

# Blockchain Technology Adoption: Factors Influencing Intention and Usage

**Francisco Cesario**

*ISEG (Lisbon School of Economics and Management), Universidade de Lisboa, Lisbon, Portugal City/Town, Country*

[fcenario@kpmg.com](mailto:fcenario@kpmg.com)

**Carlos J. Costa**

*Advance/ISEG (Lisbon School of Economics and Management), Universidade de Lisboa, Lisbon, Portugal*

[cjcosta@iseg.ulisboa.pt](mailto:cjcosta@iseg.ulisboa.pt)

**Manuela Aparicio**

*NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Portugal*

[manuela.aparicio@novaims.unl.pt](mailto:manuela.aparicio@novaims.unl.pt)

**Joao Tiago Aparicio**

*INESC-ID, Instituto Superior Técnico, University of Lisbon, Portugal*

[joao.aparicio@tecnico.ulisboa.pt](mailto:joao.aparicio@tecnico.ulisboa.pt)

## Abstract

Blockchain technology is already being discussed as an emerging trend for the upcoming years. Researchers and organizations are beginning to recognize the potential benefits of this technology and are exploring how it can disrupt our world. However, the reality is that there has not been much progress in getting blockchain from a concept to widespread adoption. This study aimed to investigate the factors that influence the adoption of blockchain technology. We proposed a model that incorporated relevant features to blockchain technology adoption, specifically the role of Trust and Security as mediating variables. Data was collected using a questionnaire administered to people working in companies independently of their technology usage. Structural equation modeling using partial least squares (SEM-PLS) was used to analyze the data and construct the model. Results indicated that performance expectancy, social influence, and trust positively influenced people's actual use or intention to adopt blockchain technology. Additionally, environmental concerns had a negative effect on the intention to adopt. These findings suggest that individuals are more likely to adopt blockchain technology when they perceive it as valuable and trustworthy and receive support from their social networks.

**Keywords:** Blockchain, Technology acceptance, Technology use behavior.

## 1. Introduction

During the 2008 financial crisis, an unidentified individual or organization wrote out a white paper about a new technology that claimed to change the financial world. This new technology was the basis for a new digital currency called Bitcoin, which was a distributed, peer-to-peer currency that solved the problem of double spending. [39]. The blockchain is a distributed system that makes this currency work. All events are recorded and put together in a group of data called a block. Once a block is created, it is linked to the rest of the transaction records. This makes a chain of blocks, as its name suggests.[1]. Data is immutable and undeletable, encrypted, and certified by a collection of machines sharing the network and investing processing resources to keep it safe from malicious users

and errors made by humans. [41].

A new blockchain version that allowed decentralized transactions and apps might threaten established commerce. Companies no longer need centralized architectures or trusted third parties. This technology might decentralize their systems, reduce transaction costs, and make them safer, transparent, and faster. [16].

Blockchain distributed technological infrastructure has become more and more important, with multiple use cases in industry, from financial, passing to logistics and supply chain management, to health records [57]. It is estimated that approximately 1000 C-suite executives (33%) have used blockchains or are considering it. [32]. Financial, healthcare, energy, telecommunication, and logistics industries use this technology. Data integrity, supply chain management, and item checking can be simplified [3]. Blockchain technology, enables safe, decentralized transactions, has grown in popularity over the past decade. Despite its potential benefits, blockchain technology is still underutilized, especially by people and small businesses [56]. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to explore a model which examines the factors that drive blockchain technology adoption. Blockchain adoption has been explained here, using the UTAUT framework. Performance expectancy, effort expectancy, social influence, and conducive conditions drive technology adoption, according to the model. Energy consumption has been an important factor in blockchain adoption [6]. Few studies have used the UTAUT paradigm to study blockchain acceptance and use. This study seeks to explore the elements that influence blockchain technology adoption and identify ways to promote it among individuals and small enterprises.

The study collected quantitative data. To add to blockchain technology adoption and use literature, we distributed a survey to operationalize a theoretical model. This research may impact individuals, corporations, and policymakers seeking to use blockchain technology.

