



UNIVERSIDADE
CATÓLICA
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FACTORS INFLUENCING CONSUMER ADOPTION OF
PEER-TO-PEER BLOCKCHAIN-BASED ENERGY TRADING

Dissertation submitted to Universidade Católica
Portuguesa to obtain a Master's Degree in Psychology in
Business and Economics

BY

JAKOB KUNGEL

Faculty of Human Sciences

September 2023



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Abstract

Studies on the distribution of energy are increasingly focusing on blockchain-based Peer-to-Peer (P2P) energy trading, a promising method to distribute sustainable energy on a local level. This thesis aimed to contribute to the existing literature by investigating the following research question: What are the factors influencing consumer intention to use P2P blockchain-based energy trading? Based on the second version of the “Unified Theory of Acceptance and Use of Technology”, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived privacy risk, trust, risk and technology savviness were investigated to measure acceptance and to understand potential differences between the new but upcoming blockchain technology and a common comparable technology, in the form of a cloud solution.

The results of the study ($N=352$) show that the intention to use P2P energy trading can be predicted by five out of nine constructs and that there are significant differences between the two technologies in certain areas, namely performance expectancy and hedonic motivation, what was identified through a multi-group analysis (MGA). Therefore, organisations using or introducing blockchain-based P2P energy trading should take special care in communicating these areas, as they are perceived significantly differently. However, social influence, facilitating conditions trust and risk perception, were equally predicted behavioural intention to use blockchain technology and a cloud solution for both technologies. These contexts can be an important opportunity for organisations providing P2P energy trading technology to inform and educate energy consumers and prosumers, thereby essentially increasing the acceptance of the technology. This, in turn, could significantly advance the energy transition.

Keywords: P2P energy trading, energy communities, blockchain, PLS-SEM, MGA, TAM, UTAUT2, energy transition,

Sumário

Os estudos sobre a distribuição de energia estão a centrar-se cada vez mais no comércio de energia Peer-to-Peer (P2P) baseado em cadeias de blocos, um método promissor para distribuir energia sustentável a nível local. Esta tese teve como objetivo contribuir para a literatura existente, investigando a seguinte questão de investigação: Quais são os factores que influenciam a intenção do consumidor de utilizar o comércio de energia baseado na cadeia de blocos P2P? Com base na segunda versão da "Teoria Unificada da Aceitação e Utilização de Tecnologia", foram investigadas a expectativa de desempenho, a expectativa de esforço, a influência social, as condições facilitadoras, a motivação hedónica, o risco de privacidade percebido, a confiança, o risco e o conhecimento da tecnologia para medir a aceitação e compreender as potenciais diferenças entre a nova, mas futura, tecnologia de cadeia de blocos e uma tecnologia comparável comum, sob a forma de uma solução de nuvem.

Os resultados do estudo (N=352) mostram que a intenção de utilizar o comércio de energia P2P pode ser prevista por cinco dos nove constructos e que existem diferenças significativas entre as duas tecnologias em determinadas áreas, nomeadamente a expectativa de desempenho e a motivação hedónica. Por conseguinte, as organizações que utilizam ou introduzem o comércio de energia P2P baseado em cadeias de blocos devem ter especial cuidado na comunicação destes domínios, uma vez que são percebidos de forma significativamente diferente. No entanto, a influência social, as condições facilitadoras, a confiança e a percepção de risco, previram igualmente a intenção comportamental de utilizar a tecnologia de cadeia de blocos e uma solução de nuvem para ambas as tecnologias. Estes contextos podem constituir uma oportunidade importante para as organizações que fornecem tecnologia de comércio de energia P2P informarem e educarem os consumidores de energia e os prosumidores, aumentando assim essencialmente a aceitação da tecnologia. Este facto, por sua vez, pode fazer avançar significativamente a transição energética.

Palavras-chave: P2P Energy Trading, Energy Communities, Blockchain, PLS-SEM, MGA, TAM, UTAUT2, Transição Energética,

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List of Abbreviations

BC	Blockchain
BM	Business model
DERs	Distributed energy resources
EE	Effort Expectancy
ETP	Energy trading platform
FiT	Feed-in-tariff
FC	Facilitating Conditions
HH	(Private) household
HM	Hedonic Motivation
LFM	Local flexible market
P2P	Peer-to-peer
PBC	Perceived behavioural control
PE	Performance expectancy
PEM	P2P Energy Markets
PLC	Product life cycle
PPA	Power purchase agreement
PPR	Perceived Privacy Risk
PV	Solar photovoltaic
RES	Renewable energy sources
RP	Risk Perception
SI	Social Influence
TPB	Theory of planned behaviour

