Lisbon School of Economics & Management
Universidade de Lisboa

MASTER IN MANAGEMENT (MIM)

MASTER'S FINAL WORK

DISSERTATION

Blockchain Technology Adoption: Factors Influencing Intention and Usage

Francisco de Pina Cesário

MARCH - 2023

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SUPERVISOR:

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KNOWLEDGMENTS

I don’t want to be too cliché, keeping this short and straight forward. I want to thank people that were directly helping me during this work. A huge thank you to my supervisor, professor Carlos, for his continuous support over the course of this study, and for using his time in my interest. Thank you to my friend Vasco. Thank you to my dad, he is the best and I don’t even value it.

RESUMO

Tecnologia Blockchain já é discutida como uma tendência emergente para os próximos anos. Investigadores e organizações estão a começar a reconhecer os potenciais benefícios desta tecnologia e a explorar como a mesma pode perturbar o mundo em que vivemos. No entanto, a realidade é que não tem havido grandes progressos na passagem do conceito de blockchain para uma adoção abrangente. O objetivo deste estudo foi o de investigar os fatores que influenciam a adoção da tecnologia blockchain. Foi desenvolvida uma versão modificada da Teoria Unificada da Aceitação e Utilização de Tecnologia (UTAUT) que incorporou características consideradas relevantes para a adoção desta tecnologia, especificamente o papel da Confiança e Segurança como variáveis mediadoras.

Os dados foram recolhidos utilizando um questionário administrado a pessoas que trabalham em empresas, independentemente se estes trabalhadores utilizam tecnologia ou não. Uma modelagem por equações estruturais utilizando mínimos quadrados parciais (SEM-PLS) foi utilizada para analisar os dados e construir o modelo. Os resultados indicaram que a expectativa de desempenho, influência social, e confiança influenciaram positivamente a utilização das pessoas ou a intenção de adotar a tecnologia blockchain. Além disso, a preocupação ambiental teve um efeito negativo na intenção de adotar. Estes resultados sugerem que os indivíduos são mais propensos a adotar esta tecnologia quando a consideram útil e digna de confiança, e quando influenciados socialmente. As conclusões deste estudo têm implicações práticas para organizações que procuram implementar a tecnologia blockchain e podem informar o desenvolvimento de estratégias de adoção eficazes.

Palavras-Chave: Blockchain, Aceitação de tecnologia, UTAUT, Comportamento de uso de tecnologia

ABSTRACT

Blockchain technology is already being discussed as an emerging trend for the upcoming years. Researchers and organisations are beginning to recognise the potential benefits of this technology and are exploring how it can disrupt the world we live in. Yet the reality is that there hasn't been much progress in getting blockchain from a concept to a widespread adoption. The purpose of this study was to investigate the factors that influence the adoption of blockchain technology. A modified version of the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed 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 modelling using partial least squares (SEM-PLS) was used to analyse 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 concern had a negative effect on intention to adopt. These findings suggest that individuals are more likely to adopt blockchain technology when they perceive it as useful, and trustworthy, and when they receive support from their social networks.

The findings of this study have practical implications for organisations seeking to implement blockchain technology and can inform the development of effective adoption strategies.

Keywords: Blockchain, Technology acceptance, UTAUT, Technology use behaviour

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1. INTRODUCTION

During 2008 financial crisis an anonymous person or group of people released the white-paper for a new technology that promised to revolutionise the financial sector. This new technology was the structure for a new digital currency, a distributed, peer-to-peer currency that came to solve the double spending problem, given the name of Bitcoin (Nakamoto, 2008). The technology where this currency operates over is called blockchain. Here transactions are registered and grouped in a block of data, once a block is full it is chained to the rest of the transaction history, forming, what its name suggests, a chain of blocks. Here data is immutable and undeletable, and it is secured via encryption and validated through a group of computers sharing the network and spending computational power to maintain data reliable and safe from malicious actors or human error (Nofer et al., 2017).

Blockchain started to be a potential disrupter of the traditional business when a new version emerged, where not only transactions but applications could be run over it in a decentralised manner. Companies' centralised architectures or need of trusted third parties are now unnecessary. As this technology has the potential to decentralised architectures and minimise transaction costs as they become inherently safer, more transparent and, in some cases, faster (Christidis & Devetsikiotis, 2016).

Blockchain technology is therefore becoming more and more important (Zhao et al., 2016). Around 1000 (33%) C-suite executives claim to have already been actively engaged with blockchains or are at least thinking about it (IBM, 2017). Several industries are taking advantage of this technology, with some prominent ones being financial, healthcare, energy, telecommunication, and logistic industries. In all of these, a reliable user's data, supply chain management or even items verification can be eased (Al-Jaroodi & Mohamed, 2019).

Blockchain technology has become increasingly popular over the past decade, with its potential to revolutionise various industries by enabling secure, decentralised transactions. Despite the potential benefits, the adoption and use of blockchain technology remains relatively low, particularly among individuals and small businesses (Yli-Huumo et al., 2016). This research aims to investigate the factors that influence the intention and use of blockchain technology using the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

The UTAUT model is a well-established framework that has been used to explain the adoption and use of various technologies, including blockchain. The model proposes that four main factors influence an individual's decision to adopt and use a technology: performance expectancy, effort expectancy, social influence, and facilitating conditions (Ayaz & Yanartaş, 2020).

While previous research has explored the factors that influence the adoption and use of blockchain technology, few studies have used the UTAUT model specifically. By using this framework, this research aims to provide a comprehensive understanding of the factors that drive or hinder the acceptance and use of blockchain technology.

Additionally, it seeks to identify potential strategies to increase its adoption among individuals and businesses.

The research will employ a quantitative data collection method. A survey will be used to gather data using the UTAUT model for the question items with adaptations, aiming to contribute to the existing literature on blockchain technology adoption and use. The findings of this research could have important implications for individuals, businesses, and policymakers looking to leverage the potential benefits of blockchain technology.

The research is structured as follows. The next section explains blockchain technology, with an overview of the UTAUT model and some studies. Therefore, there is an explanation on how the model and data were handled and operated. Finally, results, discussions and a conclusion are presented.

2. Literature Review

2.1. Blockchain

Blockchain is a database that is stored among the computers that are connected to a network, unlike regular databases which are locally stored. In addition to this characteristic of being distributed, it is constantly growing and all the information that is recorded is kept permanently. It can be a form to transfer money, property, contracts, and more, and it is usually pronounced along with the words, secure, immutable, and chronological order, we will dive into these later (Abreu et al., 2018).

Conception of blockchain

In 1991, blockchain technology idea was originally conceived by two American scientists, W. Scott Stornetta and Stuart Haber. Their objective was to find a method for ensuring the integrity and authenticity of digital documents. By stamping the date and time when they were created, and by securing and adding them to a chain of blocks secured via a system of encoding and decoding data, using cryptography, they could prevent any changes from being made subsequently and fraudulently (Haber & Stornetta, 1991).

In 1992, to allow the collection of several documents in one block, Merkle Trees were implemented into the system (Anandan & Deepak, 2022). A Merkle Tree is a data structure that allows for secure and efficient verification of large sets of data. It is composed of leaves (representing chunks of data) and branches (representing their combined hash – a numeric string assigned to a piece of data by applying a function whose output values are all the same number of bits in length) leading to a single root (Haber & Stornetta, 1997).

Recapping, Merkle Trees are used to allow the creation of a secure chain of blocks and making it more efficient since it enables the collection of more documents in a single block. However, after the implementation of Merkle Trees this technology went unused.

Possible reasons for the lack of interest in blockchain technology, in the 1990s, could be because the technology was not yet mature, and people had a limited understanding of its potential uses. Additionally, the necessary infrastructure and devices to support blockchain technology were not yet available (Anandan & Deepak, 2022).

Blockchain 1.0

A digital currency came to solve the double-spending problem, a problem that arises in the digital money context. This is an issue that involves the repetition of spending the same currency multiple times, given that standard digital money networks can be easily attacked, and digital currency can be easily reproduced. This led to the announcement of the first blockchain in 2008, that was the support for the first cryptocurrency: Bitcoin.

Bitcoin was the starting point for blockchains. Blockchain 1.0 emerged with the focal point being the revolution of finance (Mukherjee & Pradhan, 2021).

In 2009, following the financial crisis, Bitcoin was finally released to the public by Satoshi Nakamoto. Satoshi was an anonymous person, or group of people, that designed a system that allows pure peer-to-peer electronic cash. Bitcoin is created, distributed, traded, and stored using this cryptographic system known as blockchain. The objective is to allow online payments to be sent directly from one party to another without relying on the trust from a financial institution. Cryptographic digital signatures and the Proof-of-Work mechanism ensure control of ownership, form a solution to the double-spending digital money problem, and form a protection against online attacks (Nakamoto, 2008).