## 2. Literature Review

Blockchain technology can potentially play a substantial important role in achieving the Sustainable Development Goals by enabling more transparent, secure, and sustainable solutions [11]. Healthcare practitioners and organizations can develop unique coins on the MediBloc blockchain [8]. It improves food safety and authenticity by tracking high-end products [18]. In June 2019, VeChain, PwC, and Walmart China launched the Walmart China Blockchain Traceability Platform on ToolChain. VeChain ToolChain tested and implemented the first 23 product lines. Q.R. Codes provide detailed product information. Supply chain participants will exchange their data and improve visibility and management by embracing decentralized and tamper-proof blockchain technology [49]. In 2018, O.N.U.'s W.W.F. launched a pilot project called the "Blockchain Supply Chain Traceability Project" to help prevent illegal, unreported, and unregulated (I.U.U.) fishing in the tuna industry in the Western and Central Pacific Ocean. The project used blockchain technology to create a transparent and secure system for tracking the entire tuna supply chain, from fishing vessels to processing plants to markets. This enabled W.W.F. and its partners to verify the tuna's origin and legality and ensure it was sustainably caught and transported [52]. The Theory of Planned Behaviour, Theory of Reasoned Action, Diffusion of Innovations Theory, and Social Cognitive Theory can help explain and forecast technological uptake and success. [48]. DeLone and McLean's model, TAM, and UTAUT are just a few of the models that use these theories to analyze the spread and success of new technologies. The idea calls for a heightened focus on user acceptance elements in order to boost technology adoption and usage. Researchers [56] conducted a study on blockchain systems. According to recent studies, Bitcoin has been the primary topic of 80% of the chosen scholarly articles. All the first publications in this subject weren't even published until 2012, demonstrating how new it is. This research also found that academic authors had written and published more scientific publications than their industrial counterparts. The United States accounted for the lion's share of their publication, followed by Europe (particularly Germany and Switzerland) and Asia. Security, privacy, the protocol, energy efficiency, waste, usability, and transparency were shown to be given greater weight in these investigations. Companies who recognize blockchain's full potential stand to reap the biggest rewards from embracing the

technology, according to a study by [55], which also concludes that the business's transitional impact is more important than the technology itself when considering whether or not to use blockchain. The transfer to the blockchain, according to some scholars, necessitates substantial modifications in business procedures. [49]. Casino et al. [14] conducted a survey of scholarly papers to determine whether businesses were utilizing blockchain. Governance, integrity verification, finance, data management, privacy and security, education, health, the Internet of Things, industrial management, and process management were among the key results. Janze [33] did a study for a theoretical framework based on DeLone & McLean model and the technology acceptance model, which was not evaluated and merely stayed as a suggestion. Recently, we have discovered significant studies for the unified theory of blockchain technology acceptance and utilization.. Jena [34] through the UTAUT. found that the key factors influencing whether bankers have the intention to adopt blockchain for financial transactions are facilitating conditions, initial trust, and performance expectancy. On the client's side, Dam et al. [21] discovered that the quality of information has the greatest positive impact on customers' intentions to use the bank's international payments with integrated blockchain. According to most scientific studies, the primary blockchain use case is supply chain management. Studies based on the UTAUT model on adoption assign facilitating conditions as the primary motivator for adopting this technology in this industry [35]. While [46] identified the primary challenges to adoption at the inter-organizational, intra-organizational, technical, and external levels.

### 3. Research Model

Considering that the main point of this study is to understand what thrives to the adoption and usage of blockchain technology and considering the previous literature review and the UTAUT. model, the following constructs were identified.

**Table 1** – Constructs' definition

| Construct                      | Concept                                                                                                                                                                      | Author |
|--------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|
| Performance Expectancy         | <i>"The degree to which an individual believes that using the system will help him or her to attain gains in job performance"</i>                                            | [53]   |
| Effort Expectancy              | <i>"The degree of ease associated with the use of the system"</i>                                                                                                            | [53]   |
| Personal Technology Acceptance | <i>"Person's propensity to embrace and use new technologies for accomplishing goals in home life or work"</i>                                                                | [54]   |
| Social Influence               | <i>"The degree to which an individual perceives that important others believe he or she should use the new system."</i>                                                      | [53]   |
| Security                       | <i>"The level where information is protected from security threats, leakage, and infringement."</i>                                                                          | [15]   |
| Trust Transparency             | <i>"The belief that blockchain technology and its services are safe, error-free, and transact transparently"</i>                                                             | [15]   |
| Environmental Concern          | <i>"Represents the attribute of a person's compassion, worries, likes, and dislikes about the environment."</i>                                                              | [31]   |
| Behavioural Intention          | <i>"Behavioral intention to adopt a technology describes the individual's subjective likelihood that he or she will use or purchase that specific technology in future."</i> | [49]   |
| Use Behaviour                  | <i>"Actual use of the technology"</i>                                                                                                                                        | [49]   |