TR	Trust
TS	Technology Savviness
VP	Value proposition

1. Introduction

The world used more energy in 2022 than ever before and energy prices reached new records (Mikayilov, 2022; Catiforis, 2022). At the same time, in accordance with the Paris Climate Agreement, it is essential to stop producing energy with high levels of carbon dioxide intensity and there is already a proven trend consumers towards sustainability and higher price sensitivity (Fischer, et al., 2012). To fulfil the European climate targets, at least 65% of the required electricity must be produced from sources of clean energy by 2030. Political and security considerations also make it imperative to generate a greater amount of sustainable energy and reduce dependence on fossil fuels (The Paris Agreement, 2015).). The need to reach this target is real. According to some, if we do not meet the international climate targets and climate change continues, not only will a large part of the earth be uninhabitable in the future, but the next major extinction of species will also occur (Román-Palacios & Wiens, 2020). It is already foreseeable that the expansion of commercial renewable energies in most countries will not be sufficient to achieve these goals. To achieve this objective, we need more prosumers, which are individuals or households who consume and produce energy, intelligent distribution networks, which can manage energy flows efficiently and reliably, and enhanced utilization practices, such as energy storage and demand response, at the community level. This significant increase in decentralised energy resources could help to achieve these goals. Energy trading with prosumer and consumer could be a means by which to achieve this goal. This new marketplace is based on the concept of bidirectional power flow, allowing customers to become prosumers with power generation capabilities (Almarzooqi et al., 2023). Local flexibility markets are upcoming as a promising way to use demand-side flexibility to address the challenge of integrating more renewable energy into the grid. These markets allow prosumers to sell their excess energy to other consumers or to the grid, and they can also incentivize consumers to reduce their energy use during peak times (Pressmair et al., 2021).

A promising and effective method to distribute or purchase energy on a local level is blockchain-based peer-to-peer energy trading. P2P energy trading is a decentralized market where individuals and households (peers) can purchase and sell electricity directly without a middleman. The application of blockchain technology to the energy market has been shown to provide essential advantages, such as more stable usage and lower grid utilization

(Borges et al., 2022). Decentralized systems can essentially support sustainable energy procurement. The goal of these decentralized systems is to create their own ecosystem that is independent and decentralized. Such decentralised blockchain energy systems have already proven themselves at a pilot level in several energy communities (Kotilainen, 2019). The technology of blockchain has emerged as a potentially disruptive force with a diverse range of applications across various sectors, including industry, banking, healthcare, and now energy (Laurence, 2023). Its distinctive characteristics make it an indispensable tool for businesses. Nonetheless, the process of adopting the technology is filled with potential pitfalls and obstacles that may impede its efficacy. One of the challenges faced in this regard pertains to the insufficient level of consumer awareness, which can potentially harm overall user acceptance. Pilot projects in several European countries have found a lower acceptance than originally predicted. There is currently a lack of willingness to participate, as well as a lack of education about the technologies and the resulting benefits. Blockchain novelty and complexity, leads to skepticism, prejudices and distrust. While generally secure, there have been high-profile security breaches. Additionally, concerns about energy inefficiency, e.g. in blockchain-based systems such as Bitcoin, which now consumes two times more energy than Portugal, could reduce the adoption of blockchain (Pernice & Scott, 2021; Agur et al., 2023; Olkusi, 2023).

Therefore, it is essential to conduct adoption and user acceptance studies to identify the key factors which impact the adoption of blockchain technology and to address any obstacles that may impede its adoption. Given this perspective, the present investigation undertakes a methodical review of the literature to identify common models of technology adoption and their principal determinants across diverse domains. The subsequent segment delves into the findings of this study and furnishes perspectives on the uptake and approval of blockchain technology.

This work is thus intended to explore which factors influence consumer acceptance of the use of blockchain technologies in a P2P energy marketplace. Chapter 2 will investigate the current literature and explain the technology with a brief background about the explained technologies. Following recent literature recommendations, intend to measure the technology acceptance of blockchain technology in this field using a quantitative survey based on an modified version of the Unified Theory of Acceptance and Use of Technology

2 (UTAUT2). The following chapter will focus on the methods used to conduct the quantitative research and assess the hypothesis's support. The adapted UTAUT2 model was tested whether to verify the correlation of the constructs or not, and the constructs are tested for differences with a multigroup analysis (MGA). Chapter 4 will present the results which are supplemented by attachments in the appendix. Chapter 5 will focus on the discussion, followed by a brief limitation and further outlook before the topic will be complemented by the conclusion. The results obtained from this assessment can contribute to the better understanding of individual's responses to this technology, thus contributing to its acceptance and use. Only if organisations know which factors prevent or influence participants from taking part in P2P energy trading, these issues can be specifically addressed and clarified, which can increase technology acceptance.