How does bitcoin's blockchain work?

Blockchain is a distributed database shared among the nodes of a network. Its name comes from its formation, new data comes in and is grouped into a new block, once this block is full, it is connected (chained) to the latest block of the blockchain. In this manner blocks are linked in a chronological order, where each one contains its data, its timestamp, an attributed hash, a nonce, and the previous block's hash (Nakamoto, 2008).

Nonce stands for Number Used Once, used in a cryptographic communication such that the block's hash meets a certain criterion. Miners try different nonce numbers repeatedly and calculate the block's hash, until they find a nonce-hash pair that meets the requirement. Once they find the right nonce, they can add the block to the blockchain and receive a reward for their work (Nakamoto, 2008).

In simple terms, a hash is like a fingerprint of digital data, it is formed by a long string of numbers and letters, it is an encrypted output that is generated by a mathematical function that converted the input data (Haber & Stornetta, 1991).

Miners are one of the three types of the network nodes. They use specialised software and hardware to validate the transactions and add them to the blockchain, by solving the mathematical function through computational power. This is bitcoin's Proof-of-Work mechanism, and for their PoW they get newly mint bitcoins as a reward (Nakamoto, 2008).

A node is a computer connected to the network. These are divided into three categories, miners, full nodes, and light nodes. The first ones, we just saw what they are. A full node is a participant in a blockchain network that stores a copy of the entire blockchain and participates in the validation of transactions and blocks. A full node is also responsible for forwarding transactions and blocks to other nodes in the network, and can also act as a miner, which consists of computers that validate a block's transactions. The main difference between the function of miners and the rest of the full nodes, is that, a miner validates transactions and adds them to the blockchain, while a full node validates transactions and blocks and stores a copy of the entire blockchain. A light node is a participant in a blockchain network that does not store a full copy of the blockchain, instead relies on other nodes to provide the necessary information. Light nodes are typically used by individuals or organisations that want to participate in a blockchain network without incurring in a large amount of storage or processing power. Light ones validate transactions without committing disk space, they use the full node's data, which can reject light's validations (Cao et al., 2020).

To recap, in a blockchain, there are several blocks linked together. Each block contains some data that originated a hash through computational power that solved a mathematical function. A block carries out the hash number of the precedent block, that prevents someone from going into a block and modify its information. Since they are all linked together, modifying a block would change its hash, thus, this block would need to generate another hash. The following block, that had the previous block's hash number, would also be invalidated, since that hash would no longer exist, having the need to generate again another hash. Which would cause all the succeeding blocks the need of using computational power to solve every block's mathematical function to validate the chain again, which makes it impractical for cyber-attacks. Also, a blockchain's network isn't just being approved by one computer, there are thousands of computers. The rest of the nodes notice any malicious action and do not approve the validation of these new blocks, this is a way of preventing attacks or even human error (Nakamoto, 2008).

So, each new block contains its new information plus a cryptographic key to access the previous block's information. Once a block is chained it cannot be modified, you can only add information to the blockchain, you cannot edit it or delete it. Making it great against cyber-attacks and information counterfeiting or forgery (Nakamoto, 2008).

The process of buying, selling, sending, or receiving a bitcoin goes by. First a transaction is submitted, then it is transmitted to the network of nodes. Once a block is filled up with data, the equation gets solved through computational power, and the nodes confirm the validity of the transaction. Then it gets chained to the other blocks and the transaction takes place (Nakamoto, 2008).

Reviewing bitcoin's blockchain characteristics

This blockchain is a distributed ledger technology that allows multiple parties to access, validate and update records in a secure and unchangeable way, due to being shared, replicated, and synchronized among the members of a decentralised network. All the data on this ledger is secured and accurately stored using cryptography. There is no central authority, or third-party mediators, which make information prone to cyber-attack (Keesara et al., 2020).

In this decentralised system, even if an attacker can pass through the cryptography that secures the data, all the other participants in the network are still holding the right version of the blockchain, which is the unattacked. Thus, for an attack to succeed, the attacker needs to hold more than 50% of the computational power of the network, to be a majority when it comes to agreeing on the blockchain's data (Nakamoto, 2008). In a network composed of millions of computers like bitcoin, that becomes nearly impossible. Even if this nearly impossible scenario, is made possible, and a blockchain is still hacked, there is a way to answer this. The community can agree that there was an attack and reach a consensus on performing a fork (Zhang et al., 2022). A fork can either be a hard or soft fork, very briefly, respectively, this would mean. Either choosing the last trusted block and begin the process of attaching new blocks to that one, i. e., choosing a block and from that one a second path is created. Or choosing the corrupted or few corrupted blocks and skip them, creating one or a few alternative blocks that would then link again to the original blockchain's pathing (Bouraga, 2022).

So, summing up its characteristics. This technology offers a high level of security, it is disintermediated, transactions are peer-to-peer, there is no need of an inefficient middleman. It is distributed, the work is shared across thousands of computers which are all running and sharing the workload, therefore less likely to fail because there is no single point that, if it were to malfunction, would cause the entire system to go down. It is decentralised, there is no central control, management, and repository of data, consequently there is no central point of failure. It is said that it is *trustless*, because there is no need of trusting a third party, like a bank or a database management entity, it generates its own reliability (Nakamoto, 2008). Transparent, in the way that the blockchain's code is open source, anyone can check its code, verify its trustworthiness, and suggest changes. Also, transactions are public. Time, sender, receiver, can be checked, all bitcoin is traceable. It allows for privacy, since sender and receiver can be checked, but only their addresses, we have no idea who those are behind those long strings of numbers and letters that cannot be in any way related to any person, but despite not knowing who a person is, we can keep track of a wallet's transactions. Not forgetting the characteristics of data being unchangeable, undeletable and kept in a permanent record (Nakamoto, 2008).

Blockchain 2.0

In 2015, Vitalik Buterin launched Ethereum, a blockchain system with its own cryptocurrency, called Ether. Instead of just recording transactions, it also allows a new generation of application to be built into the blockchain's network, decentralised applications, also known as DApps. That makes it to be often referred to as the first blockchain 2.0 platform (Tikhomirov, 2017).

While Blockchain 1.0 came to disrupt the financial sector through the creation of a digital currency. In Blockchain 2.0 terms can be agreed in a contract and be automatically executed, allowing people to record other assets, while acting as a platform to develop DApps. Thus, its concept relies on allowing the exchange of value in a decentralised and peer-to-peer fashion (Zhao et al., 2023).

Ethereum was the first blockchain with Smart Contracts integrated into its protocol. Smart Contracts are self-executing computer programs that operate based on predetermined terms between two parties. They are secure and tamper-proof, reducing the need for verification, lowering the cost of execution, and preventing fraud. They provide a clear and transparent way of defining agreements (Tikhomirov, 2017).

Using computer code along with Proof of Work consensus mechanism, these contract agreements are facilitated, verified, or negotiated, and included into the blockchain. Users accept a set of terms under which smart contracts operate. When those conditions are met, the terms of the agreement are automatically carried out (Tikhomirov, 2017).

Recapping, the creation of the two parties' contract comes first. The agreement's terms, guidelines, and requirements must be agreed upon by the two counterparts and then it is converted into a code. Without the agreement of all parties, the contract cannot be changed. Following that, the smart contract is introduced into the blockchain. The code automatically runs once the contract's specified events take place. Examples of such events in real life include when products are delivered or when property right are transferred. The contract will automatically send the value to the appropriate receiver after the code execution is finished. Thus, the settlement is instantly, no notary or other middleman required, securely, and effectively accomplished. The blockchain has a record of this transfer as well (Tikhomirov, 2017).

The emergence of this new blockchain brought some new concepts, DApps, DeFi, DAOs, Tokens, NFTs…

Decentralised Applications are a type of application whose operation does not depend on a checkpoint or central it operates based on a decentralised network. A network in which its users have total control over its operation. It allows people to access different services securely, and can be used on personal computers, smartphones, or even accessed via web.

A DApp uses blockchain at the core of its data storage and processing. This is complemented using smart contracts. Conventional applications typically got their data stored on the user's computer or on servers controlled by third parties. This way of working has many points of failure. A user may lose the information from the app if the computer is damaged, it may also happen that the servers are out of or a cyber-attack occurs. Therefore, the primary distinction is that the blockchain provides the data and computation for a secure, strongly structured, and a reliable new generation of applications (John William et al., 2022).

