Technology in Society 71 (2022) 102108

Contents lists available at ScienceDirect

Technology in Society

journal homepage: www.elsevier.com/locate/techsoc

The mediator and moderator roles of perceived cost on the relationship between organizational readiness and the intention to adopt blockchain technology

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A R T I C L E I N F O

Keywords:
Technology readiness
Blockchain
PLS-SME
Intention to adopt
Perceived cost

A B S T R A C T

Blockchain is a disruptive technology that is expected to revolutionize the world of trusted transactions. Through a combination of cryptographic techniques, a distributed, shared, and immutable ledger, consensus validation of transactions, and a financial audit trail, blockchain is poised to do for businesses what the Internet did for communication. With its promise of reducing cost, time, friction, and fraud in business transactions and ensuring trust, identity management, and reputation management, companies around the world are now contemplating their transition to blockchain versions of themselves. However, the cost of implementing such technology and its effect on the readiness of the organization to adopt blockchain has not been fully explored yet. This study examines the mediation and moderation roles of the perceived cost on the relationship between organization readiness and the intention to adopt blockchain. Data was collected from blockchain experts and Partial least squares structural equation modeling (PLS-SEM) was used as the analytical tool to test all of the framework hypotheses. To investigate the potential managerial implications of this topic, Importance-Performance Map Analysis (IPMA) was utilized. The findings reveal that perceived cost is not a mediator; rather, it moderates the relationship between the TRI (Technology Readiness Index) enablers and the TRI inhibitors with the intention to adopt blockchain. In terms of importance, the empirical data analysis through IPMA revealed that the enablers construct is the most important factor, while perceived cost has the highest performance on the intention to adopt blockchain. With this discovery, our findings are expected to aid decision-makers in prioritizing and improving the enabling aspects required for the successful adoption of blockchain technology.

1. Introduction

A substantial digital revolution is taking place worldwide, as we navigate the industry 4.0 and digital transformation era. Therefore, organizations must adapt to change if they want to survive. One way to do so is to adapt to emerging technologies such as IoT, AI, Cloud Computing, and Blockchain. Nowadays, blockchain technology has moved into focus for many countries, entities, and organizations, since it provides an innovative way to solve current system inefficiencies. Countries such as the United Arab Emirates, United States, Australia, Estonia, Singapore, China, Georgia, and others, have started adopting this technology either experimentally or at the level of production services [1–3]. According to Jun [2], the main inducement for these countries to adopt blockchain technology is its ability to replace bureaucracy with a consensus-driven alternative. One of the countries that have taken the initiative to implement blockchain technology, is the UAE, with a plan to transfer 50% of the government's transactions to blockchain platforms by 2025 [4]. However, many challenges affect the intention to adopt and implement a process, even though blockchain may offer a solution to various problems such as lack of trust and

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https://doi.org/10.1016/j.techsoc.2022.102108
Received 23 March 2022; Received in revised form 21 August 2022; Accepted 2 September 2022
Available online 7 September 2022
0160-791X/

information security [5]. The adoption process needs fundamental changes in infrastructure, people's perceptions, and processes. These factors can be divided into institutional factors, market factors, and technical factors [6,7].

Additionally, the cost of technology implementation is considered one of the main factors impacting the feasibility of technology adoption and its usage intention [8–10]. These costs include both direct costs such as hardware, software, and installation, and indirect costs such as staff training, technology development, and the cost of the transition from the current system to a system that uses the new technology [9]. Implementation costs, on which the intention to adopt depends, are often estimated in light of previous experiences and projects. In the case of new and innovative technology, the cost of adoption is saddled by many uncertainties [11,12]. According to Haskins, Forsberg, and Krueger [13], the system requirements for innovative products undergo many changes throughout the implementation process, due to the absence of past experiences and historical data. Therefore, it is difficult to estimate the cost of such products. Ullah et al. [10] studied the Technology Acceptance Model (TAM) and cost-saving in blockchain adoption in the energy sector. The findings were consistent with the positive and significant impact of cost-saving with blockchain technology adoption. On the flip side, Pandey, Pant and Snasel [14] listed high cost of operation as one of blockchain challenges along with scalability, privacy, and interoperability, in the food supply chain sector. However, no studies about the estimated or the actual cost of blockchain adoption were found.

Another important factor that contributes significantly to the successful adoption of innovative technology is measuring the readiness of the stakeholders to deal with this technology [6,15–17]. According to Alshawi [18], readiness can be viewed as the willingness of organizations or individuals to take part in organizational development. Technology readiness refers to the capability of the organization to adopt new technology, and its ability to benefit from it [19,20]. In the latest update of the CHAOS report published by the Standish Group in 2020 investigating the failure of IT projects in the USA in different various economic sectors, it was found that only 35% of IT projects were completed without overruns, 46% were completed with cost and time overruns, and 19% were canceled before completion [21]. Lack of attention to organizational readiness and the inability to assess the readiness before implementation are among the main causes of failure for technology projects [6]. Although the literature reports some attempts to develop theoretical frameworks for the adoption of blockchain technology [7,16,22,23], blockchain technology is still immature technology; with few projects carried out [24,25]. A study conducted by Iosif et al. [24] extended a blockchain readiness index developed by Vlachos et al. [26] (referred to as the blockchain readiness score) in measuring a country's maturity/readiness levels in adopting blockchain and cryptocurrencies, while Alharbi and Sohaib [25] used TRI, PLS-SEM, and IPMA to assess which factor significantly influences the intention to adopt cryptocurrency.

To fill these gaps in technology-based research, the present study extends the previous research [7,10,22–25,27], by empirically using PLS-SEM and Importance-Performance Map Analysis (IPMA). This paper examines the readiness factors (enablers and inhibitors) that directly affect the intention to adopt blockchain technology and the indirect relationship through the perceived cost as a mediator/moderator. Given the fact that the UAE is in its early stages of blockchain implementation, it is the intention to adopt blockchain that is studied here, rather than the actual adoption of this technology. The contribution of this study can be summarized in three main points:

1. First, this study is considered, to the best of our knowledge, the only study that examines the mediating and moderating roles of the perceived cost between organization readiness and the intention to adopt blockchain, considering the lack of previous experience from which to estimate the cost of blockchain implementation [9,10].
2. Second, although the literature reports some attempts to develop theoretical frameworks for the readiness to adopt blockchain technology [7,22–25,27], few studies focus on blockchain technology adoption using the TRI scale.
3. Finally, to assess the managerial implications, we investigated the importance and performance of each factor in the readiness model using the importance-performance map analysis (IPMA) technique to complement the results of PLS-SEM.

The paper is structured as follows: section two presents the Literature review and hypotheses development. Section three details the methodology, followed by the results and data analysis in Section four. We draw our conclusions in section five.

2. Literature review and hypotheses

2.1. Blockchain technology

Blockchain technology first came to public notice in 2008 as the technology behind Bitcoin and since then has been used globally in many applications [16,28–30]. Blockchain can be described as a fully distributed digital ledger that stores data over a peer-to-peer network of computers called nodes. This ledger is replicated across all the nodes, thereby making it decentralized and preventing it from being lost [30–32]. It consists of data transaction records, which are called blocks. Each block holds a block header, a hash, a transaction counter, and its transactions [33–35]. Records in these blocks are connected to all the preceding transactions via a hash signature, similar to a chain [29,32]. Blockchain systems combine well-established techniques from cryptography and distributed systems to ensure the integrity of data, protocols for nodes to join and leave the network, mechanisms for nodes to maintain and update data collectively, and safeguards against manipulations and takeover from malicious participants [32,34,36]. Any implementation of blockchain needs to tackle these aspects. In specific implementations of blockchain platforms, each of these functionalities can be solved in different ways, which gives rise to many different variants of the technology; the most prominent among them are Bitcoin, Ethereum, and several commercial offerings. At the heart of any implementation is the choice of an appropriate and robust consensus mechanism [33,35,37].