The following hypotheses were developed after giving thought to the research objectives, the UTAUT. model for examining technological adoption, and the existing literature. According to Venkatesh et al. [53] performance expectancy is "the degree to which an individual believes that using the system will help him or her achieve gains in job performance." This concept integrates five preceding theories' elements: relative advantage, perceived utility, work fit, result expectations, and extrinsic motivation. According to various studies, one of the most important ideas in technology use is performance expectancy (e.g. [4, 9]). According to the findings of Venkatesh et al. (2003), it is expected that in this study, individuals will use blockchain technology if they believe it will have positive outcomes. Performance expectations have been shown to have a considerable impact on behavioral intention [40]. As a result, performance expectancy (PE) is expected to have a beneficial impact on behavioral intention (BI). According to Zhou et al. (2010), PE has a significant impact on user adoption. The following hypothesis is proposed based on validations from previous investigations:

H1: Performance Expectancy (PE) positively influences Behavioural Intention (BI)

Venkatesh et al. [53] social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" Social influence is comprised of social variables, subjective norms, and image. Although several

theories are labeled differently, all social influence-producing constructs have the explicit or implicit assumption that an individual's behavior is influenced by how they believe others will perceive them as a result of their use of technology. Mazman et al. [38] assert that several studies explain the importance of social influence in the adoption of new technologies, suggesting that people's social environment can influence whether they will use technology. The role of social influence from various and important groups, including hierarchical (managers) and departmental groups, is investigated [26]. They discovered that managers had the most impact on people's usage of information systems, whereas the IT department had the least impact [26]. Das et al. [22] researched the social interaction around cybersecurity and agreed on the necessity of social influence on security behavior transformation. Friends, demonstrations, and security talks were the key social triggers observed, which either improved the examined participants' awareness of security tools or threats and pushed them to better protect themselves, or boosted people's knowledge on how to be better protected. Another study [23] suggests that having friends from diverse social groups employ a security feature is a major social motivator. According to these studies, societal influence will improve blockchain technology use and security perception..

H2a: Social influence (SI) will positively influence blockchain technology's use behaviour (UB).

H2b: Social influence (SI) will positively influence security (S) to use blockchain technology.

It is the propensity to adopt and exploit new technology to achieve personal or professional goals. [54]. Technology acceptance variables have been integrated in a good number of recent studies in various contexts [24] [36] [54]. Various technology acceptance studies have consistently demonstrated and encouraged the integration of technology readiness in models [54]. Walczuch and Lundgren [50] study found that a lack of understanding and knowledge of the Internet leads to low trust levels. Caldeira et al. [13] showed a substantial positive association and said technical readiness can affect trust in a product or service. Dimitriadis and Kyrezis's [25] Research shows that a person's attitude toward new technology affects their perception of a financial services invention. Thus, tech-savvy people trust technology more. [13], and the following hypothesis is formulated:

H3: Personal technology acceptance (TA) positively influences trust transparency (TT)

Because there is less research on this variable, and because it may have a double standard, environmental concern is an interesting variable to explore for its effect on behavioral intention. At the business level, there is study being done on potential applications for this technology to improve environmental management and preservation efforts [45] [43], even calling it a "game changer for green innovation". Despite these pro-green projects and ideas for blockchain technology, they are still in very early development with no significant impact. Due to bitcoin's mining effort, blockchain technology is still seen as a major energy consumer and CO<sup>2</sup> emitter to the public and environmentalists [7]. Environmental concern represents the attribute of a person's compassion, worries, likes, and dislikes about the environment [31]. Antecedent studies confirm that behavioral intentions are positively influenced by consumers' environmental concerns [29]. Thus, the following hypothesis is formed:

H4: Environmental concern (EC) has a negative influence on Behavioural Intention (BI)

Following certain antecedent theories researched by, security is defined as a level in which information is safeguarded against security risks, leakage, and infringement [15]. Security was discovered to be a crucial element that affects one's intention to adopt new technology or to influence one's level of trust [37]. Yli-Huumo et al. [56] found that security was an important topic in one or more of the main research fields covered in scientific papers on blockchain technology. Concerning Bitcoin and blockchain safety, 14 of the 41 publications, or 33%, were devoted to examining problems and limitations. Along with other studies, Ray et al. [44] studied the influence of security perception on gaining trust in online services. They came to the conclusion that an increased sense of security leads to increased trust, and one of the models they proposed suggested that future study should prioritize using perceived security as a path to trust. Suh and Han's [47] The impact of security on trust was also investigated in this study, and trust was used as a moderating

factor between security and behavioral intention. The same effect was confirmed throughout the research. Therefore, we formulate the hypothesis:

H5: Security (S) has a positive influence on Trust Transparency (TT)

People's perceptions of technology's reliability have an impact on whether or not they plan to use it [27]. In this and earlier research, trust transparency was defined as the assumption that blockchain technology and its services are secure, error-free, and transact transparently. [15]. This additional variable to the UTAUT.'s original model is backed by other studies on the blockchain ([20]; [27];[36]). Trust in behavioral intention regarding technology has been demonstrated to have a favorable and strong predictive effect across its different components, particularly transparency and user data ownership. [54]. Thatcher et al. [50] It should be noted that a lack of faith in IT may induce consumers to quit using or investigating technology due to concerns about its performance or reliability. The flexibility, ease, and benefits that users see in the technology to their activities appear to be the foundation of initial trust. Furthermore, for new or less tech-savvy consumers, early trust is critical for embracing new technologies such as blockchain. [34]. These results appear to be consistent with the literature study, which revealed that blockchain technology enables the creation and management of contracts, transactions, and records in a cryptographically and transparent manner. The following hypothesis is developed:

H6: Trust (TT) positively influences Behavioural Intention (BI)

Behavioural Intention (BI) is the probability that an individual will use a particular technology. Social scientists have primarily investigated behavioral and user intent to perform a possible behavior. BI favorably influences use behavior in the original UTAUT model [53]. Numerous technology adoption models incorporated in UTAUT theory support this relationship between behavioral intention and technology usage [36]. There it is anticipated the following hypothesis:

H7: Behavioural intention (BI) positively influences use behavior (UB)

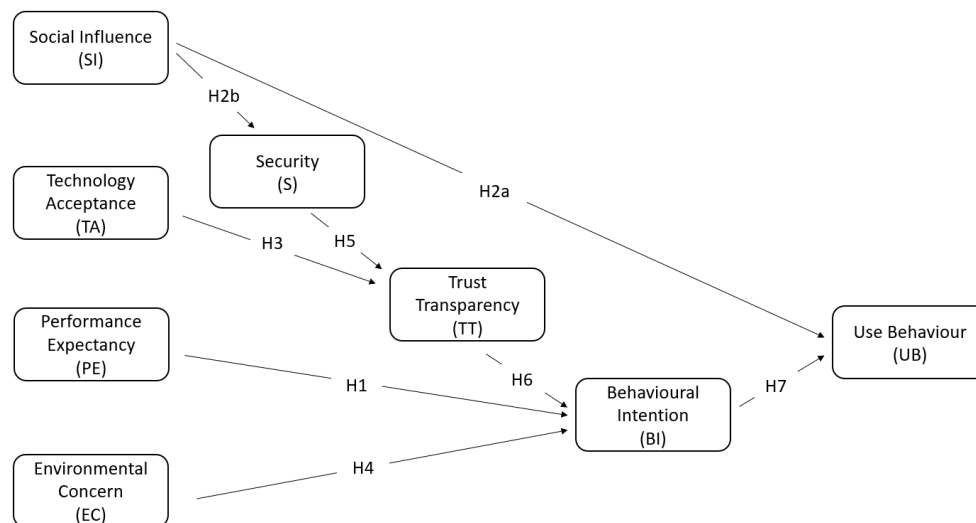


Fig. 1. Blockchain adoption research model.

#### 4. Method

This research aims to predict the factors that will determine blockchain's acceptance and adoption. This study is founded on the original UTAUT constructs. [53] framework with adaptations of various elements based on research from [2], [42], [31]. A review of the literature enabled the identification of a user acceptance model and additional variables to be studied.

