top five industries with the highest percentage are science and technology (22.9 %), manufacturing (19.8 %), finance and insurance (14.7 %), health and social services (11.9 %), and wholesale and retail (7.9 %), which shows that the application of blockchain is not limited to finance and has the possibility of being used in various industries in the future.

However, we must realize that the strength of the above relationships is not static. The intensity between certain variables is influenced by the differences in personal characteristics in terms of age and the degree of blockchain experience. The following paragraphs discuss the influences of the above characteristics.

5.2. Personal characteristics and intention to adopt blockchain

First, the results of this study suggest that the effects of social influence, effort expectancy, and facilitating conditions on opportunity recognition are amplified when an individual has more experience with blockchain. That is, compared to individuals who have no blockchain experience, those with more experience in blockchain-related knowledge or products, such as smart contracts, cryptocurrencies, NFTs, product tracking services, and virtual certificates, among others, have stronger effects of facilitating conditions, social influence, and effort expectancy on opportunity recognition. This study, therefore, argues that, in comparison to the current situation, increased promotion of blockchain products or services and wider dissemination of blockchain knowledge will encourage the adoption of blockchain among professionals by raising awareness of the opportunities.

Second, the results show that the effect of task-technology fit on performance expectancy is stronger for younger generations, referred to in this study as digital natives, than for older generations, referred to in this study as non-digital natives. In addition, when the fit between respondents' work characteristics and blockchain technology characteristics is low, digital natives exhibit higher performance expectancy than non-digital natives. That is, unlike non-digital natives, who are also referred to as digital immigrants, digital natives believe that blockchain can provide performance benefits even when blockchain technology and the task at hand are not well-aligned. This could be attributed to the characteristics of digital natives. According to Prensky, one of the characteristics of digital natives is the desire to create [55]. Digital natives expect to have powerful tools, which in this study can be considered as blockchain, and they seek to understand the benefits the tool can provide by teaching themselves and others. Additionally, as noted by Stockham and Lind, digital natives are the driving force behind organizational decisions [56]. Therefore, they are less constrained by the adaptability of work and technology, which influences their expectation that technology will result in superior performance.

6. Conclusion

6.1. Theoretical and practical implications

This study categorizes current blockchain research into three areas: financial technology, business processes, and technical implementations. Some scholars are also beginning to suggest misconceptions about the universal applicability of blockchain; that is, everyone is rushing to adopt blockchain, regardless of whether it is suitable for their business or not. To understand the mindset of users adopting blockchain amidst this frenzy, this study aims to investigate the relationship between the alignment of respondents' work characteristics and blockchain technology on blockchain adoption intention, as well as adoption intentions across different age groups and respondents' experience levels.

This study contributes to academia by bridging gaps in blockchain-related literature, combining Task-Technology Fit (TTF) and a modified Unified Theory of Acceptance and Use of Technology (UTAUT) to examine how the fit between task and technology influences adoption intention. Additionally, this study takes into account "perceived policy uncertainty" due to unclear regulations in many countries regarding blockchain in the current environment.

Except for theoretical contributions, the results of this study also provide valuable insights for practical implications. First, for blockchain technology providers, the results of this study provide insights into factors that may influence people's adoption intentions for blockchain. Therefore, this study suggests that when offering blockchain technology services, blockchain practitioners and technology providers should first consider the organizational and technological infrastructure of potential users, as well as whether the people they interact with are already using blockchain technology.

In addition, it's important not to overlook the nature of potential users' work, as their perception of how well blockchain technology aligns with their job characteristics can significantly impact their expectations of blockchain performance and their willingness to use it, especially among young generations. The aforementioned impacts on willingness to use will be amplified if potential users have relevant prior experience with blockchain technology. Therefore, education and promotion of blockchain technology are also key strategies for blockchain practitioners and technology providers.

Second, for individuals and professionals seeking to embrace blockchain technology or acquire a deeper understanding of its adoption dynamics, this study offers a more extensive survey. The breadth of the study's participants, spanning multiple industries and age groups, contributes to its comprehensiveness. This study wishes to cultivate potential users' perspectives on aligning blockchain utilization with appropriate business models and environments rather than advocating for hasty adoption during the current blockchain hype without proper knowledge of blockchain.

6.2. Limitations and future research

This study also has some potential limitations. First, it was conducted exclusively with respondents from Taiwan. Therefore, future studies could utilize samples from other countries to expand the research scope and examine differences in blockchain adoption across various cultures and environments. Second, the effects of the factors examined in this study may vary across different industries. The demographics of this study suggest that blockchain applications are not limited to finance and can be applied in various industries. It is recommended that future studies focus on individual industries to gain a better understanding of the intentions behind blockchain adoption across different sectors.

This study hopes to encourage blockchain researchers to explore not only the technical applications of blockchain but also the psychological factors that influence users' willingness to adopt blockchain technology, as well as the effects stemming from users' various professions, demographic characteristics, and adoption trends, especially given the recent hype surrounding blockchain.

Data availability statement

Data associated with this study have been deposited into HARVARD Dataverse at https://doi.org/10.7910/DVN/KOA3T8.

CRediT authorship contribution statement

Hang Lee: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix A. List of measurement items

Performance Expectancy.

1. I think blockchain is useful at work.
2. I think blockchain can help me complete work faster.
3. I think blockchain can help me increase my productivity.
4. I think blockchain can increase the chances of getting invested or raised.

Effort Expectancy.

1. I think blockchain is understandable.

2. I think blockchain is easy to navigate.
3. I think blockchain is easy to use.
4. I think it is easy to learn how to use blockchain.