Blockchain has many characteristics and features that define it as a technology. The most prominent of these features in the literature are the following:

- Decentralization*:* Blockchain is a peer-to-peer architecture. The state of the system is maintained collaboratively, and data in the blockchain are stored in all nodes, sometimes totaling thousands of copies [30,38].
- Trust: Blockchain eliminates the need for trust in transactions [38,39]. Every transaction is validated by the nodes without the need for a third-party facilitator [34].
- Immutability: Any modification of the data in a blockchain can quickly be detected by the nodes that constantly validate each block. Moreover, changing the data requires massive computing power, thereby making it unfeasible [30,34,40].
- Redundancy: When a new node joins the network, it saves a copy of the blocks and validates the entire chain; this provides redundancy but at the same time introduces scalability and throughput issues [30,31,41].
- Blockchain has three distinct architectures that were developed for different uses. They are mainly distinguished by how permissions are defined, how privacy and pseudonymity are managed, and what consensus protocol is employed, as follows:
- Public Blockchain (Permission-less): This type of blockchain is open to the public and fully decentralized; everyone can contribute to the network and become a user [37,39,42]. Although transactions in this

type of blockchain can be read by everyone in the network, it is almost impossible to manipulate them because the ledger is distributed in thousands of places at the same time [33,43].

- Private Blockchain (Permissioned): Unlike public blockchains, private blockchains are permissioned and prioritize known identity over anonymity and endorsement over proof of work as a transaction validation mechanism. Typically, private blockchain networks are restricted to specific stakeholders, and consist of endorsement nodes who endorse or reject transactions – thus representing some sort of centralized authority in system. A certifying authority determines what kind of permission is being given to each node [32,41,42]. This type of blockchain is more resource efficient and more responsive than public blockchains [44,45]. Although a private blockchain centralizes the endorsement of transactions to specific nodes (rather than any mining node), it uses the same concepts and consensus protocols as a public blockchain. Therefore, a private blockchain was described by some researchers as a variation of blockchain technology. However, Konashevych [46] does not consider a private blockchain as a true blockchain, but rather a type of distributed ledger, because it is not fully decentralized.
- Consortium Blockchain (Hypered): This type of blockchain is a blend of public and private blockchains: i.e., it is freely available to a certain group of users. It is partially decentralized and uses the consensus of known servers [33,37,43].

2.2. Adoption intention

Adoption intention and adoption behavior are terms often used interchangeably in the literature. Both terms are explained in the context of a consumer's purchase and where adoption intention is defined as the consumer's expressed desire to purchase new products and services in the near future, based on his perception of these products and services. However, adoption behavior is defined as the actual purchases and trials of new products and services [47,48].

Behavioral intention is generally explained by four theories called social psychology adoption theories, which are referred to as the 4T theories [49,50]. These are the theory of reasoned action (TRA) [51], the theory of planned behavior (TPB) [52], the technology acceptance model (TAM) [53], and the Triandis model of choice behavior [54]. All of these theories have been used to explain technology adoption and use; of these theories, the theory of reasoned action (TRA) has received the most attention as the basis for the TPB and TAM. The theory of reasoned action (TRA) model was developed by Ajzen and Fishbein in 1967 and later in 1980 was used to study human behavior [49,55]. It examines the behavioral intention to adopt technology through four main dimensions, namely, behavioral attitudes, subjective norms, intention to use, and actual use [55,56]. However, the TAM is considered the most often used model for explaining technology adoption through the intention to use and actual use [57,58].

Davis et al. [59] have explained the behavioral intention in the context of computer-based technology acceptance using the TRA model as the strength of someone's intention to use this technology. Zuiderwijk, Janssen, and Dwivedi [60] elaborated on this explanation, to include planning, prediction, and the use of the technology in addition to mere intention.

2.3. Blockchain adoption

The adoption of any new technology is driven by the aim of generating value either for the customer or for the organization itself, and blockchain technology is not different from that [61]. Blockchain has evolved rapidly throughout the years and with the evolution of its technological aspects, the value created by blockchain has evolved as well [27]. When talking about blockchain, often all the concentration in literature is directed toward its design and features, neglecting the value created by this powerful technology [22]. The value created through the adoption of blockchain together with the cost associated with this adoption are among the most controversial topics regarding blockchain implementation [22].

Although blockchain technology is still in its early stages, some researchers have studied the factors influencing the intention to use it or adopt it in disciplines such as finance, the supply chain, and hospitality [62–67]. For example, Lee, Kriscenski, and Lim [65] studied the intention to adopt blockchain using the unified theory of acceptance and use of technology (UTAUT) model and found that operational usefulness and perceived ease of use positively influence the intention to adopt blockchain. Another study using the UTAUT model was conducted by Heidari et al. [68], in which the authors examined the factors affecting the intention to adopt blockchain specifically in the financial sector, using blockchain as a financial instrument. They found a positive direct relationship between initial trust, task technology fit, and performance expectancy. Similarly, Chang et al. [69] investigated blockchain adoption in the tourism industry using the UTAUT model and found that trust transparency has the biggest effect on the system's performance.

Shin [63] took this avenue of research a step further and explored the features of blockchain that most influence the intention to adopt it; he then proposed for this purpose a model linking trust, security, and privacy. He also empirically verified the positive relationship between them.

Blockchain is an emerging technology, therefore many authors have attempted to develop frameworks that explain the value that blockchain can add to the organization when adopted while others have chosen to step one step ahead and create a framework for the technology adoption itself. Risius and Spohrer [22] have proposed a framework that assesses the adoption of blockchain type that best fits the requirement of the service by analyzing the value generated from each feature or enabler upon the implementation together with the feasibility and viability of the implementation and linking that with the appropriate technology that can be integrated. Another framework was proposed by Oguntegbe, Paola, and Vona [70] to asses blockchain implementation in the agri-food supply chain. They linked organizational adoption strategies, technical benefits, and environmental barriers to blockchain adoption intention.

A more focused approach was embraced by Janssen et al. [7] where they introduced a framework that divides the factors affecting the adoption of blockchain from an organizational perspective. They divided these factors into three main categories, which are: institutional factors (e.g. culture, regulations, and governance), market factors (e.g. contracts and business processes), and technical factors (e.g. Information exchange and shared infrastructure). From the same perspective, Prasad et al. [23] have identified and analyzed different critical success factors (CSFs) which determine the success of the adoption of blockchain-based cloud services. They identified 19 CSFs and analyzed the relationship between them using total interpretive structural modeling (TISM) and found that Regulatory clarity, industry collaboration, leadership readiness, and technology investment and maturity are the main drivers for the success of adopting blockchain technology for cloud services.

Few studies investigated the direct impact of cost on Blockchain adoption. For instance, Ullah et al. [10] research focused on cost savings resulting from the use of distributed ledger technology and argued that cost saving shows a direct positive effect on perceived ease of use and perceived usefulness of the technology. AlShamsi et al. [143] presented a review of the literature on Blockchain adoption. Their review showed that trust in the technology, perceived cost, and social influence were among the key factors influencing the adoption of Blockchain. Other highlighted influencing factors included facilitating conditions and performance expectations. Unlike existing studies that focus on cost-saving potential and its direct impact, in this work, we conduct a blockchain technology adoption study focusing on mediation effects towards decision-making. More specifically, we investigate the mediating and moderating roles of perceived cost on the intention to adopt blockchain technology for organizations in the UAE. This angle brings novel insights and recommendations related to Blockchain adoption.

2.4. Technology readiness index

The Technology Readiness Index was introduced by Parasuraman in 2000 to measure individuals' belief in emerging technologies [71,72]. The concept of technology acceptance was introduced many years before the development of Parasuraman's TRI model. However, Parasuraman put the concept together from previous studies and designed it as a way of measuring how people act, react and adapt to new technologies [57,71]. Initially, the TRI model scale consisted of 36 attributes; however, later on, it was shortened to 16 attributes in the updated version of TRI 2.0, which was proposed after almost a decade by Parasuraman and Colby [73]. The authors justified the need for this updated version of TRI in light of the evolution of current technologies and the emergence of the new technologies that had started to impact people's lives, such as social media, mobile commerce, and cloud computing. The literature soon recorded the need for a shorter version that would allow researchers to measure other constructs that were not present in the original TRI model. Both TRI 1.0 and TRI 2.0 have four main dimensions, namely, innovativeness and optimism, which represent TRI enablers, and discomfort and insecurity, which represent TRI inhibitors [72,73].