Also, as smart contracts are visible and public, this ensures a high level of transparency and security. Users can be sure that the DApp will not do anything beyond what the smart contract specifies.

In traditional applications' services, for example social media apps, data and decisions are made on central servers. This allows the company behind these services to take censorship actions, change behaviour, or even discriminate against or harm only certain users, constantly questioning neutrality and equality conditions (Yano et al., 2020).

When DApps are applied to finance, a new concept emerges, Decentralised Finance – DeFi – which, basically, is financial services in open protocols running in blockchains.

These services remove the control of banks or other intermediaries and, consequently, are more transparent, borderless, and interoperable (Piñeiro-Chousa et al., 2023).

As banks and bitcoin usually do, banks and blockchain do not need to compete. A blockchain implementation by banks could benefit, not only its customers, but the institution itself. Clients could make a transaction at any day of the week, any time of the day that the transaction would only take a few minutes to process instead of some days. Institutions can exchange funds more quickly and ensure its clients transparency and secure accounts.

Digital fiat currencies are already being emitted by private organisations, under the name of Stablecoins. These are cryptocurrencies whose market prices are fixed to another currency, usually the US dollar. A third party ensures that each coin produced has a collateral in US dollars, using different methods such as collateral debt positions, elastic supply, or any form of collateral or bond (Piñeiro-Chousa et al., 2023).

DAO stands for Decentralised Autonomous Organisation, as suggested by its name, it is an organisation that does not require managers and hierarchies, these are substituted by smart contracts performing automated tasks. A DAO is the most complex form of a smart contract, its rules and records run over a blockchain which are encoded as a computer programme that is transparent, controlled by shareholders, and not influenced by a central government. A DAO has its own cryptocurrency or token, which allows token owners and investors to participate in the entity’s management and decision-making through voting that is run in the blockchain, making all activity and user’s actions publicly viewable (Santana & Albareda, 2022).

A token is a type of digital asset that is built upon and managed in a blockchain network. Although tokens are a form of cryptocurrency, they differ from more established ones like Bitcoin or Ethereum because they are not intended to be used as a mean of exchange. Instead, tokens are created using a smart contract to represent a variety of assets and can be used to facilitate various transactions and interactions.

Tokens are usually divided into utility or security and into fungible or non-fungible.

Utility tokens are used to access a particular service or product on a blockchain platform and can function as currency for some ecosystems. They are often used to provide access to a DApp, a platform, or other types of services. Utility tokens are built on smart contracts that enforce specific rules and conditions for their use, and they can be exchanged for other tokens or cryptocurrencies. Thus, they incentivise users to participate in the platform or ecosystem by providing them with access to certain features or functions (Van Der Linden & Shirazi, 2023).

Security Tokens represent financial assets, like shares, bonds, commodities, or real-estate assets. They are designed to represent an ownership stake in a particular asset or company while being backed by assets or revenue streams, and they are subject to regulation by financial authorities and must follow certain guidelines to be legally compliant. Security tokens are designed to be used in financial markets, and they can allow for fractional ownership of assets, which can make it easier for investors to participate in markets that were previously inaccessible. Security tokens offer a way to create an efficient and transparent way to trade ownership of real-world assets on a blockchain network. Unlike utility tokens, security tokens represent a financial interest in the company or asset, making them more attractive to investors who are looking to invest in a potentially profitable venture (Van Der Linden & Shirazi, 2023).

Fungible tokens are digital assets that are interchangeable with other tokens of the same type and value. These tokens have a uniform value and can be traded or exchanged without any loss of value. If a token is fungible then it doesn’t matter which unit you are holding, just like regular coins or notes. Fungible tokens are often used as a medium of exchange, where they can be easily traded for other tokens or assets of the same value. They are also used in smart contracts, where they can be used to represent a specific asset or value in the contract (Van Der Linden & Shirazi, 2023).

Non-Fungible Tokens, widely known as NFTs, are unique and cannot be exchanged for other tokens on a one-to-one basis. NFTs are often used to represent digital art or collectibles, but can also represent a person’s identity, a house, a health file or other unique item. Each NFT has a unique identity on the blockchain, which makes it non-fungible and impossible to replicate. Real-world items can also be tokenised, like artwork and real estate. Tokenising these real-world tangible assets makes buying, selling, and trading them more efficient while reducing the probability of fraud as they may function as proof of authenticity and ownership, assuring data integrity, easy and *trustless* transfers (Bhujel & Rahulamathavan, 2022).

Web 3.0 is described by Chen et al. (2022) as the next iteration of the internet that is currently being developed. It is also referred to as the decentralised web or the blockchain web, and it promises to revolutionise the way we interact with the internet. Web 3 builds on the existing infrastructure of the internet and integrates it with blockchain technology to provide a more decentralised, secure, and private internet, with the use of smart contracts, and decentralised applications

The current version of the internet, Web 2.0, has been around since the early 2000s. It is characterized by the dominance of centralised platforms such as Google, Facebook, and Amazon, which have become gatekeepers of user’s data and digital identities. Web 2.0 has also been plagued by issues such as online surveillance, censorship, and the exploitation of user’s data by large tech companies.

Web 3, on the other hand, aims to address these issues by leveraging blockchain technology to create a decentralized and distributed network. In this network, users will have greater control over their data and digital identities, and will be able to participate in the creation and governance of online platforms. Web 3 is essentially about empowering users to take control back of the internet from centralised platforms (Chen et al., 2022).

Blockchain 3.0

Blockchain technology has come a long way since the introduction of Bitcoin in 2008. While the first generation of blockchain technology, known as Blockchain 1.0, was focused primarily on the creation of a decentralised digital currency, the second generation, Blockchain 2.0, saw the development of smart contracts and the ability to create decentralised applications beyond simple financial transactions. Today we are on the cusp of the third generation of blockchain technology, known as Blockchain 3.0, which promises to take the technology to even greater heights by increasing functionality, scalability, interoperability, and privacy. As well as achieving a broader scope in terms of industries and sectors it can incorporate (Terzi et al., 2019).

One of the most significant developments in Blockchain 3.0 is the focus on scalability. As blockchain technology has grown in popularity, the number of transactions on blockchain networks have increased dramatically, leading to network congestion and slower transaction speeds. Blockchain 3.0 aims to address this issue by incorporating new technologies such as sharding, which addresses this problem by dividing the network into smaller, and more manageable groups of nodes called shards. Each shard processes a subset of the network's transactions, and only stores a portion of the blockchain data. This allows the network to process transactions more quickly and efficiently, reducing the storage and number of process' requirements for each node. This can greatly increase transaction's speeds and enable the blockchain network to handle a much higher volume of transactions (Velloso et al., 2021).

Another key feature of Blockchain 3.0 is interoperability. In the past, each blockchain network was a separate ecosystem with its own set of DApps and services. This fragmentation has made it difficult for different blockchain networks to communicate and work together. Blockchain 3.0 aims to address this issue by enabling different blockchain networks to communicate and interact with each other through cross-chain communication protocols. This creates a more interconnected and seamless ecosystem of DApps and services, which can greatly enhance the potential uses of blockchain technology (Velloso et al., 2021).

In addition to scalability and interoperability, Blockchain 3.0 also introduces new features to enhance privacy and security. One of the main criticisms of blockchain technology is that it is not truly anonymous, as every transaction is recorded on a public ledger. Blockchain 3.0 aims to address this issue through the use of zero-knowledge proofs, which enable a user to prove that they know something without revealing what that knowledge is, by using complex mathematical algorithms to create a proof that a statement is true. This can be used to provide greater privacy and anonymity to users on blockchain networks. Additionally, Blockchain 3.0 incorporates new consensus algorithms, which are more energy-efficient and secure than the Proof of Work algorithm used in previous generations of blockchains (Di Francesco Maesa & Mori, 2020).

Another key development in Blockchain 3.0 is the integration of artificial intelligence (AI) and the Internet of Things (IoT). AI and IoT can greatly enhance the capabilities of blockchain technology by enabling DApps to automatically collect, analyse, and process data from a wide range of sources. For example, blockchain technology can be used to create a more efficient supply chain management system, with AI and IoT sensors monitoring the movement and condition of goods as they move through the supply chain.

Finally, Blockchain 3.0 also promises to make blockchain technology more accessible to a wider range of users. In the past, creating and deploying a DApp on a blockchain network was a complex and time-consuming process that required specialised knowledge and expertise. Blockchain 3.0 aims to simplify this process by providing tools and frameworks that make it easier for developers to create and deploy DApps on blockchain networks. This can greatly increase the number and variety of DApps available on blockchain networks, making blockchain technology more useful and accessible to a wider range of users.