We collected data using quantitative and deductive methods with an empirical focus in order to better comprehend reality and society's perspective. [12]. The initial target individuals was formed by personnel of Portuguese companies that require technology for daily operations. We distributed the questionnaire using the survey platform Qualtrics. The initial questions gathered individuals' employment function, as well as their company based-operation in Portugal, and whether or not their company required this technology for its activity. The questionnaire had three sections. The first section introduced the researchers, the university, the study's purpose, anonymity, and voluntariness, as well as a

summary on how blockchain technology is used, this helped respondents to contextualize. The following section included demographic questions, allowing a segmentation of the target audience and the comparison of various genders, ages, and occupations. The third section included the model constructs. All variables were measured with a seven point scale (“1 – *Strongly Disagree*” to “7 - *Strongly Agree*”). The dependent variable, use behavior, was measured with three items that were adapted from literature [2]. A sample item is “*I depend on blockchain to achieve my work tasks*”. Regarding the predictor variables, performance expectancy was measured with four items adapted from the same previous study. A sample item is “*I would find blockchain technology useful in my job*”. Social influence was measured with four items adapted from the same previous study. An example is, “*People who influence my behavior think that I should use blockchain technology*”. The behavioral intention was measured with three items adapted from the same previous study. An example is “*I intend to use blockchain technology in 6 months*”. Personal technology acceptance was measured using three items adapted from the same previous study. A sample item is “*Typically, I do not hesitate to try out new information technologies*”. Trust transparency was measured with four items used in a previous study by [15] “*Data in blockchain technology would be handled transparently*”. Security was measured with four items from the previous study. An example of an item is “*Using Blockchain technology would be a way to protect from external threats, such as hacking*”. Environmental concern was measured with four items based on a previous study by [17]. A sample item is “*I find Blockchain technology to be against environment conservation*”.

The questionnaire was developed and distributed in both Portuguese and English language. To preserve and affirm the value and substance of the questions after translation, a native speaker of both English and Portuguese reviewed the questionnaire.

We collected the participation of 198 organizations in Portugal that responded voluntarily. Non-probabilistic, expedient, and deliberate sampling was employed. Email was the most common method of distribution, followed by LinkedIn and personal contacts. It was observed that many respondents were opening the questionnaire and answering the demographic questions, but not the defined items. This likely occurred because the technology is still relatively new and the topic is complex [10]. As a result, when the number of new responses slowed down, the general strategy shifted towards blockchain technology in an effort to increase the percentage of respondents and acquire more knowledgeable individuals. The Orbis database of private corporations was accessed, and an e-mail was sent to every company discovered to have open activity in Portugal related to the blockchain. During data collection, responses were frequently downloaded and analyzed to determine their reliability and validity. The sample characteristics are then detailed in Table 2. From December 2022 to February 2023, a total of 90 valid responses were gathered. The majority of respondents are male (80%) and between the ages of 30 and 49 (46%). Regarding their professional experience, the majority (60%) has ten or more years of work, 20% of the sample works in the field of information technology, and the largest sample (38%) responded with a non-optional field. Last but not least, 42% of them are team members.

**Table 2 - Sample characterisation**

| Sample (n=90)        |    |     |                              |    |     |
|----------------------|----|-----|------------------------------|----|-----|
| <b>Gender</b>        |    |     | <b>Job Role</b>              |    |     |
| Male                 | 72 | 80% | Team Member                  | 38 | 42% |
| Female               | 18 | 20% | Supervisor/Leader            | 9  | 10% |
|                      |    |     | Director                     | 10 | 11% |
| <b>Age</b>           |    |     | Manager                      | 15 | 17% |
| <18                  | 0  | 0%  | Other                        | 18 | 20% |
| 18-29                | 23 | 21% | <b>Years of Experience</b>   |    |     |
| 30-49                | 41 | 46% | <2                           | 17 | 19% |
| 50+                  | 26 | 29% | 3-9                          | 18 | 20% |
|                      |    |     | 10+                          | 54 | 60% |
| <b>Business Unit</b> |    |     | <b>Company depends on IT</b> |    |     |
| IT                   | 18 | 20% | Nothing                      | 0  | 0%  |
| Marketing            | 3  | 3%  | Slightly                     | 8  | 9%  |
| Finance              | 14 | 16% | Highly                       | 45 | 50% |
| Sales                | 10 | 11% | Totally                      | 37 | 41% |
| Customer Care        | 5  | 6%  |                              |    |     |
| Human Resources      | 6  | 7%  |                              |    |     |
| Other                | 34 | 38% |                              |    |     |

## 5. Results

The structural equation modeling (SEM) with partial least squares (PLS) method was used to test the proposed model [30][19]. PLS-SEM was used to assess a non-normally distributed sample for a model with over six components to find relevant drivers and constructs [28]. The measurement model was examined to evaluate the reliability and construct validity [19]. A common rule of thumb is a value greater than 0.7 [28].