2.4.1. TRI enablers

TRI enablers (ENs) occupy the positive side of the TRI model, its innovativeness and optimism, and are sometimes referred to as TRI motivators [71]. These enablers represent variables that positively contribute to the individual's technology readiness [73]. According to Parasuraman and Colby [69, P. 2], optimism is defined as "a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives". Optimism is seen as a direct influence of behavioral intention. It is often considered a reflection of a positive attitude toward technologies, which results in a higher value creation perspective for new technologies [72,74]. Optimism is also linked with productivity; it has been observed that optimistic technology users are often convinced that new technologies will help them do the work faster or with less effort, which consequently increases adoption [74,75,76].

The other construct that forms TRI enablers is innovativeness, which was defined by Rogers and Shoemaker [71, P. 27] as "the degree to which an individual is relatively earlier in adopting an innovation than other members of his system". A more recent definition was provided by Parasuraman and Colby [73]; i.e., "a tendency to be a technology pioneer and thought leader." They have also added to that definition the desire to learn, experiment, and talk about these technologies. According to Ismail and Wahid [57], innovators are more open to trying new technologies. Not only are they early adopters of new technologies, but they also motivate and persuade others to adopt them too. This is attributed to the innovativeness trait that urges innovators to explore new technologies, services, and products [74]. People with strong innovativeness traits often like to share their experiences and give advice regarding new products and services. This results in other people being more attracted to acquiring these new products and services and adapting to new technologies [57,73]. Therefore, we hypothesize the following:

H1. *TRI enablers (innovativeness and optimism) are positively related to the intention to adopt blockchain technology.*

2.4.2. TRI inhibitors

TRI inhibitors negatively affect adoption and weaken adoption; in other words, they detract from technology readiness. TRI inhibitors include discomfort and insecurity [25,73]. Parasuraman [71] associated discomfort with the lack of perceived control and the feeling of being overwhelmed by technology. The discomfort originates from the prejudice that people have against new technologies when they believe them to be complicated and perceive them as difficult to adopt [57]. Moreover, perceived control is considered a direct determinant of behavioral intention and behavioral use in the theory of planned behavior. Therefore, discomfort can be seen as a direct inhibitor of the intention to adopt technology since it results in the loss of control.

The second construct that was presented by Parasuraman [71] as an inhibitor is insecurity. Insecurity is defined as the skepticism and distrust that people have of a technology and the way that it operates, which prevent them from embracing it [25,73]. Although discomfort and insecurity might appear the same, they are fundamentally different. Discomfort is related to the physiological and mental status of the users, such as anxiety and the perception of difficulty [57]. Insecurity is more concerned with the transition associated with the adoption of a technology and the uncertainty around it, such as the way it operates, the safety aspects, and the lack of trust. However, the feeling of insecurity that technology users have usually evolves from a feeling of anxiety to a feeling of pessimism. It originates from anticipating the harm that can be caused by adopting this new technology and results in a negative effect on its perceived value and usefulness [72]. Thus, we hypothesize the following:

H2. *The TRI inhibitors (discomfort and insecurity) are negatively related to the intention to adopt blockchain technology.*

2.5. Perceived cost

One of the critical factors that influence system adoption is the cost factor [77–79]. In the adoption of any new technology, two cost factors play an important role in the intention to adopt it, namely, perceived cost and cost savings [80–82]. These two cost factors have the opposite effect on the intention to use. For instance, the greater the perceived cost of adopting the technology is, the lower the intention to adopt it. In contrast, the more cost is saved by adopting technology, the greater the intention to adopt it is [79,80,83]. According to Neuburger [75, P. 370], the perceived cost of an activity can be defined as "the unit cost which a consumer thinks he incurs by undertaking a particular activity". This activity may adopt a technology that can incur many costs, such as planning, hardware, installation, and training [82]. Perceived cost is a very important determinant for sustaining a business and for enabling it to compete in the market. In blockchain adoption, substantial start-up costs must be invested, especially in IT-related preparations for blockchain technology [84]. Operational-wise, Osmani, et al. [83] have divided the cost of operating blockchain in the financial sector into three main costs: transaction, energy, and storage costs. Before actual adoption, the cost incurred by adopting blockchain and the cost-saving results from blockchain adoption should be compared; this is particularly helpful for its success.

Several researchers have studied the cost-saving effect resulting from the adoption of technology, while others have studied the perceived costs of doing so. For example, Ko, Lee, and Ryu [84] studied the cost-saving results from the adoption of blockchain technology in manufacturing firms and found that adopting blockchain improves their profitability and competitiveness. In contrast, AlSoufi and Ali [85] studied the perceived cost of adoption of mobile banking and considered it a barrier to its adoption. Later, Al-Saedi et al. [86] investigated the effect of perceived cost on mobile payment and found that perceived cost is negatively affecting mobile payment adoption. Further, Bello, Bhatti, and Alshagawi [82] studied the effect of perceived cost on E-learning adoption and found a significant relationship between them. Based on the above, we hypothesize the following:

H3. *Perceived cost is negatively related to the intention to adopt blockchain technology.*

2.6. Perceived cost and TRI enablers

Innovativeness often requires generous investment in oneself, the process, the service, or the product. Such investment can be perceived as an additional cost that is incurred when adopting new technology. Being eager to learn, teach, or follow the latest technological trends usually comes at a high financial cost, which increases as the complexity of the innovative technology increases [87,88]. Therefore, the more innovative a person is, the higher the perceived cost of keeping up with new technology is.

The other TRI enabler that influences the perceived cost is optimism. People often tend to spend more when they are optimistic. They make decisions informed by this optimism without calculating the gains and losses, decisions that usually depend on a false estimation of cost [72,89]. This phenomenon, called the planning fallacy, was proposed by Kahneman and Tversky [90]. It predicts optimism bias in completing a task or a project as a result of incorrect time estimation, which results in higher overall costs. These higher costs are generated from the additional resources that need to be allocated to finish the project or, in our case, to finish the project of adopting blockchain technology [91]. From the above points, we hypothesize the following:

H4. *TRI enablers (innovativeness and optimism) are positively related to the perceived cost of blockchain technology.*

Innovativeness as a trait plays a major part in any innovation adoption, and many variables contribute to it, such as the socioeconomic variables represented by income and upward social mobility. These two variables are particularly important when we link innovativeness with cost [92]. According to Arts, Frambach, and Bijmolt [87], the perceived cost of adopting innovation may impact adoption behavior heavily since some behavioral changes are required to adjust to this innovation. The more complex the innovation, the higher the perceived cost associated with the learning expenses of the innovation. This inhibits the behavioral intention of adoption because the behavior change becomes less feasible with these increased costs [87,93]. Similarly, optimism influences the adoption behavior regarding innovation. While optimism may show a higher tendency to intend to adopt, perceived cost becomes an issue that keeps this adoption from taking place, especially with an optimism bias [89,91]. Thus, we hypothesize the following:

H5. *The relationship between TRI enablers (innovativeness and optimism) and the intention to adopt blockchain technology is moderated by the perceived cost.*

H6. *The relationship between TRI enablers (innovativeness and optimism) and the intention to adopt blockchain technology is mediated by the perceived cost.*

2.7. Perceived cost and TRI inhibitors

Discomfort is often associated with anxiety, difficulty, and the feeling of being overwhelmed when dealing with anything new, including new technologies [25,71]. This is a natural reaction to the unknown among human beings. To reduce this difficulty and anxiety, something must change: i.e., one must either adapt to this new technology, which includes a change in perception and behavior, or switch to another technology. Both options involve economic and psychological costs that result from this discomfort [94]. For instance, changing the perception of difficulty and anxiety in dealing with a new technology requires training and takes up much time. These two requirements incur additional costs for the new technology [10,81]. In addition to the cost of the substituted technology, returning to the original technology as a result of discomfort and anxiety results in additional costs such as re-installation and re-planning. According to Ashurst, Doherty, and Peppard [95], investments in information systems in the past 30 years have a generally low success rate. This level of failure is explained by innovation resistance theory (IRT), which states that resistance to innovation may be a result of rational thinking about the change requirements from the current status to the new status of adoption [96,97]. This change can bring discomfort and anxiety when dealing with innovative technologies such as blockchain. Therefore, the higher the discomfort felt about blockchain technology, the higher the perceived cost associated with its adoption and the intention to adopt it. Thus, we hypothesize the following:

H7. *The TRI inhibitors (discomfort and insecurity) are positively related to the perceived cost of blockchain technology.*

H8. *The relationship between the TRI inhibitors (discomfort and insecurity) and the intention to adopt blockchain technology is moderated by the perceived cost.*

H9. *The relationship between the TRI inhibitors (discomfort and insecurity) and the intention to adopt blockchain technology is mediated by perceived cost.*

Based on the hypotheses developed from the literature review, the conceptual model depicted in Fig. 1 was constructed, which shows the relationship between the two dimensions of TRI, where perceived cost moderates/mediates the relationship between the intention to adopt blockchain and the enablers and inhibitors of adopting it.