2. Literature Review

2.1. Introduction

2.1.1. P2P Energy Trading

To evaluate the acceptance of blockchain-based peer-to-peer energy trading technology, it is important to understand previous approaches to study this construct and to look at the individual components as well as the historical background of the technology. Peer-to-peer (P2P) energy trading is a new, decentralized system that allows individuals to buy and sell electricity directly from each other, eliminating the need for intermediaries (Brühl 2017). P2P energy markets are expected to enable further adoption of renewable energy; however, concrete applications of these concepts have only just begun to be deployed in practice (Mengelkamp et al. 2018).

The components of the present work are still part of a new technology, that has not been fully explored, which is why the growing literature does not yet provide evidence of user acceptance of its technology (Ableitner, 2019; Mengelkamp, 2018). Therefore, a brief theoretical background is provided to explain their components.

The technology behind P2P energy trading communities can be summarized as a network, in which participants can trade energy bidirectional on a real-time basis, without the need for a central authority to manage the transactions (Soto et al., 2021). Participants in the P2P energy communities (EC) can generate their energy from renewable sources such as solar systems or wind turbines and sell any excess energy they produce to others in the network. This system allows individuals to take control of their energy consumption and production and promotes the use of renewable energy sources (ibid.). The P2P EC also allows for the use of energy more efficiently as excess energy can be sold to those who need it, reducing the need for centralized power plants and reducing carbon emissions. It is a promising solution to the challenges of climate change and energy security. This, combined with the technology of blockchains, results in an even more promising energy distribution technology, as the blockchain makes it safer and more transparent (Brühl 2017). Several studies have been conducted on the technology of blockchain in the field of energy P2P trading and scientists agree that the advantages of this technology outweigh the disadvantages and that the resulting financial aspects in particular offer benefits. Profit

potentials arise as the individual profit margin in relation to classic energy sales, or the reduced price concerning classic energy purchases offers a financial benefit for both parties (Khorasany, 2018).

2.1.2. Blockchain

Blockchain is a decentralized digital ledger that stores transactions securely and transparently (Tapscott & Tapscott, 2016). It uses cryptography to ensure that once a transaction is recorded, it cannot be altered or deleted. All the blocks in the chain contain an individual code known as a hash that connects it to the preceding block, creating an unbreakable chain of data. This technology is usually associated with cryptocurrencies but has a wide range of potential applications in various industries, though it has yet to become as mainstream as some scientists originally predicted (Laurence et al., 2017).

In subsequent chapters, I will look more into the intricacies of energy trading technologies. Subsequently, I will provide a comprehensive analysis of blockchain technology, elucidating its potential for integrating peer-to-peer energy trading and blockchain mechanisms. Furthermore, many studies analyse why people like to use blockchain in technologies or reasons why they do not use them, but no study looked at P2P technology in EC yet. After discussing energy trading technologies in more detail in the next chapters, I will then elaborate on the current literature on blockchain technology and explain reviews on the possibilities for combining it with p2p energy trading.

2.2. Energy markets and energy trading

Energy markets encompass the trading and distribution of energy resources, constituting a distinct category within the realm of commodity markets. They can be organized in a variety of ways, but they all share the common goal of facilitating the exchange of energy between buyers and sellers (Saranya et al., 2023).

Energy markets are undergoing profound change as they transition to a cleaner and more sustainable energy mix. This transformation is being driven by several factors, including the increasing cost of fossil fuels, the need to reduce greenhouse gas emissions,

and the growing popularity of renewable energy sources. The development of European energy markets is a complex and challenging process, but the region needs to achieve its climate and energy goals (Hafner & Tagliapietra, 2020).

In order to understand why energy supply has been centralised so far, one has to take a closer look at the historical context. The birth of centralized energy supply can be traced back to 1807 when gas lanterns were first used. Gas companies were subsequently founded, bringing energy conveniently into homes. However, in the mid-19th century, electric current emerged as a new competitor to gas. Siemens developed the first generator in 1866, enabling large-scale electricity production primarily for public lighting. However, the distribution of electricity as an affordable commodity for all citizens proved challenging for many companies. As a result, by the end of the 19th century, numerous utilities transitioned from private to public ownership, leading to the emergence of municipal utilities. Despite changes in electricity consumption and the introduction of new electronic devices, the centralized system of energy supply has remained largely unchanged to this day (Clifton et al., 2011; Sovacool, 2011).