To evaluate the constructs, indicators for reliability and validity were measured, following [30] proposed measurement model: Cronbach's alpha, Composite reliability, Average Variance Extracted (AVE), Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT). All the measurements proposed above are identified in the tables below, following [30] and are supported by other authors [28]

**Table 3 - Model measurements**

|    | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|----|------------------|-------------------------------|-------------------------------|----------------------------------|
| BI | 0.884            | 0.889                         | 0.928                         | 0.812                            |
| EC | 0.897            | 0.973                         | 0.934                         | 0.825                            |
| PE | 0.945            | 0.949                         | 0.964                         | 0.900                            |
| S  | 0.910            | 0.913                         | 0.937                         | 0.787                            |
| SI | 0.913            | 0.924                         | 0.938                         | 0.793                            |
| TA | 0.768            | 0.793                         | 0.895                         | 0.810                            |
| TT | 0.936            | 0.937                         | 0.955                         | 0.840                            |
| UB | 0.864            | 0.865                         | 0.917                         | 0.788                            |

**Table 4 - Fornell–Larcker criterion and AVE squared root, and Heterotrait-Monotrait (HTMT)**

|    | BI           | EC           | PE           | S            | SI           | TA           | TT           | UB           | BI           | EC           | PE           | S            | SI           | TA           | TT           | UB |
|----|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|----|
| BI | <b>0.901</b> |              |              |              |              |              |              |              |              |              |              |              |              |              |              |    |
| EC | -0.322       | <b>0.908</b> |              |              |              |              |              |              | <b>0.341</b> |              |              |              |              |              |              |    |
| PE | 0.584        | -0.182       | <b>0.949</b> |              |              |              |              |              | 0.633        | <b>0.209</b> |              |              |              |              |              |    |
| S  | 0.517        | -0.073       | 0.547        | <b>0.887</b> |              |              |              |              | 0.576        | 0.094        | <b>0.591</b> |              |              |              |              |    |
| SI | 0.476        | -0.122       | 0.560        | 0.375        | <b>0.890</b> |              |              |              | 0.518        | 0.128        | 0.590        | <b>0.395</b> |              |              |              |    |
| TA | 0.342        | -0.054       | 0.238        | 0.238        | 0.119        | <b>0.815</b> |              |              | 0.434        | 0.096        | 0.243        | 0.268        | <b>0.145</b> |              |              |    |
| TT | 0.624        | -0.135       | 0.534        | 0.820        | 0.397        | 0.374        | <b>0.917</b> |              | 0.687        | 0.146        | 0.567        | 0.884        | 0.427        | <b>0.428</b> |              |    |
| UB | 0.576        | -0.132       | 0.491        | 0.406        | 0.563        | 0.186        | 0.376        | <b>0.888</b> | 0.649        | 0.155        | 0.542        | 0.458        | 0.635        | 0.221        | <b>0.418</b> |    |

To ensure that there is no multicollinearity, which threatens model experimental design, the variance inflation factor (V.I.F.) was examined for all constructs before the structural model evaluation [19]. After validating exterior model estimates, bootstrapping assessed structural model quality. Bootstrapping uses the sample as a population representation to evaluate the sampling distribution's shape, spread, and bias. The structural model's route significance was determined using 5000 subsamples. The validity of the structural model ensured the structural paths were assessed to measure the research hypotheses. Looking at Figure 2 we see that all hypotheses were supported.

SI ( $\hat{\beta} = 0.375$ ,  $p < 0.001$ ) explains S variation by 14.1%. S ( $\hat{\beta} = 0.774$ ,  $p < 0.001$ ) and T.A. ( $\hat{\beta} = 0.171$ ,  $p = 0.05$ ) explain 69.9% of TT variation. TT ( $\hat{\beta} = 0.425$ ,  $p < 0.001$ ), PE ( $\hat{\beta} = 0.319$ ,  $p < 0.05$ ), and EC ( $\hat{\beta} = -0.207$ ,  $p < 0.05$ ) explain 51.8% of BI variation. 44.0% of UB variation is explained by BI ( $\hat{\beta} = 0.398$ ,  $p < 0.001$ ) and SI ( $\hat{\beta} = 0.374$ ,  $p < 0.001$ ). All paths are statistically significant, at  $p < 0.05^{**}$  or  $p < 0.001^{***}$ , and all hypotheses are supported (Hair et al., 2014).