3. Research methodology

3.1. Study instrument

A multiscale questionnaire based on the literature was developed as the tool for quantitative analysis. It used a 5-point Likert scale ranging from "1- strongly disagree'' to "5-strongly agree". To ensure the reliability and validity of the questionnaire, scales from previous studies were used and modified as necessary. The scale for measuring organization readiness was adopted from the Technology Readiness Index (TRI 2.0) developed by Parasuraman and Colby [73]. The scale for the perceived cost construct was adopted from Naicker et al. [98], and the scale for the intention to adopt construct was adopted from Nuryyev et al. [67].

The questionnaire was built using an online platform and distributed via a link to targeted respondents through their email accounts; the response rate was increased by subsequent reminders. The questionnaire started with a brief

Introduction about the research project, which assured the participant of the confidentiality and anonymity of the collected data. The questionnaire was divided into two sections. First, demographic data were collected. The second was divided into four subsections, namely, blockchain readiness, enablers and inhibitors, the perceived cost of blockchain adoption, and finally the intention to adopt blockchain

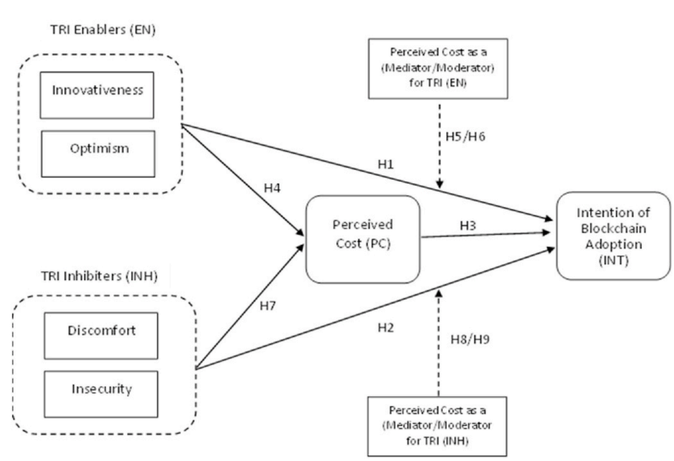


Fig. 1. Proposed conceptual model.

technology.

Before the questionnaire was distributed, a pilot study to test the instrument on a sample of 10 respondents from both academic and professional backgrounds was conducted, as recommended by Hassan and Mazza [99]. As a result, some questions were revised and reworded.

3.2. Sample size

The sample frame for this study included experts from information technology organizations considering the adoption of blockchain technology from both the public and private sectors. A nonprobability convenient sampling technique was used for the targeted respondents from a database of an IT company in the UAE. The final survey was sent to a total sample of 240 potential respondents through LinkedIn and email accounts. A response rate of 42% was achieved, with 101 complete responses in total.

3.3. Statistical analysis tool

Structural equation modeling (SEM) was chosen as the quantitative tool of analysis because this method provides a well-established means of analysis [100]. According to Hair et al. [101], this technique is able to perform multivariable regression for conformity and exploratory research questions. A partial least square (PLS-SEM) type was chosen because it provides flexibility in terms of the type of data and the examination of complex associations [102]. PLS-SEM is a method that uses the weighted composites of construct variables to account for the measurable error without prior distributional assumptions about the data. Moreover, PLS-SEM provides the relationship significance of the constructs to evaluate how the model is performing [103,104].

The Importance-Performance Map Analysis (IPMA) was also used to provide more insights regarding the importance of each construct regarding the intention to adopt blockchain. According to Ringle and Sarstedt [105], combining PLS-SME with IPMA offers deeper insights into the impacts of certain factors on a specific behavior (in this case the intention to adopt blockchain). IPMA enables us to identify the important factors but is weak in enabling us to improve them and prioritize managerial actions. However, it allows us to investigate the importance and performance at the indicator level, which helps identify the individual critical factors for the improvement of the antecedent constructs [106]. IPMA is a two-dimension matrix that considers the average latent variable score of the construct for the performance and the total effect of the construct for the importance [105,107]. In this research, SmartPLS (V3) was used to perform our PLS-SEM and IPMA analysis.

4. Results and data analysis

The first step in the analysis was to examine the data for any duplicate or incomplete responses. This resulted in the deletion of two responses that were found to be duplicated, thus reducing our analyzed responses from 101 to 99. Table 1 shows the demographic results of the respondents, which confirms the variety of the sample in terms of gender, educational level, and employment sector. The age of most respondents ranged between 25 and 44 years. In terms of technology fluency, 90.91% of the respondents reported working in a technology-related field, which confirms their knowledge and involvement in new technology trends. Moreover, most of the respondents were found to be either pioneers or explorers in terms of their knowledge of new technologies, the latter having the highest percentage of 85.86%.

To test our hypotheses and the proposed model, two types of assessment were conducted following the recommendations of Hair et al. [104]; namely, measurement model assessment, which is used to examine the relationship of each construct with its latent variable, and structural model assessment, which is used to determine the significance of the variables [101].

Table 1
Respondents' demographic characteristics.

Demographics	Frequency	Percentage
Gender		
Female	53	53.54%
Male	46	46.46%
Age Group		
over 55	1	1.01%
45–54	2	2.02%
35–44	28	28.28%
25–34	62	62.63%
18–24	6	6.06%
Current Employment Status		
Employee-Private Sector	71	71.72%
Employee-Public Sector	20	20.20%
Self-employed	8	8.08%
Highest Educational Level Achieved		
Doctoral Degree	9	9.09%
Master's Degree	71	71.72%
Bachelor's Degree	19	19.19%
Current Professional Role Is Technology Related		
Yes	90	90.91%
No	9	9.09%
Knowledge of Technology		
Pioneer	9	9.09%
Explorer	85	85.86%
Hesitater	5	5.05%

4.1. Measurement model assessment

This paper examined technology readiness from two dimensions, TRI enablers, and TRI inhibitors. We analyzed our model combining optimism and innovativeness as TRI enablers, and discomfort and insecurity as TRI inhibitors. The dimensionality of TRI constructs has been a question in the literature, where it is unclear if the conceptualization of TRI is best captured by all four dimensions of the TRI model, by two dimensions (enablers and inhibitors), or by one dimension as an overall composite [72]. According to Parasuraman and Colby [73], an individual may praise and fear a technology simultaneously, which influences her or his technology readiness. Therefore, they have analyzed the TRI model in four dimensions since each construct of TRI is considered unique. However, many researchers have found that innovativeness and optimism often manifest the same behavior when tested with behavioral intention. This observation also applies to the discomfort and insecurity dimensions [108–111]. Nevertheless, according to Edwards [112], first-order models give a stronger explanatory power than models of higher-order in the context of organizational behavior and social psychology. The same conclusion was reached by Gounaris and Koritos [113] when they studied the factors affecting the adoption of internet banking. Therefore, because blockchain is still considered to be in its early stages, it is more effective to study the effect of TRI negative and positive traits as two dimensions only, since it makes the overall constructs more reliable and the predictive power stronger [72].

The model was assessed by checking the construct's reliability, internal consistency, convergent validity, and discriminant validity. Parasuraman [71] found some reliability issues for the insecurity construct; i.e., it had the lowest reliability coefficient of all the TRI constructs. During the initial assessment, it was found that the insecurity construct suffers from reliability issues where the thresholds of the indicator's factor loading were found to be below 0.30, which is less than our threshold of 0.50 as recommended by Hulland [114]. Composite reliability (CR) thresholds of >0.70 recommended by Fornell [115] were also found not fulfilled. Similar results were reported in the literature, such as:

1. Alharbi and Sohaib [25] studied the effect of technology readiness on cryptocurrency adoption. They ranked the TRI constructs in terms of importance and impact using three different statistical methods; namely, PLS-SEM, Importance Performance Mapping (IPM), and

Artificial Neural Network (ANN). They found that insecurity was the least important construct out of the four TRI constructs when using PLS-SEM and IPM. Moreover, it ranked second before last when using ANN analysis.