Despite the longstanding utilisation of energy in a manner comparable to contemporary practises for more than a century, it was not until 1992 that the inaugural power exchange was established in Norway (Bolton, 2022). This development facilitated the introduction of tiered pricing for energy trading, a practice that remains accessible to private individuals in contemporary times. Subsequently, in the ensuing years, the initial European Union member states implemented national exchanges. The liberalisation of the electricity market in 1996, which eliminated state monopolies in the electricity sector, was a crucial requirement for the implementation of power exchanges in the European Union member states. This illustrates that energy exchanges are a relatively new concept and people are not yet fully familiar with it, which still leads to challenges with a lack of understanding, complexity and risks (Wang & Xing, 2020).

In the 2000s, based on the first energy markets, dynamic tariffs evolved with the technology and visualisation of smart meters, whose distribution in Italy began in 2001 (Enel). These so-called intelligent metering devices have an internet connection and can therefore not only measure the energy used (or produced) but also calculate and multiply that with the energy spot prices. For the first time, consumers were able to directly benefit

from fluctuating electricity prices, and the spread progressed in other countries. Nevertheless, the acceptance of dynamic tariffs is still very different today, with a distribution of 65% in Norway, 10% in Finland or 47% in Spain, just to highlight some examples (Meeus, 2011). In some Eastern European countries, on the other hand, less than 5% of the population can use this innovative approach to energy distribution. This is also due to the distribution of smart meters, which are required for providing dynamic tariffs. In Europe, only 23% of its population had the requirements to be able to have a dynamic tariff (Jones, 2022).

2.3. P2P Energy trading and energy communities

As previously stated, P2P energy trading stands for direct energy trading between peers (prosumer and consumer), where energy from small, distributed energy resources (DERs) is traded between local prosumers and consumers in energy communities (EC) or a Peer-to-peer energy market (PEM) (Frieden et al, 2021). Both forms are legally defined by the European Union and can be initiated as energy cooperatives or renewable energy initiatives in communities (European Parliament, 2018, 2019). 2% of the worldwide energy is produced by DER and the most popular way of generating electricity is using a PV system (IRENA, 2019; Ableitner et al., 2020). To understand the development of DERs, it's important to underline the novelty of the technology.

The technology of dynamic tariffs was and is the pioneer for PEM (Freier & von Lössl, 2022). To analyse the acceptance of PEM it is important to delimit its features from the attributes of the dynamic tariffs. While both profit from the dynamic and time-based pricing, PEM are not regulated and the prices are only set by the market. Therefore, they are considered to be less oligopoly-regulated and have higher competition. Also, PEM have a different granularity. Dynamic tariffs are available from the energy stock; therefore, their prices are similar in the whole market. Whereas PEM need local granularity to send price signals (Lundin, 2022). Historically, privately consumed energy was always distributed by large energy providers. Even until the large dissemination of private solar systems, privately produced energy was also nearly always fed into the national grid. DERs are not only households or companies that generate their electricity and consume it or store it, but also

who can feed it into a specified grid either by a predetermined price per kWh or by a price that arises at that moment due to supply and demand (Paudel & Gooi, 2019).

Before P2P energy trading was developed, the only possible and legal option was to feed produced energy into the whole grid. The fixed compensation does not change in the short term in almost all European countries and is independent of the general electricity consumption within the grid, but it is often considered too low. Due to national laws, it is often common for prosumers to receive 0.05-0.10 euros per kilowatt hour produced, but have a purchase price of often around 0.30-0.40 euros. Due to this fact and lack of flexibility, there is a strong desire for private electricity trading by prosumers (Campoccia, 2014). Various degrees of the spread of energy communities can be attributed to the legal ambiguity or illegality of energy trading in several European countries. Van Summeren (2020) through a multinational analysis identified that EC have therefore different shareholder forms. Typically, EC are created when several people, local businesses, or organisations band together to generate, administer, and share energy resources. Promoting the switch from energy sources such as fossil fuel systems to cleaner, more sustainable alternatives is similar to the general energy markets one of the key goals of energy communities. Simpler structures, smaller networks, and lower-cost organizations allow EC to adapt more quickly to changing circumstances and more easily pass on potential savings to consumers. Because ECs, unlike most electricity suppliers, do not have to be profit-making enterprises, savings can usually be better and more effectively passed on to the end consumer. EC want to maximise the potential of locally available renewable energy sources like solar, wind, and hydropower. By doing this, they aid in lowering greenhouse gas emissions and promoting energy independence. Policymakers and regulatory agencies in Europe are paying much more attention to and supporting the energy community. The European Union has acknowledged their significance in attaining its energy and climate goals as well as in fostering civic engagement and regional economic growth (ibid.). According to Koehrsen (2017), by encouraging decentralized energy production and local energy collaboration, these communities promote community members to take part in the energy transition, and present chances for engagement in society, social harmony, and regional economic gain. Additionally, energy communities support energy resilience and lessen the load on the central energy system.