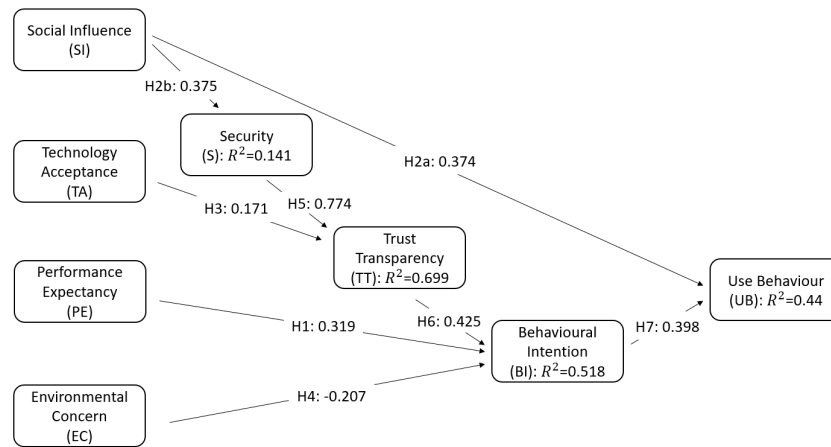


Fig 2 - Structural Blockchain adoption model results

As observed in Table 5, the presented model supports all trajectories with at least a moderate predictive impact. Checking the threshold values from previous studies ([19] [5]), we observe that hypotheses H3 and H4 have a moderate predictive impact, whereas hypotheses H1, H2, H5, H6, and H7 have a large effect.

Table 5. Hypothesis test.

| Hypothesis | Independent Variable | Dependent Variable | Standard deviation | $\beta^{\wedge}$ | T Value | P Value |
|------------|----------------------|--------------------|--------------------|------------------|---------|---------|
| H1         | PE ->                | BI                 | 0.08               | 0.319            | 4.997   | 0.000   |
| H2A        | SI ->                | UB                 | 0.083              | 0.374            | 2.267   | 0.023   |
| H2B        | SI ->                | S                  | 0.1                | 0.375            | 3.409   | 0.001   |
| H3         | TA ->                | TT                 | 0.066              | 0.171            | 11.745  | 0.000   |
| H4         | EC ->                | BI                 | 0.091              | -0.207           | 3.751   | 0.000   |
| H5         | S ->                 | TT                 | 0.066              | 0.774            | 4.477   | 0.000   |
| H6         | TT ->                | BI                 | 0.095              | 0.425            | 2.574   | 0.006   |
| H7         | BI ->                | UB                 | 0.08               | 0.398            | 4.456   | 0.000   |

## 6. Discussion

The research aims to comprehend employees' attitudes toward blockchain adoption. Therefore, Use Behaviour (UB) and Behavioural Intention (BI) variables were adopted from UTAUT.'s original model to measure the user's intention to implement this technology and actual adoption of it. Other variables affecting these two have been conceived. Social Influence (SI) and Performance Expectancy (PE) come into play from the original model to measure the impact on the individual, assessing the individual's perception of what his/her social circle thinks and the extent to which an individual believes that using a particular technology will help them perform their tasks more effectively or efficiently, respectively. Following research from [15], [31], [54], new variables were added, Trust Transparency (TT), Security (S), Environmental Concern (EC), and Personal Technology Acceptance (TA). These variables measure an individual's belief that blockchain technology and its services are safe, error-free, and transparent, their perception of how well information is protected from security threats, leakage, and infringement, their compassion, worries, likes, and dislikes about the environment, and their propensity to adopt and use new technologies to achieve home life goals.

The study's objective can be highlighted by the UB variable, which is positively influenced by SI ( $\hat{\beta} = 0.374$ ,  $p < 0.001$ ) and BI ( $\hat{\beta} = 0.518$ ,  $p < 0.001$ ). These two variables explain 44% of UB's variation, with BI having the biggest impact, as predicted [53]. Several studies indicate that the bigger the individual's intention to use a specific technology in the future, the increased likelihood of performing a potential behavior. UTAUT theory's technology adoption models support this behavioral intention-technology usage link. [36]. Venkatesh et al. [53] have found that the degree to which an individual perceives that important others believe he or she should use the new system influences an individual's behavior of using the technology. In line with our findings [38] study concludes that people's social environment can impact whether that person will use technology. Being BI the main impactor of UB, it is also essential to identify and