2. In a study examining the influence of technology readiness on entrepreneurial orientation conducted by Penz et al. [116], it was found that insecurity and discomfort constructs were weak, and therefore they were omitted from the model keeping only innovativeness and optimism. Insecurity and discomfort were both found unreliable in a study conducted by Liljander et al. [109], which investigated the adoption of self-service technologies.

In our case, the technical characteristics associated with managing trust and ensuring security are very prominent in the blockchain discussion. In this context, trust refers to how blockchain eliminates the need for a mediator or trusted third party, and security refers to the cryptographic algorithms and consensus mechanisms that ensure data integrity and resistance to manipulation [30,33,39,117]. However, this language clashes with the TRI construct term "insecurity," highlighting the trust factor and its role in the adoption process. Although the TRI measures the perception of the adopters of a particular technology and not the level of information security that this technology provides, keeping the insecurity construct might have created confusion for the respondents, especially since most of them are familiar with it. This might have led to a false estimation of the statistical power of this construct. Therefore, the insecurity construct was dropped from our model, keeping only discomfort as a measurement of TRI inhibitors.

To determine constructs' reliability, factor loading (FL) was checked for each construct. According to Hulland [114], a threshold of >0.50 is considered acceptable. All the constructs fulfilled this requirement except for (INT2, INT3) from intention to use, (INO4, OPT2) from TRI Enablers, (DISC2) from TRI Inhibitors, and (PC3) from Perceived Cost. These constructs were removed from the model, as recommended by Hair et al. [118] because they were considered weak. The measurement model was then run again. It was found that all the constructs met the threshold, as shown in Table 2. Furthermore, composite reliability (CR) with a threshold of>0.7 [119], reliability coefficient (rho_A) with a threshold of >0.6 [101], and Cronbach's alpha (Cα) with a threshold of>0.50 [120] were tested to check the internal consistency and reliability. Composite reliability (CR) measures the reliability of the constructs by using standardized loading, whereas the reliability coefficient (rho_A) uses unstandardized loading for the constructs [101]. Average variance (AVE) with a threshold of >0.50 [120] was also tested to check the convergent validity. Convergent validity is measured to determine the model's ability to explain the variance in its constructs [121]. Table 2 shows the results of the measurement model assessment, where all the requirements were fulfilled.

Discriminant validity was also assessed following the Fornell-Larcker criteria by examining the average variance (AVE) [119]. It was found that the AVE square root for any construct exceeded any correlation between any two other constructs, as shown in Table 3.

The Heterotrait-Monotrait ratio (HTMT), developed by Ref. [122] was used to confirm the discriminate validity further. For a well-fitting model, the ratio of Heterotrait correlations (between indicators of different constructs) and Monotrait correlations (between indicators of the same construct) should be below 1 [123]. All the correlations fulfilled the threshold of <0.90, which was recommended by Henseler et al. [122], as shown in Table 4.

Table 3
Fornell-Larcker discriminant validity.

Variable	Indicator	FL	Cα	Rho_A	CR	AVE
Intention to adopt (INT)	INT1	0.927	0.811	0.819	0.913	0.840
	INT4	0.906				
Enablers (EN)	INNO1	0.703	0.789	0.817	0.835	0.500
	INNO2	0.500				
	INNO3	0.804				
	OPT1	0.723				
	OPT3	0.655				
	OPT4	0.774				
Inhibitors (IN)	DISC1	0.842	0.709	0.726	0.835	0.629
	DISC3	0.734				
	DISC4	0.800				
Perceived Cost (PC)	PC1	0.927	0.521	0.600	0.800	0.669
	PC2	0.906				

4.2. Structural model assessment

After confirming the reliability and validity of the measurement model, the model itself was assessed for structural modeling to determine the significance of the variables. The collinearity assessment for the model was tested by examining the variance inflation factor (VIF) to test the linear association between the constructs. All the constructs were found to meet the threshold of the VIF value of less than 5, as recommended by Hair et al. [104], and as shown in Table 6. Fig. 2 depicts the measurement model assessment results.

In addition, the capabilities and relationships between the constructs were tested using R^2 (coefficient of determination), Q^2 (predictive relevance), and f^2 (effect size). According to Hair et al. [101], the coefficient of determination (R^2) can be categorized as a weak, moderate, or strong coefficient, with values of 0.25, 0.50, and 0.70 respectively. The coefficient of determination (R^2) was found to be 0.532 for the intention to adopt blockchain, which indicates that the enablers, inhibitors, and perceived cost moderately explain 53.20% of the variance in this intention. Similarly, R^2 was found to be 0.483 for perceived cost, which indicates that both TRI enablers and TRI inhibitors explain moderately 48.30% of the variance in it. Stone-Geisser's predictive relevance (Q^2) assessment was also conducted to check the accuracy of prediction for the model constructs. The blindfolding technique in SmartPLs was used in this test. Table 5 shows the results, where both latent variables (INT and PC) show a Q^2 of more than 0 as recommended by Chin [120].

According to Khalizadeh and Tasci [121], it is important to look at the effect size (f^2) of the relationship between the variables, which measures the relationship quantitatively. According to Cohen [124], the interpretation of the effect size can be divided into three main degrees; namely, small effect, moderate effect, and large effect, with values of 0.02, 0.15, and 0.30, respectively. In the proposed model, the effect size of the TRI enablers (EN) construct shows a large effect on the intention to adopt blockchain (INT) ($f^2 = 0.4619$), whereas it has a small effect on perceived cost (PC) ($f^2 = 0.1322$).

In contrast, TRI inhibitors (INH) have a small effect on the intention to adopt blockchain (INT) ($f^2 = 0.0200$) and a moderate effect on perceived cost (PC) ($f^2 = 0.2562$). It was also found that the perceived cost does not affect the intention to adopt blockchain (INT) ($f^2 = 0.0017$)

Table 2
Factor loading, reliability, internal consistency, and validity.

Variable	(INT)	(PC)	(EN)	(IN)
Intention to adopt (INT)	0.917			
Perceived Cost (PC)	0.491	0.818		
Enablers (EN)	0.718	0.593	0.698	
Inhibitors (IN)	0.525	0.644	0.593	0.793

Table 4
HTMT discriminant validity.

Variable	(INT)	(PC)	(EN)
Intention to adopt (INT)			
Perceived Cost (PC)	0.708		
Enablers (EN)	0.859	0.807	
Inhibitors (IN)	0.710	0.801	0.844

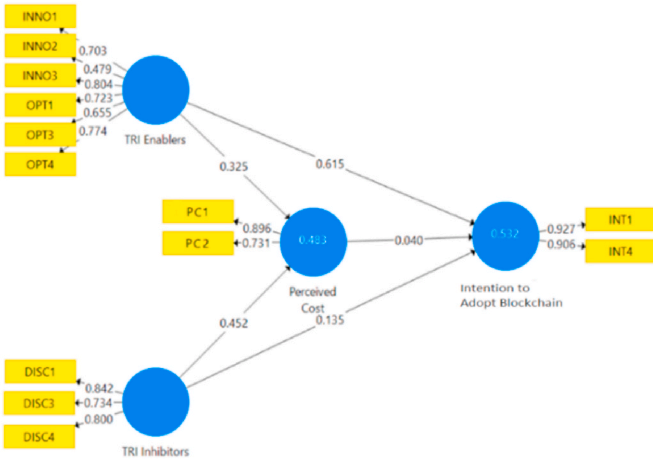


Fig. 2. Measurement model assessment results.

Table 5
Coefficient of determination and predictive relevance.

Variable	Coefficient of Determination (R^2)	Predictive Relevance (Q^2)
Intention to adopt (INT)	0.532	0.415
Perceived Cost (PC)	0.483	0.293

because it does not meet the minimum effect size of 0.02 as shown in Table 6.