Gui and MacGill (2018) identified the activities that energy communities in Europe are involved in, particularly the construction of renewable energy systems, the implementation of energy efficiency measures, the trading of energy, and the growth of regional energy markets. They provide users people the ability to produce their clean energy, use it locally, and share any extra with their neighbours or the larger grid. European energy communities have come a long way, yet there are still problems. These include overcoming regulatory obstacles, gaining access to capital, overcoming technical challenges, and assuring fair participation for all societal members. However, energy communities can play a significant role in determining a sustainable and decentralised energy future in Europe with sustained commitment and support from policymakers (Reis et al., 2021).

Another advantage of the P2P technology is that it provides prosumers the opportunity to participate in a genuinely decentralised mode of energy trading, eliminating the requirement for an intermediary (Soto, 2020). According to Morstyn et al. (2018), peer-to-peer (P2P) energy trading offers increased flexibility, thereby creating a significant potential for the utilisation of renewable energy sources. This, in turn, contributes to expediting the transition towards sustainable energy systems. In addition to the mentioned advantages for prosumers, various stakeholders within the electricity market can also derive benefits. These include the reduction of peak electricity demand, decreased maintenance and operational expenses, and enhanced reliability, transparency, and security of the electricity grid. These benefits contribute to mitigating the risk of energy market failure (Khatoun, 2019).

The likelihood of experiencing short-term overproduction or underproduction rises as the deployment of centralised renewable energy sources expands. During periods commonly referred to as "dark phases," such as when dense fog occurs in a specific region of a national power grid, the electricity generation from wind turbines and photovoltaic (PV) power plants experiences a decline. If a different region of the national grid possesses a reduced quantity of centralised renewable energy sources, it is plausible that a deficit in power supply may arise. The prevalence of private and decentralised renewable energies in the other part, serves as a mitigating factor in this regard. In the context of a peer-to-peer (P2P) power grid, wherein pricing is contingent upon the interplay between supply and demand, private households residing in the part with less energy production are motivated

to contribute electricity to the grid due to the provision of comparatively elevated remuneration. Peer-to-peer (P2P) energy trading enhances both the national and local energy balance by fostering a more diverse range of energy producers, as implied by the decentralised nature of this approach (Linnemann & Vallana, 2018).

The pricing, contrarily to what happens in typical systems, is typically determined as a range between the export price and the retail price. Consequently, both generators and consumers, irrespective of their role as sellers or buyers of electricity, derive advantages from the peer-to-peer energy exchange. The reduction in prices for peer-to-peer (P2P) traded electricity can be attributed to the elimination of costs associated with taxes and grid fees, which are typically incurred for the transportation of electricity. Nevertheless, in a hypothetical situation where the prices offered by alternative energy providers are less favourable compared to those of conventional energy providers, consumers retain the option to revert to the conventional distribution and selling methods available to all European Union citizens. Hence, individuals who engage in an EC should not experience a deterioration in their disposition towards it (Paudel & Gooi, 2019).

2.4. P2P Energy trading technology possibilities

P2P energy trading is a promising new technology that has the potential to revolutionize the energy sector. However, there are a few technologies that can be used for P2P energy trading. One possibility is centralized platforms using a cloud solution. Centralized platforms are a traditional way to facilitate P2P energy trading. These platforms act as intermediaries between buyers and sellers, and they take a commission on each transaction. Centralized platforms are easy to use and reliable, but lack security and transparency. A contrasting option is blockchain based p2p energy trading, which, as previously stated, is a system that allows individuals to trade energy directly with each other, using blockchain technology to record the transactions. This system eliminates the need for intermediaries, such as utilities, making energy trading more efficient, transparent, and secure. In general, the best alternative for P2P energy trading depends on the specific needs of the market. Blockchain is a good choice for markets that require a high level of security and transparency and is therefore seen as a promising technology for the future in the P2P Energy trading market (Aganavakis et al., 2018; Erturk et al., 2019).

In the next chapter, I will go into further detail about blockchain technology and how its digital platforms can be used to support peer-to-peer energy trade, guaranteeing its transparency, security, and just pay (Gui & MacGill, 2018).