In contrast to Proof of Work (PoW), which requires miners to solve complex mathematical problems to create new blocks and receive rewards, Proof of Stake (PoS) assigns the right to create a block based on the amount of cryptocurrency a participant holds and locks up as collateral. The size of the stake determines the chances for a node to be selected as the next validator to forge the next block. When a node gets chosen to forge the next block, he will check if the transactions in that block are valid, signs the block, and adds it to the blockchain. As a reward, the node receives the transaction fees that are associated with the transactions in the block (Li et al., 2017).

One of the primary benefits of PoS is its energy efficiency and throughput efficiency. PoW requires miners to consume massive amounts of electricity to solve mathematical problems, which has led to concerns about the environmental impact of cryptocurrencies. In contrast, PoS does not require such intensive energy consumption, as the validator's stake serves as collateral and incentivises them to act in the network's best interest. Another advantage of PoS is that it allows for more significant participation in the network, enabling anyone with a minimum stake to become a validator and earn rewards by securing the network (Li et al., 2017).

One of the major concerns is that it favours those who hold a significant amount of cryptocurrency, which could lead to centralisation. Participants with large stakes may have more influence over the network's decision-making process, which could lead to a concentration of power in the hands of a few. However, many PoS networks have implemented measures to mitigate these risks and ensure decentralisation, such as delegation and slashing (Ko et al., 2020).

Types of Blockchain

The appearance of blockchain 3.0 brought a broader scope in terms of decentralised enterprise level applications, and with that, new levels of decentralisation appeared. There are three main types of blockchains: public, private, and consortium. Each type has its unique characteristics and is suitable for specific use cases (Paul et al., 2021).

Public Blockchains are open and permissionless networks that anyone can participate in without requiring permission from any central authority. In a public blockchain, anyone can create an account, verify transactions, and minee new blocks. This type of blockchain is entirely transparent and all transactions are visible to anyone on the network. Examples of public blockchains include Bitcoin and Ethereum.

Private blockchains are closed and permissioned networks that require permission from a central authority before allowing anyone to participate in the network. In a private blockchain, only a limited number of participants can access the network. This type of blockchain is often used in enterprise settings where access to the blockchain needs to be restricted to specific individuals or organisations.

Consortium blockchains are similar to private blockchains but are governed by a group of organisations instead of a single entity. In a consortium blockchain, a group of companies or organisations come together to collaborate on the network. This type of blockchain is often used in industries where multiple stakeholders are involved, in settings where multiple organisations operate in the same require a common ground on which to carry out transactions or relay information.

Real world use cases

Blockchain technology even has the potential to play a significant role in achieving the Sustainable Development Goals by enabling more transparent, secure, and sustainable solutions. Whether we look at objectives related to animal and nature preservation, good health and well-being, or even responsible consumption and production.

MediBloc is a South Korean blockchain-based platform that has partnered with some healthcare institutes, like the Myongji Hospital, Seoul National University Bundang Hospital, or even Samsung's Medical Centre, as it aims to improve the healthcare industry by providing a secure and transparent way to store and share medical informationMediBloc allows patients to store their medical records and personal health information on a decentralised and secure platform. This data can then be easily accessed and shared with healthcare providers, enabling them to make more informed decisions about patient care. The platform also provides patients with complete control over their data, allowing them to choose which healthcare providers can access their records.

One of the key features of MediBloc is its use of smart contracts, which are particularly useful in the healthcare industry, as they can be used to automate and streamline processes such as insurance claims and payments. The platform also supports the creation of customed tokens, allowing healthcare providers and organisations to create their own digital assets on the MediBloc's blockchain (Bae et al., 2021).

VeChain is a blockchain-based platform that aims to improve supply chain management and business processes. The platform uses blockchain technology to, securely and transparently, track the movement of goods and information across various stages of the supply chain, from production to the end consumer. It has been used to track the authenticity and origin of high-end products, as well as in the food and beverage industry to improve food safety and traceability (Clincy & Shahriar, 2019).

The Walmart China Blockchain Traceability Platform was introduced on the VeChain ToolChain platform in June 2019 in collaboration with VeChain, PwC, and Walmart China. The VeChain ToolChain has been used to test and implement the first batch of 23 product lines where customers can obtain comprehensive product information by scanning a QR Code. By adopting the decentralised and tamper-proof blockchain technology, participants in the supply chain will also share their portion of the data and increase the visibility and management effectiveness of the entire chain (Tan et al., 2018).

In 2018, ONU's WWF launched a pilot project called "Blockchain Supply Chain Traceability Project" to help prevent illegal, unreported, and unregulated (IUU) 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 supply chain of tuna, from fishing vessels to processing plants to markets. This enabled WWF and its partners to verify the origin and legality of the tuna, and to ensure that it was sustainably caught and transported (Tsolakis et al., 2021).

2.2. Technology Adoption

There are many theories that can be applied to understand and predict technology adoption and success, such as Theory of Planned Behaviour, Theory of Reasoned Action, Diffusion of Innovations Theory, and Social Cognitive Theory (Taherdoost, 2019). These theories have been incorporated in models, such as DeLone and McLean Model, TAM, and UTAUT, that study technology adoption and success. The thesis is that, in order to increase the level of technology usage and user adoption, the emphasis on factors that can influence user acceptance should be raised.

The DeLone and McLean Model is a model that aims to explain the relationships between information systems (IS) success factors, including system quality, information quality, service quality, use, user satisfaction, individual impacts, and organisational impacts. The model suggests that these factors are interrelated and that improvements in one area can lead to improvements in others. For example, improving system quality can lead to increased user satisfaction, which can lead to increased use, and ultimately to positive individual and organisational impacts. The model has been used to evaluate the success of information systems in a variety of contexts (Dwivedi et al., 2012).

The Technology Acceptance Model (TAM) is a model that explains how users accept and adopt new technologies. According to TAM, users' acceptance of technology is influenced by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the degree to which users believe that the technology will improve their performance or make their life easier, while perceived ease of use refers to the degree to which users believe that the technology is easy to use. TAM suggests that users are more likely to adopt new technologies if they perceive them as both useful and easy to use (Dwivedi et al., 2012).

Unified Theory of Acceptance and Use of Technology (UTAUT) is a model used to understand the factors influencing the adoption and usage of new technologies. Developed by Venkatesh, Morris, Davis, and Davis in 2003, UTAUT is an extension of previous technology acceptance models, such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). UTAUT seeks to provide a comprehensive framework for understanding the factors influencing technology acceptance and usage (Venkatesh et al., 2003). By combining elements across eight different theories and models which are: the Motivational Model (MM), Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA), Model of PC utilisation (MPCU), Combined TAM and TPB (TAM-TPB), Diffusion of Innovations Theory (DIT), and Social Cognitive Theory (SCT) (Salem & Ali, 2019).

Venkatesh et al. (2003) propose that the intention to use a technology is influenced by four key factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the extent to which the technology is perceived to improve the user's performance. Effort expectancy refers to the degree of ease associated with using the technology. Social influence refers to the degree to which the user perceives social pressure to use the technology. Finally, facilitating conditions refer to the degree to which the user perceives that the necessary resources and support are available to use the technology effectively. In addition to these four key factors, the UTAUT model includes four moderating variables: experience, voluntariness of use, gender, and age. According to the model, these variables can influence the impact on up to the three key factors of user's intention to use the technology or even its behaviour.

UTAUT has been widely used to comprehend the adoption and usage of various technologies, including mobile devices (Liu et al., 2022), social media (Alvi, 2021), and e-learning platforms (Alfalah, 2023). The model has also been used in a variety of contexts, such as healthcare (Liu et al., 2022), education (Alvi, 2021), and business (Yuniarty et al., 2023).

One of the strengths of UTAUT is its ability to provide a comprehensive framework for understanding technology adoption and usage. By including multiple factors and moderating variables, UTAUT allows for a more nuanced understanding of the complex factors influencing technology adoption and usage. Additionally, UTAUT has been shown to have high predictive power, making it a valuable tool for researchers and practitioners alike (Venkatesh et al., 2003).

In conclusion, UTAUT is a valuable framework for understanding the factors influencing technology adoption and usage. Its comprehensive nature and high predictive power make it a useful tool for researchers and practitioners in a variety of contexts. However, as with any theory, UTAUT has its limitations and should be used in conjunction with other theories and methodologies to provide a more complete understanding of technology adoption and usage.