Bootstrapping technique was used and a bootstrapping sample of 5000 bootstraps was evaluated, as recommended by Henseler et al. [125]. According to Streukens and Leroi-Werelds [126], bootstrapping is a non-parametric resampling procedure that determines the precision of estimation by examining the variability of the data. The bootstrapping results indicate that most of the hypotheses were supported. Hypotheses H1, H4, and H7 were found to be significant because they satisfied the threshold recommended by Hulland [114], by obtaining a T-value >1.96 and a P-value <0.05. Hypotheses H2 and H3 were found to be not significant; they did not satisfy the threshold for significance noted above and as shown in Table 7. Fig. 3 shows the structural model assessement results.

4.3. Mediating effect

The mediating effect of perceived cost (PC) with TRI enablers (EN) and TRI inhibitors (INH) on the intention to adopt blockchain (INT) was tested. The test was conducted following Preacher and Hayes's [127] procedure, where the significance of the direct and indirect effects of the mediator variable (PC) was calculated using the bootstrapping technique. Zhao, Lynch, and Chen [128]. proposed a model based on Baron and Kenny's procedure [129] classifying moderation into five types depending on the significance of the indirect effect, the significance of the direct effect, and the product direction (sign) of the constructs involved in the mediation. These types are:

Table 6
Collinearity assessment and effect sizes.

Hypothesis	Path	Inner Collinearity (VIF)	Effect Size (f^2)
H1	EN → INT	1.747	0.462
H2	INH → INT	1.938	0.020
H3	PC → INT	1.936	0.002
H4	EN → PC	1.543	0.132
H7	INH → PC	1.543	0.256

1. No mediation (no effect): if both the indirect effect and the direct effect are not significant
2. No mediation (direct relationship only): if the indirect effect is not significant but the direct effect is significant.
3. Full mediation: if the indirect effect is significant but the direct effect is not significant.
4. Partial mediation (competitive): if both the indirect effect and direct effect are significant but the product sign is negative
5. Partial mediation (complementary): if both the indirect effect and direct effect are significant but the product sign is positive.

The results show that the indirect effect of TRI enablers (EN), on the intention to adopt blockchain (INT) through perceived cost (PC) (EN→PC→INT) was not significant (T = 0.372, P = 0.327). However, TRI enablers (EN) have a significant direct effect (EN→INT) of (T = 6.836, P = 0.000) on the intention to adopt blockchain (INT). Therefore, no mediation effect for the perceived cost (PC) was observed between the TRI enablers (EN) and the intention to adopt blockchain (INT). It was also found that the indirect effect of TRI inhibitors (INH), on the intention to adopt blockchain (INT) through perceived cost (PC) (INH→PC→INT) was not significant (T = 0.372, P = 0.327). Moreover, the significance of the direct effect on the intention to adopt blockchain (INT) was not fulfilled for the TRI inhibitors (INH) (T = 1.419, P = 0.078); therefore, no mediation effect occurred [130]. Because of these findings, neither H5 nor H8 was accepted. Table 8 shows the mediation test results.

4.4. Moderating effect

The moderating effect of the perceived cost (PC) variable on the relationship between TRI enablers (EN) and TRI inhibitors (INH) and the intention to adopt blockchain (INT) was tested following the recommendation by Hair et al. [104], and Henseler and Chin [131]. They recommended a two-stage moderation approach if the test aimed to determine the significance of the relationship and when the moderator or the dependent variable or both are formative.

The two-stage approach is carried out in two steps, hence the name. These steps are:

1. The latent variables' scores' significance is estimated and calculated in the first stage.
2. In the second stage, the interaction term for each element between the moderator and the latent dependent variable is estimated, and the scores are used in a multiple-liner regression on the independent variable.

The model was run in Smart PLS first without the moderation relationships to estimate the latent variable scores and the second time with the moderation relationships to estimate the interaction term scores; all the scores for both situations were recorded. According to Baron and Kenny [129], a moderating relationship exists if the interaction's path coefficient (β) is significant. Moreover, the strength of this significant relationship needs to be assessed. R2 was found after adding the moderation effect (R2 = 0.565), which increases from the R2 of the model without the moderation effect (R2 = 0.532). This finding indicates that the moderation imposed an increase in the explained variance of approximately 0.033, representing an increase of 6.23% on the original model.

The second step in the moderation assessment was to determine the effect size of the moderating relationship by calculating the effect size (f2). According to Ref. [132], the effect size can be calculated through the following formula:

$$f^2 = \frac{R^2_{with\ moderation} + R^2_{without\ moderation}}{1 - R^2_{with\ moderation}}$$

Table 7
Hypothesis testing results.

Hypothesis	Path	β	T-vale	P value	Significance
H1	EN→INT	0.615	6.836	0.000	Significant
H2	INH→INT	0.135	1.419	0.078	Non-Significant
H3	PC→INT	0.040	0.3347	0.364	Non-Significant
H4	EN→PC	0.325	3.416	0.000	Significant
H7	INH→PC	0.452	4.555	0.000	Significant

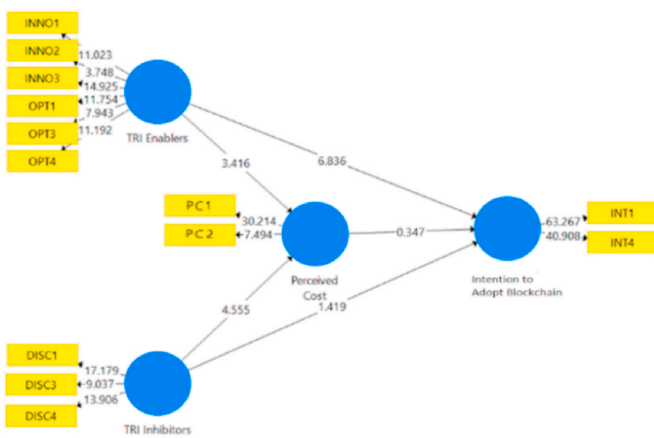


Fig. 3. Structural model assessment results.

$$= \frac{0.565 - 0.532}{1 - 0.565} = 0.076$$

Aguinis et al. [133] recorded in their research that the average effect size when testing moderation was found to be 0.009. Based on this, Kenny [129] proposed values of 0.005, 0.01, and 0.025 as small, medium, and large effects, respectively, since these numbers present more realistic values than those proposed by Cohen [124] for the effect size, especially when testing the moderation effect [134]. However, we follow the recommendations of Cohen [124] for the effect sizes, because they provide more reliable values. Our model effect size ($f2 = 0.076$) lies between 0.02 and 0.15, which according to Cohen [124] is considered a small effect.

To confirm the significance of the moderation, the bootstrapping technique was used again for the model with the moderation effect. Table 9 shows that both moderation effects PC*EN ($T = 2.1654$, $P < 0.05$) and PC*INH ($T = 2.7922$, $P < 0.01$) were statistically significant. Fig. 4 depicts the moderation effect results.

4.5. Importance-performance map analysis (IPMA)

The Importance-Performance Map Analysis (IPMA) was performed based on the recommendations of Ringle and Sarstedt [105]. They set up three main requirements for a successful analysis using IPMA, as follows:

1. The scale used for data gathering should be a quasi-interval scale such as the Likert scale.
2. The coding for all indicators must have the same scale direction, where the minimum score
3. Represents the worst result, and the highest score represents the best result.
4. The outer weight for all the indicators should be positive.

The model was run after confirming the fulfillment of all of the above requirements. The analysis of the Importance-Performance Map was applied to the four constructs and their indicators in the model. At the construct level, Table 10 shows that the Perceived cost (PC) construct had the lowest importance but the highest performance on the intention to adopt blockchain (INT). Similarly, the TRI inhibitors (INH) construct had a relatively high performance but low importance. Conversely, the TRI enablers (EN) construct had shown very high importance, but its

Table 9
Moderating assessment results.