2.5. Blockchain

To explain the technology of the blockchain in a simplified way, it is a public register (ledger) of transactions (Kewell, Adams & Parry, 2017). Blockchain is a decentralized, distributed digital ledger (DLT) that archives transactions securely and transparently. DLT is considered to be the 4th industrial revolution, of which the blockchain is probably the best-known representative (Zheng et al., 2017)). It is a database that stores information across a network of computers in a series of blocks. Each block includes a unique code known as a hash that connects it to the preceding block. Once a block has been added to the blockchain, it becomes immutable and cannot be modified or removed without obtaining agreement from the network participants. This makes blockchain a tamper-proof and immutable system for recording and verifying transactions, which can be used for a variety of purposes, from financial transactions to supply chain management. These transactions contain the following information: Who transfers what, where something is transferred from, and when it was transferred. In many different sectors, it has already been proven that the technology is financially attractive by lowering transaction costs (Kewell et al., 2017; Ullah, 2021).

Blockchain technology has evolved over a span of thirty years through extensive research and development efforts. It originated in the early 1990s with the introduction of concepts like Merkle trees and linked timestamping. In 1997, Nick Szabo proposed the idea of smart contracts to improve contractual procedures using the Internet. But it was the release of Satoshi Nakamoto's white paper on Bitcoin in 2009 that drew significant attention to blockchain technology. Despite differences, blockchains generally exhibit decentralization, public accessibility, and encryption. Subsequent milestones include the establishment of Ethereum in 2013 as a platform for blockchain-based applications and the introduction of the Hyperledger project by Linux in 2015, with partners like IBM and SAP. Major companies like Microsoft and IBM have integrated blockchain technology into their cloud services. In 2016, Deutsche ReiseBank AG successfully conducted a payment transfer using

blockchain, demonstrating its speed and efficiency compared to traditional systems like SWIFT (Tapscott & Tapscott, 2016).

2.6. Blockchain-based P2P energy trading

Smart contracts, which are founded on computer protocols, are required for P2P energy trading utilising the blockchain. This refers to a type of digital contract founded on blockchain technology. The corresponding contract between a "buyer" and "seller" is written explicitly in lines of code. Simply stated, a smart contract is a small programme that executes simple if-then rules on a blockchain. The developers predefine conditions and actions that are then carried out autonomously (Wongthongtham et al., 2021).

Smart contracts are, then, contracts that automatically go into effect when certain already defined activities arise and consequently do not need human oversight. If these entry conditions are satisfied, the algorithm starts an operation, which is then validated and recorded in a block. Consequently, smart contracts allow for the fulfilment of reliable transactions and agreements within individuals. Transparency, trust, efficiency, and safety are frequently cited as advantages of this technology. Like conventional sales contracts, smart contracts always include the parties' legally enforceable statements of intent. Only if developers implement backdoors in the program code could a smart contract be forgeable. Otherwise, it is true that, like the blockchain, it is forgery-proof, transparent and always available. This is also important because in some sectors it is already replacing the role of a notary. The technology is already more established in some industries and so there are already several current P2P application areas such as, digital contracts for leases, insurance, supply chains or licensing. The aspiring technology is not only promised to strongly influence the industry but also to long-term change the energy sectors, as we know it (Kaulartz & Heckmann, 2016; Kirli, 2022; PWC, 2023).

The idea, of trading virtual assets via blockchain grew already in 2009 with the introduction of Bitcoin. The first notable instance of trading virtual assets via blockchain, other than cryptocurrencies, was the launch of the Ethereum network in 2015. One year later, a pilot project in New York first ever traded decentral-generated energy from one neighbour to another. But this and most of the other early projects never made it beyond their concept

stage. Years later, in 2018 the first blockchain-based P2P energy platform was started in Vancouver (Cointelegraph, 2018). In the following years, more and more pilot projects started (Chen et al., 2022).

The energy sector exhibits distinct characteristics compared to other sectors driven by blockchain technology, such as the financial industry, due to the additional consideration of the physical product involved. Nevertheless, energy transactions encompass more than just the exchange of values and information; they also involve the transmission of electricity through the grid infrastructure. When considering market participants, prospective prosumers exhibit a preference for a privately owned yet impartial entity, such as a third-party market operator, that is engaged by either all involved parties or a government agency. The majority of studies indicated a preference for a fully decentralised system, as reported by Borges et al. (2022).

2.7. Acceptance of blockchain based P2P energy trading

The utilisation of blockchain technology for peer-to-peer energy trading holds significant potential and can bring about a transformative impact on the energy market when widely accepted. However, it is still in its early stages of development, which is why challenges have to be overcome before it is largely adopted. Recent literature pointed out the primary aspects of standardization, trust, scalability, and regulatory uncertainty (Wongthongtham et al., 2021). In a general study from Hahnel (2020), 22.6% of the participants expressed their unwillingness to engage in peer-to-peer (P2P) energy trading after being provided with comprehensive information regarding the underlying concept and 77,4% were generally open to partake in P2P energy trade, which is also consistent with other recent studies. Named concerns are privacy concerns, practical viability, legislative regulations of the safeguarding of personal data, costs, potential investment costs, the pricing of energy and its margin (ibid.).