2.3. Prior Research

Yli-Huumo et al. (2016) ran a study on blockchain technology current research, findings show that 80% of the selected scientific papers were focused on the bitcoin’s system and most of them tried to underline limitations regarding security and privacy, and proposed solutions which still lacked concrete evaluation of its efficacy. Three main different types of papers could be identified, “Blockchain Report” which reports previously identified solutions and ideas, “Blockchain Improvement” which suggests new solutions and improvements, and “Blockchain Application” which presents an application based on Blockchain technology. All the relevant papers began to be published in 2012, and in late 2013 the number of publications started to grow rapidly. Showing that this area is still . Other finding in this study is that the number of scientific papers published by academia authors are the majority, when compared to industrial. Most of them were published by universities or companies in the United States followed by Germany and Switzerland, and some Asian countries. In the end, the study found that these studies gave more importance to topics related to security, privacy, the protocol, energy efficiency and waste, usability, and transparency. Yli-Huumo, Ko, and Choi ended this study, on the different studies about blockchain technology, saying that there is still a low volume of high-quality research published at a journal level while making a call on the need of high-quality studies about this topic.

A study by Ying et al. (2018) found that companies that see the true potential of blockchain are able to transform their business and achieve the greatest benefits, and that the adoption of this technology is more about the transitional impact of the business and not so much on the technology. Other authors also found that the transition to blockchain require significant changes to business processes (Tan et al., 2018; Weber et al., 2016). Casino et al. (2019) performed a study on scientific papers, reviewing which businesses were applying blockchain. Major findings were on governance, integrity verification, finance, data management, privacy and security, education, health, internet of things, and in industrial management and to manage processes.

Janze (2017) ran a study for a theoretical framework based on the DeLone & McLean and the technology acceptance models, which was not tested and just stayed as a proposal. Some relevant and more recent studies can be found for the unified theory of acceptance and use of blockchain technology. Jena (2022) through the UTAUT found that the key factors influencing whether bankers have intention to adopt blockchain for financial transactions are facilitating conditions, initial trust, and performance expectancy. On the client's side, Dam et al. (2020) found that the quality of information has the strongest positive impact on the customer's intended use of bank's international payments with integrated blockchain. Most scientific studies attribute supply chain management as the main blockchain use case. Studies following the UTAUT model on the adoption attribute facilitating conditions as the main driver to the adoption of this technology for this sector (Kabir et al., 2021; Wamba & Queiroz, 2019).

3. RESEARCH MODEL

Considering that the main point of this study is to understand drivers to the adoption and usage of blockchain technology, and having in mind the previous literature review and the UTAUT model, the following constructs were identified.

TABLE I – CONSTRUCTS' DEFINITION

Construct	**Concept**	**Author**
Performance Expectancy	The degree to which an individual believes that using the system will help him or her to attain gains in job performance	Venkatesh et al. (2003)

Effort Expectancy	The degree of ease associated with the use of the system	Venkatesh et al. (2003)
Personal Technology Acceptance	Person's propensity to embrace and use new technologies for accomplishing goals in home life or work	Wong et al. (2020)
Social Influence	The degree to which an individual perceives that important others believe he or she should use the new system	Venkatesh et al. (2003)
Security	Level where information is protected from security threats, leakage, and infringement	Chang et al. (2022)
Trust Transparency	The belief that blockchain technology and its services are safe, error-free, and transact transparent	Chang et al. (2022)
Environmental Concern	Represents the attribute of a person's compassion, worries, likes, and dislikes about the environment	Hsu et al. (2014)
Behavioural Intention	Behavioural intention to adopt a technology describes the individual's subjective likelihood that he or she will use or purchase that specific technology in the future	Venkatesh et al. (2003)
Use Behaviour	Actual use of the technology	Venkatesh et al. (2003)

Following this study's objectives and considering UTAUT model to study the adoption of a technology, and taking into account the literature review the following hypotheses were formulated.

Performance Expectancy

Venkatesh et al. (2003) have defined performance expectancy as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". This idea combines five elements developed in earlier theories: relative advantage, perceived usefulness, job-fit, outcome expectations, and extrinsic motivation (Venkatesh et al., 2003). Performance expectancy is one of the most crucial concepts in technology use, according to numerous research (Alraja, 2015; Benbasat & Barki, 2007; Venkatesh et al., 2003).

According to Venkatesh et al. (2003) findings, it is assumed that individuals will adopt blockchain technology if they think it will have favourable outcomes. Performance expectancy has been proven to significantly affect behavioural intention (Ayaz & Yanartaş, 2020; Nazim et al., 2021). As a result, it is anticipated that behavioural intention (BI) will be positively impacted by performance expectancy (PE). According to Zhou et al. (2010), PE has a substantial impact on user's adoption.

Based on validations on these past studies, the following hypothesis is formulated:

H1: Performance Expectancy (PE) has a positive influence on Behavioural Intention (BI)

Social Influence

Venkatesh et al. (2003) defines social influence as "the degree to which an individual perceives that important others believe he or she should use the new system". Social factors, subjective norm, and image are all constituent elements of social influence (Venkatesh et al. 2003). Although many theories have various labels, all the social influence-producing constructs have the explicit or implicit idea that an individual's behaviour is influenced by how they feel others will perceive them as a result of using technology (Venkatesh et al., 2003). Mazman et al. (2009) state that there are several studies that explain the role of social influence when it comes to using new technologies, ending the study by concluding that people's social environment can impact whether that person will use a technology. The role of social influence from various and relevant groups, including hierarchical groups (managers) and departmental ones, is examined by Eckhardt et al. (2009). They discovered that managers had the most impacts on people's usage of information systems, whereas the IT department has the least impact (Eckhardt et al., 2009).

Das et al. (2014) studied the social interaction around cybersecurity and endorsed the importance of social influence on security behaviour change. The main social triggers observed were friends, demonstrations, and security discussions, which either increased the studied participants awareness for security tools or threats and motivated them to better protect themselves, or increased people knowledge on how to be better protected. In another study Das et al. (2015) suggest that having friends from different social groups that use a security feature is a strong social motivator to use that feature.

In line with these findings, it is anticipated that social influence will have favourable impacts both on use behavioural and on security perception to utilise blockchain technology.

H2a: Social influence (SI) will have a positive influence on use behaviour (UB) of blockchain technology.

H2b: Social influence (SI) will have a positive influence on security (S) to use blockchain technology.

Personal Technology Acceptance

It is the person's propensity to embrace and use new technologies for accomplishing goals in home life or work (Wong et al., 2020). Technology acceptance variables have been integrated in a good number of recent studies in various contexts (De Blanes Sebastián et al., 2022; Khazaei, 2020; Wong et al., 2020).

A variety of technology acceptance studies have consistently demonstrated and encouraged the integration of technology readiness in models (Wong et al., 2020). In

Walczuch and Lundgren (2004) study, it is found that lack of understanding and knowledge of the internet leads to low trust levels. Caldeira et al. (2021) found a strong positive correlation and state that technology readiness can influence the intention to trust or not in a particular product or service. Dimitriadis and Kyrezis (2010) research goes along with these lines, where a person's general inclination towards new technology affects how they perceive the legitimacy of an invention related to financial services. Therefore, individuals with a greater predisposition to the use of technologies tend to trust these more (Caldeira et al., 2021), and the following hypothesis is formulated:

H3: Personal technology acceptance (TA) has a positive influence on trust transparency (TT)

Environmental Concern

Environmental concern is an interesting variable to study its effect on behavioural intention, since it is the one with less research made, and it could possibly have a double standard. On an enterprise level, there is on uses for this technology to better manage, control, and preserve the environment (Rana et al., 2021; Rejeb & Rejeb, 2020), Polas et al. (2022) even call it a “game changer for green innovation”.

Despite, these pro-green projects and ideas for blockchain technology, they are still in a very early development with no significant impact. To the public and environmentalists, blockchain technology is still seen as a major energy consumer and CO_2 emitter due to the bitcoin’s mining effort (Badea & Mungiu-Pupazan, 2021; Truby, 2018).

Environmental concern represents the attribute of a person’s compassion, worries, likes, and dislikes about the environment (Hsu et al., 2014). Antecedent studies confirm that behavioural intention is positively influenced by consumers' environmental concern (Hartmann & Apaolaza-Ibáñez, 2012; Kotchen & Reiling, 2000). Thus, the following hypothesis is formed:

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

Security

Security is described as a level where information is protected from security threats, leakage, and infringement, following some antecedent theories studied by Chang et al. (2022). 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 (Lim et al., 2019).