Hypothesis	Path	Coefficient (β)	T-Value	P value	Significance
H1	EN → INT	0.567	5.829	0.000	SIGNIFICANT
H2	INH → INT	0.232	2.056	0.020	SIGNIFICANT
H3	PC → INT	0.047	0.445	0.328	NON-SIGNIFICANT
H4	EN → PC	0.325	3.458	0.000	SIGNIFICANT
H6	PC*EN → INT	- 0.196	2.080	0.019	SIGNIFICANT
H7	INH → PC	0.452	4.480	0.000	SIGNIFICANT
H9	PC*INH → INT	0.261	2.570	0.005	SIGNIFICANT

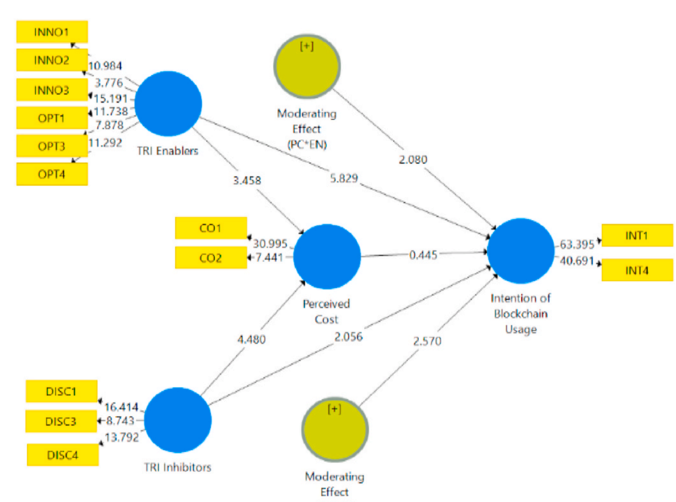


Fig. 4. Moderating assessment results.

Table 8
Mediation test results for the perceived cost construct.

Hypothesis	Path	Effect	β	Mean	STD.DEV.	T-Value	P-Value	Significance	Mediation type
H5	EN → INT	Direct	0.615	0.632	0.089	6.836	0.000	Significant	No Mediation (Direct only)
	EN → PC → INT	Indirect	0.013	0.016	0.054	0.327	0.372	Non-Significant	
H8	INH → INT	Direct	0.135	0.129	0.097	1.419	0.078	Non-Significant	No Mediation (No-Effect)
	INH → PC → INT	Indirect	0.018	0.010	0.039	0.330	0.371	Non-Significant	

Table 10
IPMA results at construct level.

Construct	Importance (Total Effect)	Performance (Laten Variable Score)
Perceived Cost (PC)	0.045	86.901
Enablers (EN)	0.620	75.765
Inhibitors (IN)	0.153	78.393

performance was lower than PC and INH, as shown in Fig. 5 (a). Table 11 shows the ranking of the constructs in PLS and IPMA according to their importance.

At the indicator level, and in terms of performance, it was found that PC1 followed by DIS4 had the highest performance. The lowest performance was recorded for INNO2 and INNO3, in that order. In terms of the importance, the highest importance was OPT4 followed by OPT1, whereas the lowest importance was conferred on PC1 and PC2, in that order, as shown in Fig. 5 (b). Table 12 shows the results of IPMA analysis at the indicator level.

Table 11
Ranking in PLS-SEM and IPMA at the construct level.

Construct	PLS-SEM	IPMA
Perceived Cost (PC)	3	3
Enablers (EN)	1	1
Inhibitors (IN)	2	2

Table 12
IPMA results at the indicator level.

Indicator	Importance	Performance
INNO1	0.084	71.97
INNO2	0.051	51.01
INNO3	0.109	52.374
DISC1	0.049	70.202
DISC3	0.034	67.172
DISC4	0.068	90.404
PC1	0.032	89.899
PC2	0.031	79.293
OPT1	0.114	85.354
OPT3	0.1	82.828
OPT4	0.162	83.333

5. Discussion and implications

The UAE was among the first nations to express its intention to adopt blockchain at the government level, as part of its vision to become one of the smartest countries in the world. Many initiatives have been launched to pursue this vision, such as the Emirates Blockchain Strategy 2021 [4]. This initiative sets the tone not only for the public sector but also for the private sector and the interaction between the public and private sectors.

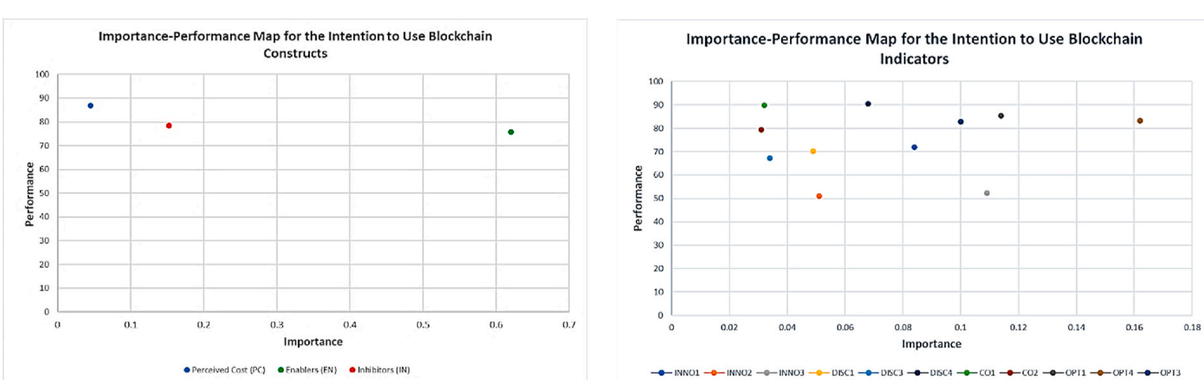
This study presents insights on the impact of perceived cost on the intention to adopt blockchain technology by organizations in the UAE, and provides several theoretical and practical implications, as follows.

5.1. Theoretical implications

From a theoretical point of view, the current study has two main contributions. First, it improves our understanding of the indirect role of perceived cost on the intention to adopt blockchain, where its role as a mediator and moderator was tested and investigated. Furthermore, it refines the understanding of TRI constructs and their relationship to the intention to adopt blockchain as an emerging and disruptive technology.

The first hypothesis (H1) was accepted and the findings confirm that TRI enablers including innovativeness and optimism positively impact the intention to adopt blockchain in UAE organizations. This result is aligned with those of other researchers who reflected on the significance of innovativeness and optimism for the intention to adopt technology. For instance, Chen et al. [135] found a significant positive relationship between innovativeness and optimism concerning the intention to adopt self-service parcel delivery.

On the other hand, the second hypothesis (H2) was not supported, since the results show that the relationship between TRI inhibitors (INH) and intention to adopt blockchain (INT) was statistically insignificant (see Table 7). This implies that there is no significant evidence in our study to support the hypothesized negative relationship between TRI inhibitors and the intention to adopt blockchain. The lack of impact of TRI inhibitors on technology adoption has been observed in the literature, such as in Ref. [136]. In our case, this result can be explained by the top-down approach adopted by the UAE government for blockchain adoption [4,137]. This compels companies to follow the new government regulations despite the discomfort that might be felt in using the blockchain technology. Grandon and Pearson [138] empirically observed this behavior; they found that organizational readiness does not influence the adoption of new technologies, whereas external pressure does. This result can also be justified by the surveyed sample since most of the respondents were familiar with blockchain technology through their work in an IT-related role and are self-identified as “technology explorers” (see Table 1); therefore, TRI inhibitors do not determine their intention to adopt blockchain. In addition, in industry and academia blockchain has received much attention, which has sometimes even been characterized as hype. Koens, Van Aubel, and Poll [139] have noted the network effects where peers within the industry influence each other; this creates social drivers, such as fear of missing



a) b)

Fig. 5. Importance-Performance Map for the intention to adopt blockchain, at: a) the construct level; b) the indicator level.

out or wanting to be involved with the latest technologies. This kind of environment can generate optimism, which sometimes extends beyond what is warranted. Gartner's hype cycle model for emerging technologies [140], while not without criticism [141], uses initial enthusiasm and over-optimistic expectations as drivers in the early days of adopting new technology. We may be observing this effect in our data.

Similarly, and contrary to our hypothesis H3, the direct relationship between the perceived cost and intention to adopt blockchain was found to be insignificant (see Table 7). This may be explained by the fact that blockchain technology is in its early stages, with no clear or tested way of estimating the financial cost of implementing such a technology in the UAE or its cost-benefit expectation. Several researchers reported this insignificant relationship between perceived cost and the adoption of technology; for instance, Yang et al. [142] found that perceived cost does not influence the technology adoption of mobile payments. Similar results were also recorded by Slade et al. [143] and by AlSoufi and Ali [85] for technology adoption in the contexts of mobile payment and mobile banking, respectively.