The acceptance of blockchain-based technologies is also strongly influenced by its prominent sub-area, cryptocurrencies, which have been discussed very controversially for years (Pernice & Scott, 2021). According to the authors, the media coverage of blockchain, is influenced by the high volatility of digital currencies, the desperate search for Satoshi

Nakamoto, whose identity is unknown, or the spread of currencies in the dark web. Other concerns that can be attributed to the influence of cryptocurrencies are mainly due to the lack of standardized regulations as well as the fact that blockchain technology is not yet mature enough in the legal arena (Golosova & Romanovs, 2018).

Despite the legal enforceability of blockchain technology in the context of smart contracts, the implementation of this technology frequently gives rise to challenges about its legal enforceability. The reason for this is that the fundamental elements of a contract, namely mutual agreement, expression and acceptance of a valid offer, sufficient consideration, capacity to form a legally binding agreement, and legality, are typically embodied in computer code that is interpreted and executed by computers (Khan, 2021).

The achievement of the nation's climate objectives necessitates the crucial element of public acceptance towards the distribution of sustainable energy. The acceptance of PEMs is primarily influenced by the emergence of tariffs for energy distribution, as well as the institution responsible for implementing them. The emergence of digitalisation, characterised by the interconnection of applications, business processes, and devices through internet technologies, along with the utilisation of sensors and self-controlling devices, has led to the emergence of novel and more conscientious approaches to energy management. The proliferation of smart home devices capable of intelligently monitoring and regulating power consumption of household appliances has transitioned from an initial phase of early adopters to a widespread market phenomenon (Soeiro & Dias, 2020; Zielonka et al., 2021).

The acceptance of using a PEM based specifically on a blockchain application is not widely explored, as the technology is so new it has so far only been used on a trial basis and has not yet become institutionally established in any country or region (Bilardo, 2021). Therefore, there are no known long-term studies about the acceptance of that technology and most of the literature is based on scenarios, where participants are asked about their potential preferences and acceptances. In this regard, Zabaleta et al. (2020) found that the main risks are administrative, standardization, trust and technology and that concerns about administrative matters, which could lower the acceptance, were lack of regulation, market restrictions and cost rules (Hahnel, 2020). Concerns about standardization are a lack of diversity and lack of compatibility. Trust issues are about the security and privacy of users but also communicating market strategies (Pressmair et al., 2020). In this regard, Eberhardt

et al. (2020) pointed out, that regarding privacy concerns, the consumption or production patterns of users cannot be erased from the blockchain once recorded, which is seen as a disadvantage. Despite various promising endeavours in this domain, the considerable challenge of eradicating this data from the ledger raises significant apprehensions regarding the practical viability of the procedure, particularly in light of the recent legislative regulations about the safeguarding of personal data. Technology concerns are also related to the reliability of the system, its maturity and algorithms. All of these factors impact the acceptance to use the technology. Less significant, yet existing concerns are about costs arising or the impact of the PEMs on current lifestyles. Individuals are concerned about potential investment costs, the pricing of energy and its margin (Borges et al., 2022). These less significant risks show that the way it works is not yet fully understood by most people because although the markets or pricing may allow for different costs or revenues, the participants in such a local market still retain the option to feed their produced electricity into the national grid or to purchase their electricity through the national grid (Kotilainen, 2019). Naturally, there remains the potential for price volatility. However, according to current developments in technology, one should never pay more or receive less than predefined by governments or power companies for the general population. This observation demonstrates that, despite being classified as low risk, there remains a considerable amount of acceptance to be covered in this particular domain. Nevertheless, price differences can occur with an LEM (local energy market). This is due to the fact, that smaller LEM might have a different price granularity, which can be an advantage but is mostly a disadvantage (CEER, 2020). Pressmair et al. (2020) figured out, that this might be a factor reducing the acceptance of PEM. The more people operating in the market, the lower the price granularity and the price volatility and also the more homogenous prices will occur. This is based on the fact that higher liquidity can lead to lower volatility. This lower volatility makes the prices more predictable and increases the general acceptance and adoption of this technology.

The influence of risks and associated perceptions on the acceptance of technology has been demonstrated in previous studies (Luo et al., 2010; Benlian et al., 2011; Martins et al., 2014). However, previous research has identified numerous additional factors that play a role in the acceptance of technology (Thomas et al., 2013). In addition, a number of theories, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the UTAUT2, have been developed to

explain this theory (Oye et al., 2014). The subsequent paragraph refers to UTAUT2, the theory and model that has been selected as the foundational framework for this study and explains the ensuing hypotheses.