Yli-Huumo et al. (2016) identified the main research areas of scientific papers on and security was a major one. 14 out of 41 papers (or 33%) dealt with issues and limitations in Bitcoin and blockchain security.

Along with other studies, Ray et al. (2011) studied the influence of security perception to gain trust in online services, they concluded that security perception increases trust, with a proposed model suggesting that should prefer using perceived security as a way to lead to trust. Suh and Han (2003) study also analyse the importance of security on trust, while also using trust as a mediating factor between security and behavioural intention that same impact was verified.

Therefore, we formulate the hypothesis:

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

Trust Transparency

Credibility of a technology affects how people feel about it, which in turn affects their intention to utilise it (Francisco & Swanson, 2018). Trust transparency was defined in this and other studies as the belief that blockchain technology and its services are safe, error-free, and transact transparent (Chang et al., 2022). This additional variable to the UTAUT's original model is backed by other studies on blockchain (Dagher et al., 2018; Francisco & Swanson, 2018; Khazaei, 2020).

Trust in behavioural intention towards a technology has frequently been found to have a positive and significant predictive effect throughout its various aspects, and also specifically on transparency and user's data ownership (Wong et al., 2020). Thatcher et al. (2011) note that lack of trust in IT may cause people to stop using or researching technology because of uncertainty about its performance or reliability. Initial trust seems to be built on the flexibility, convenience, and benefits users see in the technology to their activities. Furthermore, for new users or users who are less tech-savvy, early trust is crucial for the adoption of new technologies like blockchain (Jena, 2022).

These studies seem to follow the literature review where we saw that blockchain technology allows contracts, transactions, and records to be created and handled, in a cryptographic and transparent way. The following hypothesis is developed:

H6: Trust (TT) has a positive influence on Behavioural Intention (BI)

Behavioural Intention

Behavioural Intention (BI) is the likelihood that an individual will use a specific technology in the future. Social scientists have largely investigated behavioural and user's intention to perform a potential behaviour. In Venkatesh et al. (2003) original UTAUT model BI has a positive influence on use behaviour. Numerous technology adoption models incorporated in UTAUT theory support this relationship between behavioural intention and usage of technology (Khazaei, 2020). There for it is anticipated the following hypothesis:

H7: Behavioural intention (BI) has a positive influence on use behaviour (UB)

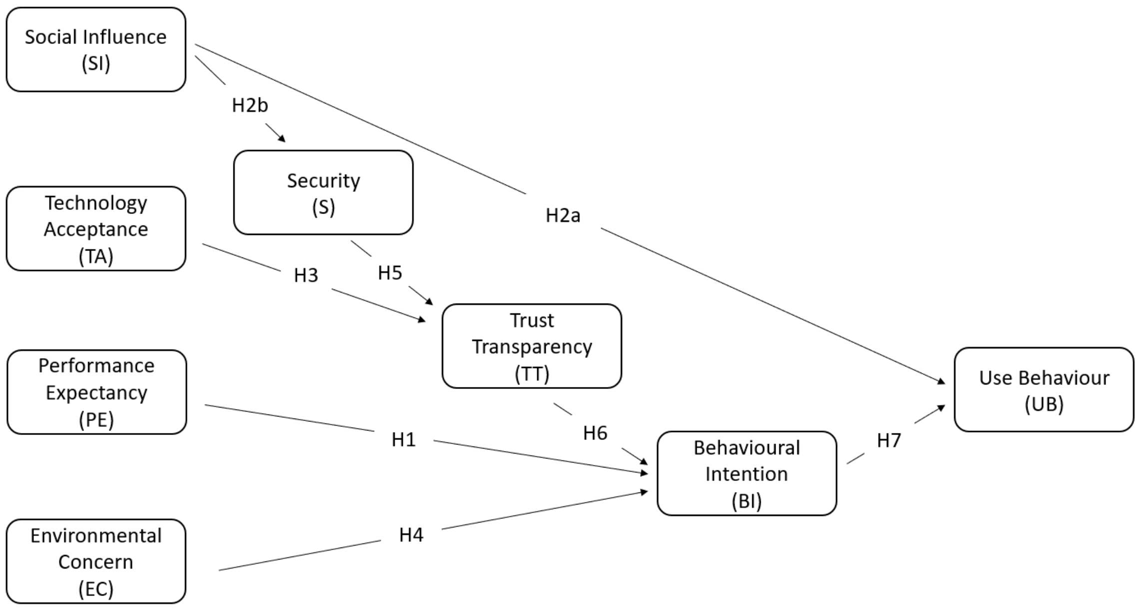

Figure 1 - Research model

4. METHODOLOGY

4.1. Measures

This study proposes to predict determinant factors that could influence blockchain acceptance and adoption. The constructs in this study are based on the original UTAUT (Venkatesh et al., 2003) structure with the adaptation of some constructs, following studies from AlAtiqi (2022), Nwaiwu et al. (2020), and Hsu et al. (2014). A literature review was conducted that allowed the identification of a user's acceptance model and additional variables to explore. The final model can be visualised in Appendix A.

To gain a better understanding of reality and society's perspective, we conducted a data collection using quantitative and deductive methods with an empirical focus (Bryman, 2012). The initial target population was employees working in companies in Portugal that require technology to operate. To reach these objectives a questionnaire was built using the survey's platform Qualtrics (*qualtrics.com*) with initial questions regarding the person's employment function, whether it operated in Portugal or not, and if the person's company requires technology to operate.

The questionnaire consisted of 3 sections. First one with an introduction regarding who is conducting the study, the university, purpose, the study's and voluntariness, a brief explanation of blockchain technology contextualise people. The second section consisted of demographic questions which allowed a filtration of the target public and to make comparations between different genders, ages, job functions, etc. The third section included the defined constructs' items that permit the analysis of the acceptance and use of blockchain technology.

All variables were measured with a Likert scale with each item ranging from “1 – Strongly Disagree” to “7 - Strongly Agree”. The dependent variable, use behaviour, was measured with 3 items that were adapted from a previous study by AlAtiqi (2022), a sample item is “I depend on blockchain to achieve my work tasks”. Regarding the predictor variables, performance expectancy, was measured with 4 items there were also adapted from the same previous study, a sample item is “I would find the use of blockchain technology useful in my job”. Social influence was measured with 4 items adapted from the same previous study, an example is, “People who influence my behaviour think that I should use blockchain technology”. Behavioural intention was measured with 3 items adapted from the same previous study, an example of an item is “I intend to use blockchain technology in 6 months”. Personal technology acceptance was measured using 3 items, adapted also from the same previous study, a sample item is “In general, I am not hesitant to try out new information technologies”. Trust transparency was measured with 4 items used in a previous study by Chang et al. (2022) “Data in blockchain technology would be handled transparently”. Security was measured with 4 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 4 items based on a previous study by Chuang and Huang (2018), a sample item is “I find Blockchain technology to be against environment conservation”.

4.2. Data Collection

The questionnaire was built and run in both Portuguese and English versions. In order to preserve and confirm the value and meaning of the questions when translated, a bilingual, English and Portuguese native speaker reviewed the questionnaire.

We counted with the participation of 198 voluntary respondents from organisations operating in Portugal. It was used a non-probabilistic, and intentional sampling. The distribution happened mostly via e-mail, some others via LinkedIn or personal contacts. What started to be noticed is that there was a lot of people opening the questionnaire, responding to the demographic questions but not to the defined items. This most likely happened because it is still a relatively new technology and a complex subject (Berdik et al., 2021). So, when the number of new responses was stagnating, the public approached started to be more turned to blockchain technology, to increase the percentage of people responding and to get more knowledgeable people on the subject. Through ISEG’s library, Orbis database for private companies was accessed and every company that could be found with open activity registered in Portugal related to blockchain was e-mailed. During collection time, responses were downloaded with some frequency and analysed to check response’s reliability and validity.

Thereafter, the sample characteristics are described in table II. Responses were collected between December 2022 to February 2023, and 90 were considered valid. respondents are males (80%), adults between 30 and 49 years old (46%). Regarding their professional experience, the majority (60%) is experienced having 10 or more years of work, 20% of the sample works in the information technology area, while the biggest sample (38%) answered another area that was not in the options. Finally, 42% of them have the role of a team member.

TABLE II - SAMPLE CHARACTERISATION

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

5. RESULTS

To examine the proposed model, the structural equation modelling (SEM) with partial least squares (PLS) method was used. This allowed the inclusion of both formative and reflective measurement models (Henseler et al., 2009), while working well with small samples, and it is considered an adequate method to test the measurement model and to validate the causality of endogenous constructs (Costa et al., 2016). Since the main objective of this study is to identify important drivers and constructs, we employed PLS-SEM to analyse a non-normally distributed sample for a model with more than six constructs (Hair et al., 2014).