Social Influence

1. People who influence me think I should use blockchain.
2. People who are important to me think I should use blockchain.
3. The social environment around me has been generally supportive of using blockchain.

Facilitating Conditions.

1. I have the necessary resources to use blockchain.
2. I have the necessary knowledge necessary to use blockchain.
3. I have a specific person (or group) to assist me with blockchain issues.

Behavioral Intention.

1. I want to use blockchain in the future.
2. I think I will use blockchain in the future.
3. I plan to use blockchain in the future.
4. I wish to use blockchain within a year.
5. I predict I will use blockchain within a year.
6. I plan to use blockchain within a year.

Experience.

1. I have been exposed to blockchain-related products or services.
2. I have had contact with knowledge about blockchain.

Task Characteristics.
In my work, I need to:

1. Gain the trust of customers or partners.
2. Improve process efficiency.
3. Accurately capture certain information or data.
4. Ensure the authenticity of content or products.
5. Ensure the privacy of customers or partners.
6. Be innovative and novel in my work.

Technology Characteristics.

I think that the following main features of blockchain, namely decentralization (no need to go through an intermediary or a third party), unfalsifiability (previous data cannot be revoked or changed), traceability (tracing the source of goods or information) can allow me to:

1. Gain the trust of customers or partners.
2. Improve process efficiency.
3. Accurately capture certain information or data.
4. Ensure the authenticity of content or products.
5. Ensure the privacy of customers or partners.
6. Be innovative and novel in my work.

Task-Technology Fit.

1. Blockchain seems to match the task of my work.
2. Blockchain is suitable to fulfil the task of my work.
3. Blockchain meets the requirements of the task of my work

Perceived Policy Uncertainty.

1. I think the government is uncertain with its policy on blockchain.

2. I do not think the policy on blockchain is mature yet.

Opportunity Recognition.

1. As I pursue routine activities, I see potential new ideas all around me.
2. I notice new possibilities very often.

Appendix B. Demographic distribution of sample

Characteristic	No. of respondents	Percentage
Gender		
Female	134	37.9 %
Male	220	62.1 %
Age		
≤17	0	0 %
18–24	4	1.1 %
25–34	49	13.8 %
35–44	94	26.6 %
45–54	149	42.1 %
55–64	57	16.1 %
≥65	1	0.3 %
Education		
Secondary School	0	0 %
High School	0	0 %
University	47	13.3 %
Postgraduate	307	86.7 %
Occupation		
Employed	240	67.8 %
Unemployed	2	0.6 %
Retired	7	2.0 %
Self-employed	105	29.7 %
Student	0	0 %
Major of the highest degree		
Education	2	0.6 %
Arts and humanities	10	2.8 %
Social sciences, journalism and library information	10	2.8 %
Business, administration and law	210	59.3 %
Natural sciences, mathematics and statistics	12	3.4 %
Engineering, manufacturing and construction	38	10.7 %
Information and Communication Technology	41	11.6 %
Agriculture, forestry, fisheries and veterinary medicine	1	0.3 %
Health and social welfare	22	6.2 %
Services	2	0.6 %
Industry		
Manufacturing	70	19.8 %
Agriculture and animal husbandry	0	0 %
Mining	0	0 %
Electricity and gas	2	0.6 %
Water supply	2	0.6 %
Construction	6	1.7 %
Wholesale and retail	28	7.9 %
Transport and storage	2	0.6 %
Hotels and restaurants	3	0.8 %
Communication and information	10	2.8 %
Finance and insurance	52	14.7 %
Real estate and property	2	0.6 %
Science and technology	81	22.9 %
Support services	7	2.0 %
Public administration and defense	1	0.3 %
Education and training	12	3.4 %
Health and social services	42	11.9 %
Arts and entertainment	12	3.4 %
Other services	21	5.9 %

Appendix C. Results of factor analysis

Variable	Item	Factor loading	Variance explained %	KMO	Bartlett's Test of Sphericity		
					Approx. Chi-Square	df	Sig.
Task Characteristics	TC1	.733	51.942	.806	667.795	15	<.001
	TC2	.707					
	TC3	.723					
	TC4	.774					
	TC5	.813					
	TC6	.545					
Technology Characteristics	TeC1	.822	64.130	.876	1117.892	15	<.001
	TeC2	.785					
	TeC3	.842					
	TeC4	.851					
	TeC5	.834					
	TeC6	.653					
Task-Technology Fit	TT1	.925	89.926	.746	1043.420	3	<.001
	TT2	.965					
	TT3	.954					
Effort Expectancy	EE1	.877	78.397	.837	936.140	6	<.001
	EE2	.911					
	EE3	.893					
	EE4	.860					
Social Influence	SI1	.844	74.691	.719	401.521	3	<.001
	SI2	.869					
	SI3	.879					
Performance Expectancy	PE1	.914	82.384	.844	1220.263	6	<.001
	PE2	.940					
	PE3	.936					
	PE4	.837					
Facilitating Conditions	FC1	.888	76.098	.724	435.405	3	<.001
	FC2	.874					
	FC3	.855					
Perceived Policy Uncertainty	PU1	.929	86.339	.500	264.052	1	<.001
	PU2	.929					
Opportunity Recognition	OR1	.866	75.028	.500	101.387	1	<.001
	OR2	.866					
Experience	EX1	.899	80.825	.500	168.073	1	<.001
	EX2	.899					
Behavioral Intention	BI1	.624	73.957	.841	2271.878	15	<.001
	BI2	.680					
	BI3	.778					
	BI4	.804					
	BI5	.765					
	BI6	.787					

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