understand how this variable behaves. Three variables seem to explain the major of its variation, TT ( $\hat{\beta} = 0.425$ ,  $p < 0.001$ ), PE ( $\hat{\beta} = 0.319$ ,  $p < 0.05$ ), and EC ( $\hat{\beta} = -0.207$ ,  $p < 0.05$ ). TT and PE are positively correlated to BI, while EC being negative, explains 51.8% of BI's variation. Trusting technology impacts how individuals feel about it and their intention to use it [51]. In line with our findings, trust in behavioral intention towards a technology has confirmed to have a positive and significant predictive effect throughout its various aspects [54]. Performance expectancy is one of the most crucial concepts in technology use, according to numerous researches [4], [9] [53]. According to Venkatesh et al. [53], it is assumed that in this study, individuals will adopt a technology if they think it will have favorable outcomes. EC has a negative meaning is not surprising since blockchain technology is still seen as a major energy consumer due to Bitcoin's mining effort [7]. TT variable could be on a big scale predicted by the other two variables. 69.9% of its variation was due to S ( $\hat{\beta} = 0.774$ ,  $p < 0.001$ ) and T.A. ( $\hat{\beta} = 0.171$ ,  $p < 0.05$ ), both influencing it positively. Some studies used and defended the use of TT as a mediator factor between S and BI Ray et al. [44] study concluded that security perception increases trust, with a proposed model suggesting that research should prefer using perceived security to lead to trust Suh and Han [47] examine the significance of security on trust while using trust as a mediator between security and behavioral intention, confirming the findings of our study. Numerous studies on technology acceptance have demonstrated and encouraged the incorporation of personal technology acceptance into models [54]. Caldeira et al. [13] discovered a strong positive correlation between personal technology adoption and the intention to trust a specific product or service. According to research conducted by Dimitriadis and Kyrezis [25] regarding financial services, a person's general disposition toward new technology influences how they perceive the legitimacy of an invention.

Das et al. [23] studied the social interaction around cybersecurity and endorsed the importance of social influence on security behavior change. In our study, SI ( $\hat{\beta} = 0.375$ ,  $p < 0.001$ ) plays a positive role when it comes to influencing security perception or awareness, explaining 14.1% of S variation. They found that SI relation may vary depending on whom a person considers in his/her social circle, especially its size, explaining the lack of expressiveness on S variation.

## 7. Conclusions and Future Works

In this study, we constructed a predictive model on blockchain adoption employing a comprehensive literature review and empirical data collection and analysis. The analysis of our proposed model, which incorporates technological, social, environmental, trust, security, and performance expectation factors, revealed a number of significant predictors of blockchain adoption, social influence, and behavioral intention. In turn, behavioral intention is largely influenced by trust transparency. The majority of its variation is justified by the perception of safety. Our research contributes in numerous significant ways to the discipline. It offers a framework for comprehending the intricate factors that influence blockchain adoption. In addition, it provides organizations seeking to implement blockchain technology with practical guidance by identifying important success factors. While the current study provides insights into the factors influencing the adoption of blockchain technology, future research could expand or build upon its findings in a number of areas. Investigating the impact of organizational factors on blockchain adoption is a possible direction for future research. This study focused on individual-level influences on adoption behavior, but organizational-level influences may also be significant. For instance, a company's culture or the level of top-down support for blockchain technology may influence adoption behavior. Examining the influence of blockchain use cases on adoption behavior is a potential avenue for future research. While the current study concentrated on the general individual adoption behavior of blockchain technology, there may be specific use cases that are more likely to drive adoption. For instance, supply chain administration and financial transactions may be notably applicable use cases for blockchain adoption. Future research could examine how adoption behavior differs across various use cases and identify the most influential factors for each use case. Lastly, this study may have overlooked additional contextual factors that influence blockchain adoption. For example, the study did not investigate the influence of regulatory environments or the availability of blockchain-specific expertise. Future research could

examine the impact of these and other contextual factors on blockchain adoption in order to provide a more comprehensive understanding of the factors that influence adoption behavior in this domain.

### Acknowledgements

The authors acknowledge financial support via ADVANCE- CSG from the Fundação para a Ciência and Tecnologia (FCT Portugal) through research grant numbers UIDB/04521/2020; research grant UIDB/04152/2020—Centro de Investigação em Gestão de Informação (MagIC); and research grant UI/BD/153587/2022.

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