5.1. Measurement Model

The measurement model was examined to evaluate the reliability and construct's validity (Costa et al., 2016). Table III indicates items' reliability through cross-loadings analysis. Researchers typically use the outer loading (highlighted in bolt) values to decide which variables to retain in their factor models and which ones to discard, a common rule of thumb is a value greater than 0.7 (Hair et al., 2014). Table III demonstrates the items with loadings superior to the wished value.

TABLE III - CROSS-LOADINGS

	BI	**EC**	**PE**	**SI**	**S**	**TA**	**TT**	**UB**
BI1	**0,855**	-0,294	0,554	0,494	0,382	0,106	0,522	0,632
BI2	**0,963**	-0,309	0,524	0,396	0,525	0,388	0,599	0,503
BI3	**0,882**	-0,263	0,492	0,386	0,496	0,410	0,565	0,399
EC1	-0,171	**0,817**	-0,225	-0,086	-0,122	-0,143	-0,089	-0,139
EC2	-0,341	**0,950**	-0,167	-0,117	-0,045	0,001	-0,091	-0,161
EC3	-0,318	**0,951**	-0,137	-0,123	-0,063	-0,021	-0,180	-0,070
PE1	0,595	-0,211	**0,930**	0,575	0,529	0,245	0,542	0,514
PE2	0,547	-0,123	**0,964**	0,509	0,525	0,218	0,510	0,435
PE3	0,512	-0,180	**0,953**	0,503	0,500	0,260	0,463	0,442
SI1	0,464	-0,086	0,536	**0,899**	0,438	0,267	0,384	0,475
SI2	0,503	-0,189	0,606	**0,926**	0,403	0,092	0,389	0,547
SI3	0,366	-0,075	0,467	**0,918**	0,277	0,116	0,365	0,474
SI4	0,339	-0,069	0,351	**0,814**	0,182	0,097	0,262	0,509
S1	0,481	-0,056	0,530	0,412	**0,895**	0,077	0,774	0,345
S2	0,385	-0,048	0,534	0,279	**0,901**	0,157	0,682	0,310
S3	0,511	-0,091	0,315	0,344	**0,845**	0,278	0,741	0,379
S4	0,444	-0,064	0,567	0,280	**0,906**	0,248	0,698	0,407
TA2	0,327	-0,051	0,094	0,063	0,181	**0,282**	0,301	0,111
TA3	0,267	-0,025	0,365	0,126	0,291	**0,877**	0,374	0,212
TT1	0,584	-0,186	0,491	0,453	0,706	0,922	**0,912**	0,356
TT2	0,545	-0,054	0,585	0,287	0,775	0,251	**0,868**	0,320
TT3	0,577	-0,130	0,471	0,380	0,745	0,316	**0,951**	0,356
TT4	0,580	-0,128	0,417	0,340	0,776	0,388	**0,933**	0,346
UB1	0,395	-0,046	0,509	0,611	0,338	0,117	0,268	**0,835**
UB2	0,579	-0,151	0,394	0,461	0,383	0,175	0,368	**0,927**
UB3	0,556	-0,153	0,406	0,428	0,360	0,200	0,363	**0,898**

To evaluate the constructs, indicators for reliability and validity were measured, following Henseler et al. (2009) proposed measurement model:

1) Cronbach's alpha: statistical measure that is commonly used to assess the internal consistency or reliability of a scale or questionnaire, a commonly accepted rule of thumb is that a Cronbach's alpha of 0.7 or higher indicates acceptable reliability. As we can see in table IV the constructs meet the criteria.

2) Composite reliability: statistical measure that is similar to Cronbach's alpha and is used to assess the internal consistency or reliability of a scale or questionnaire. Composite reliability is a more robust measure of reliability than Cronbach's alpha, particularly when items on the scale are not tau-equivalent, meaning that they may have different factor loadings. Composite reliability (rho_a) takes into account different factor loadings, and Composite reliability (rho_c) takes into account the variance explained by the underlying

construct or factor. A commonly accepted rule of thumb for both measures is that values above 0.8 are considered acceptable. Through table IV we can see that all of them comply with.

3) Average Variance Extracted (AVE): statistical measure used to assess the convergent validity of a measurement model in structural equation modelling (SEM) which should be greater than 0.5. This demonstrates the latent variables' capacity to account for at least 50% of the variance of their indicators. Once again, on table IV we verify that all comply with.

4) Fornell-Larcker criterion: statistical method used to assess the discriminant validity of constructs in a structural equation model (SEM). It is an important tool for ensuring that the constructs used in a study are reliable and valid. Each variable should share more variance with its own set of indicators. In table V, highlighted in bolt there is the squared root of AVE, through it we can verify that all variables are according to the requirement, each variable's squared AVE being greater than the correlation with other variables.

5) Heterotrait-Monotrait (HTMT): is a statistical measure used to assess discriminant validity in structural equation modelling (SEM), this comes to confirm the discriminant validity of constructs, with the reference value being lower than 0.9. Values are below the threshold and presented in table VI.

All the measurements proposed above are identified in the tables below, following Henseler et al. (2009) and are supported by other authors (Hair et al., 2014).

TABLE IV - 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 V - FORNELL–LARCKER CRITERION AND AVE SQUARED ROOT

	BI	EC	PE	S	SI	TA	TT	UB
BI	**0,901**							
EC	-0,322	**0,908**						
PE	0,584	-0,182	**0,949**					
S	0,517	-0,073	0,547	**0,887**				
SI	0,476	-0,122	0,560	0,375	**0,890**			
TA	0,342	-0,054	0,238	0,238	0,119	**0,815**		

TT	0,624	-0,135	0,534	0,820	0,397	0,374	**0,917**	
UB	0,576	-0,132	0,491	0,406	0,563	0,186	0,376	**0,888**

TABLE VI - HETEROTRAIT-MONOTRAIT (HTMT)

CONSTRUCTS	BI	EC	PE	S	SI	TA	TT	UB
BI								
EC	**0,341**							
PE	0,633	**0,209**						
S	0,576	0,094	**0,591**					
SI	0,518	0,128	0,590	**0,395**				
TA	0,434	0,096	0,243	0,268	**0,145**			
TT	0,687	0,146	0,567	0,884	0,427	**0,428**		
UB	0,649	0,155	0,542	0,458	0,635	0,221	**0,418**	

5.2. Structural Model

Before the assessment of the structural model, to assure that there is no multicollinearity, which is considered to be a threat to model experimental design, the variance inflation factor (VIF) was tested for all the constructs (Costa et al., 2016). Being the threshold of 10 the reference for multicollinearity, we can verify in table VII that every VIF is lower than that point.

TABLE VII - VARIANCE INFLATION FACTOR (VIF)

	BI	**EC**	**PE**	**S**	**SI**	**TA**	**TT**	**UB**
BI								1,294
EC	1,036							
PE	1,425							
S							1,078	
SI				1,000				1,294
TA							1,078	
TT	1,403							
UB								

After the verification of the outer model estimations, the structural model’s quality was evaluated using bootstrapping. By treating the observed sample as a representation of the population, bootstrapping enables assessment of the shape, spread, and bias of the sampling distribution. In this case, 5000 subsamples were used to determine the path's significance within the structural model (Costa et al., 2016).

With the validity of the structural model ensured, the structural paths were assessed to measure the research hypotheses, looking at the 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 TA ($\hat{\beta}$ = 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).

Therefore, the presented model supports all paths having, at least, a medium predictive impact, as seen in table VIII. Checking the threshold values in Costa et al. (2016) study, we recognise that H3 and H4 represent a medium predictive effect, while H1, H2, H5, H6, and H7 and large effect.