However, in line with our hypotheses H4 and H7, perceived cost (PC) was found to have a significant direct relationship with both TRI enablers ($T = 3.458$, $P = 0.000$) and TRI inhibitors ($T = 4.480$ $P = 0.000$). Both of these relationships were found to be positive. A simple explanation may be that high perceived cost increases the overall perception of the importance and risk of a project. It is a reasonable assumption that the perception of high stakes in a project intensifies both positive and negative emotions [144,145].

Regarding the role that perceived cost plays in the intention to adopt blockchain technology, it was found that perceived cost does not play the role of a mediator, contrary to H6 and H9; this follows from the absence of the direct influence of perceived cost on the intention to adopt blockchain. Despite this, it was found that perceived cost moderates the relationship of TRI enablers and TRI inhibitors with the intention to adopt blockchain, agreeing with H5 and H8, where it improves the explained variance from $R^2 = 0.532$ to $R^2 = 0.565$. In terms of significance, the relationship between TRI inhibitors and the intention to adopt blockchain changes from an insignificant relationship ($T = 1.419$, $P = 0.078$) to a significant relationship ($T = 2.056$, $P = 0.020$) when PC is included as a moderator – which is an interesting finding. The effect of perceived cost on the relationship of TRI enablers (PC*EN) and the intention to adopt blockchain (INT) was found to be negative ($\beta = -0.196$), which means that the positive relationship between TRI enablers (optimism and innovativeness) and the intention to adopt blockchain weakens when the perceived cost increases. This makes sense because the perceived benefits might be viewed as having less impact if they come with a high price tag. Conversely, the effect of perceived cost on the relationship between TRI inhibitors (PC*INH) and the intention to adopt blockchain (INT) was found to be positive ($\beta = 0.261$). This means that when the perceived cost of blockchain use increases, the negative relationship of TRI inhibitors (discomfort) with the intention to adopt blockchain increases as well. This implies that if there is an actual monetary cost attached to discomfort, this discomfort becomes more important in the decision-making process.

5.2. Practical implications

To investigate the potential managerial implications of this study, Importance-Performance Map Analysis (IPMA) was utilized. The findings of the analysis help identify practical implications and key areas for performance improvement.

The IPMA results show that the TRI enablers have very high importance but relatively lower performance than perceived cost and inhibitors. An analysis at the indicator level shows that INNO3 has high importance and low performance. On the other hand, the perceived cost construct had the lowest importance but the highest performance of all three constructs.

These results imply that government and private organizations contemplating the blockchain technology should prioritize the TRI enablers dimension, particularly innovativeness, to ensure successful adoption. Furthermore, as the UAE government sets the expectation for blockchain to become a building block in government services, this creates expectations for private entities to follow suit. Therefore, the private sector can start working on promoting the enablers to participate in modernization and innovation that might outweigh the financial costs of the required investments. Similarly, managerial actions should specifically consider addressing feelings of discomfort about the intention to adopt blockchain.

From a practical point of view, the outcome of this research can help decision-makers assess their organization's readiness level and develop a clear roadmap to reduce the resistance to change and hence the time and cost of implementation. Moreover, measuring the level of readiness to adopt blockchain technology can help middle management develop training sessions that are tailored to the needs of organizations for the successful implementation of blockchain projects.

6. Conclusion, limitations, and future work

To conclude, the present study found that when dealing with a disruptive technology such as blockchain, the TRI effect is best captured in two dimensions (enablers and inhibitors), because it gives improved reliability and stronger explanatory power. The study revealed that perceived costs and TRI inhibitors do not significantly affect the intention to adopt blockchain technology. It was also found that perceived cost is considered a moderator rather than a mediator where it moderates the relationship between TRI enablers and TRI inhibitors with the intention to adopt blockchain.

Although this research contributes positively to the literature on blockchain technology, it is affected by some limitations as follows:

- In our finding, the perceived cost can serve as a base for blockchain adoption. Few studies have been conducted on the cost related to blockchain technology adoption; further research is required to understand in depth how perceived cost affects the behavioral intention of the organizations [5].
- This paper's results confirmed the inevitable bond that exists between cost and technology adoption. Future studies can study the link between cost-saving or benefits and blockchain adoption.
- This paper used Smart PLS and IPMA; other software can be used for analyses that may give more significant results such as Artificial Neural Network (ANN) analysis.
- As the IPMA assumes a linear relationship, future research could focus on non-linear IPMA results.
- The current study integrated the TRI constructs with perceived cost. In future studies, other traditional adoption theories like TAM can be integrated with the theory of planned behavior. The result of such a study would be interesting.
- Blockchain is not a standalone technology. Our current study did not integrate it with other technologies; future studies can integrate it with other emerging technologies, like IoT and AI.
- Future studies can incorporate examining other mediators/moderators, like firm characteristics in the business context and in-country context (gross domestic product; human development) to get a broader perspective.
- The data were collected in one country, UAE, making our results less generalizable. Future research could consider conducting a cross-country comparative study with a larger data set.
- This model can be further extended to other technological services sectors such as education, health, and energy.
- It would be interesting to include control variables such as years of experience and digital skills for purposes of comparison.
- Another essential suggestion for further research is using multiple channels to collect the data, i.e., organizations that adopt blockchain and their customers.

- The data were collected as a convenience sample, making it vulnerable to opt-in bias. It is a great deal harder to obtain a representative sample among senior organizational leaders who may have decision-making power in the adoption of major technology investments, but this would manifest the true role of perceived cost in the adoption process.
- Although our sample size is adequate to successfully analyze the data using the PLS-SME method, it is considered relatively small. This is mainly due to the early stage of blockchain technology adoption at present, which makes it difficult to find individuals with hands-on experience related to this technology. Moreover, blockchain technology has not yet been fully implemented in the UAE; therefore, it is very hard to find actual users of this technology. It would be interesting in future research to explore the enablers and inhibitors of blockchain adoption, with a bigger sample size.
- Finally, our data were collected using the quantitative method. According to Rossman and Wilson [146], combining qualitative with quantitative methods would enrich the data and give us deeper insights into the factors affecting the intention to adopt blockchain technology.

Credit author statement

Taghreed Abu Salim: Conceptualization, data analysis, writing – original draft. **May El Barachi**: Conceptualization, Methodology, Project administration, writing – original draft & editing. **Ahmed Alfatih D. Mohamed**: Data collection and data analysis, writing – original draft. **Susanne Halstead**: Conceptualization and paper review. **Nasser Babreak**: Data collection, Data analysis.

Data availability

Data will be made available on request.

Appendix

Table 13
The Questionnaire

Code	Question
Intention of Blockchain Usage	
INT1	I intend to use Blockchain technology in my business services.
INT2[a]	I plan to use blockchain technology in the next few months.
INT3[a]	I think I will use Blockchain technology in my business in the near future.
INT4	Given a chance, I predict I will use Blockchain technology.
Innovativeness	
INNO1	In general, our company is the first in the circle of our competitors to acquire new technologies.
INNO2	I can usually figure out new blockchain technology applications without help from others.
INNO3	Other people come to me for advice on blockchain technology.
INNO4[a]	I keep up with the latest technological development in blockchain technology.
Discomfort	
DISC1	When I get technical support from a provider of blockchain technology, I sometimes feel as if I am being taken advantage of by someone who knows more than I do
DISC2[a]	Sometimes I think that blockchain technology is not designed for use by ordinary people
DISC3	Technical support lines for blockchain technology are not helpful because they don't explain things in terms, I understand
DISC4	There is no such thing as a manual for blockchain applications or services that is written in plain language.
Perceived Cost	
PC1	I think the cost to use blockchain technology may be too expensive
PC2	I think the cost to train staff on blockchain technology would be too expensive.
PC3[a]	I think the cost to support blockchain technology would be too expensive.
Optimism	
OPT1	Blockchain technology contributes to a better quality of life.
OPT2[a]	Blockchain technology gives companies more freedom of mobility.
OPT3	Blockchain technology gives companies more control over their daily business processes.
OPT4	Blockchain applications make our company more productive by providing a common language of communication between heterogeneous systems.
Insecurity[a]	
INS1[a]	The variety of existing Blockchain platforms can cause distraction to users to a point that is harmful.
INS2[a]	Blockchain technology lowers the quality of relationships by reducing personal interactions.
INS3[a]	I do not feel confident doing business with blockchain technology.

[a] Codes with Italic font were dropped from the statistical analysis since they did not meet the factor loading threshold of reliability.

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