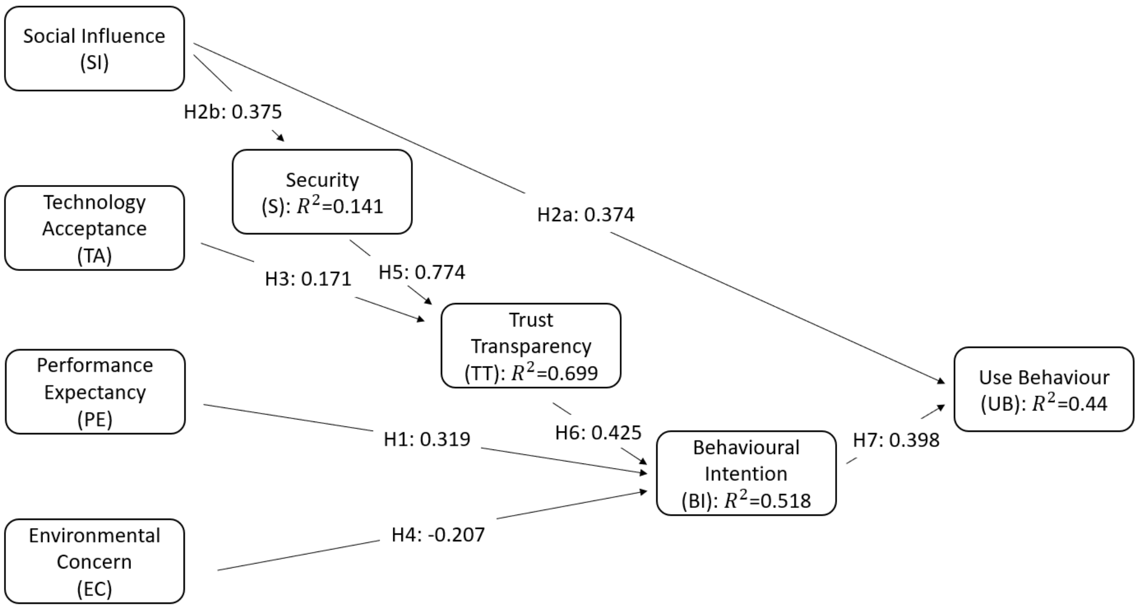

Figure 2 - Structural model results

TABLE VIII - HYPOTHESES TESTS

Hypothesis	Independent Variable		Dependent Variable	Standard deviation	β^	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 study seeks to understand employees' behaviour towards blockchain adoption. Therefore, Use Behaviour (UB) and Behavioural Intention (BI) variables were followed from the UTAUT's original model to measure user's intention to come to adoption and actual adoption of this technology. Other variables that impact these two were conceived. From the original model, Social Influence (SI) and Performance Expectancy (PE) come in play to measure the impact on the individual, assessing how the individual's perception of what his/her social circle think 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 studies from Chang et al. (2022), Hsu et al. (2014), and Wong et al. (2020) new variables were added, Trust Transparency (TT), Security (S), Environmental Concern (EC), and Personal Technology Acceptance (TA). These variables aim to identify, respectively, individual's belief that blockchain technology and its services are safe, error-free, and transact transparent, individual's perception on the level where information is protected from security threats, leakage, and infringement, the attribute of a person's compassion, worries, likes and dislikes about the environment, and individual's propensity to embrace and use new technologies for accomplishing goals in home life or work.

Given these variables and following other studies, some hypotheses were formulated. To test these hypotheses and asses a structural model, structural equation modelling (SEM) with partial least squares (PLS) was used, which is useful to test different measurement models, especially when the sample size cannot be in big scale and is a tool to explore complex relationships between variables (Hair et al., 2014).

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, having BI the biggest impact, as predicted by Venkatesh et al. (2012). Many studies have shown that the bigger the individual's intention to use a specific technology in the future, the increased likelihood to perform a potential behaviour. Numerous technology adoption models incorporated in UTAUT theory support this relationship between behavioural intention and usage of technology (Khazaei, 2020). Venkatesh et al. (2003) have found that the degree to which an individual perceives that important others believe he or she should use the new system influences individual's behaviour of using the technology. In line with our findings, Mazman et al. (2009) study concludes that people's social environment can impact whether that person will use a technology.

Being BI the main impactor of UB, it is also important 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 being positively correlated to BI, while EC being negatively, explain 51.8% of BI's variation. Trusting the credibility of a technology affects how people feel about it, which in turn affects their intention to utilise it (Tseng & Fogg, 1999). In line with our findings, trust in behavioural intention towards a technology has frequently been proven to have a positive and significant predictive effect throughout its various aspects (Wong et al., 2020). Performance expectancy is one of the most crucial concepts in technology use, according to numerous researches (Alraja, 2015; Benbasat & Barki, 2007; Venkatesh et al., 2003). According to Venkatesh et al. (2003), it is assumed that in this study, individuals will adopt a technology if they think it will have favourable outcomes. EC negative connotation does is not surprising since blockchain technology is still seen as a major energy consumer due to bitcoin's mining effort (Badea & Mungiu-Pupazan, 2021). TT variable could be in a big scale predicted by other two variables. 69.9% of its variation were due to S ($\hat{\beta}$ = 0.774, $p < 0.001$) and TA ($\hat{\beta}$ = 0.171, $p < 0.05$), both influencing it positively. Some studies used and defend the use of TT as a mediator factor between S and BI. Ray et al. (2011) study concluded that security perception increases trust, with a proposed model suggesting that researches should prefer using perceived security as a way to lead to trust. Suh and Han (2003) study also analyse the importance of security on trust, while also using trust as a mediating factor between security and behavioural intention, also verifying our study's findings. A variety of technology acceptance studies have consistently demonstrated and encouraged the integration of personal technology acceptance in models (Wong et al., 2020). Caldeira et al. (2021) found a strong positive correlation and states that personal technology acceptance can influence the intention to trust or not in a particular product or service (Caldeira et al., 2021). Dimitriadis and Kyrezis (2010) research regarding financial services goes along with these lines, where a person's general inclination toward new technology affects how they perceive the legitimacy of an invention.

Das et al. (2014) studied the social interaction around cybersecurity and endorse the importance of social influence on security behaviour 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. Das et al. (2015) found that SI relation may vary depending on who a person considers in his/her social circle and especially its size, explaining the lack of expressiveness on S variation.

Limitations

Although PLS was used in order to diminish this impact, one of the main limitations of this study is the sample size. It may not be large enough to provide a representative picture of the population. This could limit the generalisability of the findings, as the results may not be applicable to other populations with different characteristics. While the current study provides insights into the factors influencing the adoption of blockchain technology, there are several areas where future research could expand upon or build upon the findings of this study.

There was a limited geographical scope of the study. The survey was conducted in a specific geographic region, and the findings may not be applicable to other regions or demographics. This could limit the external validity of the study, as the results may not be generaliable to other populations

Another limitation is the limited scope of variables that were included in the study. While the study focused on important variables such as use behaviour and behaviour intention, other important variables such as cultural factors were not included. This could limit the comprehensiveness of the findings, as the study may not have captured all of the factors that influence use behaviour and behaviour intention.

Future research directions

While the current study provides insights into the factors influencing the adoption of blockchain technology, there are several areas where future research could expand upon or build upon the findings of this study.

A potential direction for future research is to investigate the influence of organisational factors on blockchain adoption. This study focused on individual-level factors that affect adoption behaviour, but there may be organisational-level factors that are also important. For example, the culture of an organisation or the degree of top-down support for blockchain technology may impact adoption behaviour.

Another potential direction for future research is to examine the impact of blockchain use cases on adoption behaviour. While the current study focused on general individual adoption behaviour of this technology, there may be specific use cases for blockchain technology that are more likely to drive adoption. For example, use cases related to supply chain management or financial transactions may be particularly relevant for blockchain adoption. Future research could investigate how adoption behaviour varies across different use cases and identify the factors that are most influential for each use case.

Finally, there may be other contextual factors that influence blockchain adoption that were not included in this study. For instance, the study did not explore the impact of regulatory environments or the availability of blockchain-specific expertise on adoption behaviour. Future research could investigate the impact of these and other contextual factors on blockchain adoption to provide a more comprehensive understanding of the factors that affect adoption behaviour in this domain.

7. Conclusion

In this study, we developed a predictive model for blockchain adoption based on a thorough review of the existing literature and analysis of empirical data. Our findings indicate that through the analysis of our proposed model, which includes technological, social, environmental, trust, security, and performance expectancy factors, identified several key predictors of blockchain adoption, social influence and behavioural intention.

Behavioural Intention in turn, is mostly influenced by trust transparency that has its variation mostly justified by the perception of security.

Our research makes several important contributions to the field. It provides a framework for understanding the complex factors that influence blockchain adoption. It also provides practical guidance for organisations seeking to adopt blockchain technology by identifying key success factors. Companies can utilise the findings to develop better strategies for incorporating blockchain technology into their operations. Understanding the factors that drive or inhibit blockchain acceptance allows businesses to tailor their approaches to different target markets.

However, our study is not without limitations. One limitation is the data set used for our analysis, which may not be fully representative of all organisations or industries. Additionally, our model does not account for all possible factors that may influence blockchain adoption, and future research could explore additional factors or refine the existing model.

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