2.8. UTAUT2

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a popular model used to elucidate and predict technology acceptance and was used in an adapted version. The UTAUT model, developed out of the technology acceptance model (TAM) suggests that key factors influence user acceptance of technology and by understanding and addressing these factors companies or organisations can increase the likelihood of successful technology adoption and use (Venkatesh et al., 2021; Oye, 2014). It is a framework for understanding how individuals acquire and utilize technology. It implies that behavioural intention are crucial predictors of how technology is used. The probability of embracing the technology is contingent upon the immediate impact of various fundamental constructs. And the impact of predictors is subject to moderation by various factors such as age, gender and experience as indicated by Venkatesh et al. (2021).

The UTAUT model was initially formulated by Venkatesh et al. (2003) as an adaptation of the Technology Acceptance Model (TAM, Davis, 1989). According to scholarly research conducted by Legris et al. (2003) and Rahman et al. (2017), it has been determined that the UTAUT exhibits a higher level of precision in predicting user acceptability when compared to the TAM. Four acceptance-explaining constructs are the focus of this theory. These four factors are social influence, performance expectation, effort expectation, and facilitating conditions. The constructs under consideration exhibit similarities to the variables that have been previously established in the TAM as noted by Oye (2014). The anticipation of attaining success bears resemblance to the perceived usefulness of the TAM, while the prospect of effort closely aligns with the perceived ease of use. The concept of social influence relates to the perception of external entities, specifically the degree to which the user foresees that a third party will regard the utilisation of the technology as noteworthy. Furthermore, the concept of facilitating conditions can be clarified as the degree to which a user discerns the presence of adequate technological infrastructure to effectively uphold the execution of a novel system. UTAUT factors, in turn,

are dependent upon the expectations of performance, expectations of effort, and social influence. In addition, it is noteworthy to mention that the UTAUT model encompasses three supplementary moderating factors, each of which exhibits a robust correlation with the constructs of the model. These variables include gender, age and experience, and they exert an influence on the model's variables (ibid.).

In 2012, Venkatesh et al. made a significant contribution by introducing supplementary critical constructs and subsequently developing the UTAUT2 model. This model represents the most current iteration of acceptance models and has been chosen as the framework for this particular thesis. The origins of behavioural psychology related to the acceptance of technology can be traced back to the motivational model. This model posits that the examination of user motivations can shed light on the behaviour of technology adoption and usage. The authors have introduced three supplementary components. The previously mentioned variables encompass hedonistic motivation, also known as hedonic motivation, which pertains to the pleasure derived from utilising a particular technology. Additionally, the price-performance ratio, referred to as "Price Value" plays a significant role in influencing individuals' decisions. Lastly, the habitual nature of utilising a technology, commonly known as "Habit," is another crucial aspect to consider.

According to the UTAUT2, individuals are more inclined to embrace and employ technology if they perceive it to possess utility, ease of use, and alignment with their pre-existing behaviours and values. Moreover, it is imperative to acknowledge the significant impact of social influence on the assimilation of technology, as individuals often find themselves swayed by the perspectives and behaviours exhibited by their contemporaries. The individual's choice to obtain and utilise technology can also be shifted by hedonic motivation, which pertains to the inclination for pleasure or enjoyment. In conclusion, the presence of facilitating conditions, such as the availability of resources and support, has the potential to exert an impact on an individual's capacity to obtain and effectively employ technology (Venkatesh, 2012). The theoretical framework elucidates the process by which individuals assimilate and employ technology, while duly acknowledging various factors, including perceived utility, usability, social influence, hedonic motivation, and facilitating conditions (Oye et al., 2014).

In order to expand the current body of research outlined previously, the primary objective of this thesis is to address the research question: What are the factors, influencing consumer intention to use peer-to-peer blockchain-based energy trading?

In the following paragraphs, I will discuss the individual components of the UTAUT2 model in connection with the technology of P2P energy trading (with a cloud solution or with blockchain technology) and explain the resulting hypotheses of this work.

2.8.1. Behavioural intention to use (BIU)

The concept of behavioural intention can be clarified as the individual's perception of the likelihood that they will engage in the specific behaviour under consideration, as stated by Venkatesh et al. (2003). Within the context of this research, the term "behavioural intention" relates to an individual's tendency or predisposition to partake in PEM, as outlined by Venkatesh et al. (2008). BIU has a direct impact on the use of this new technology. The concept of behavioural intention holds great importance and credibility as a reliable indicator of real-life behavioural patterns. This notion has been supported by esteemed scholars such as Ajzen (1991) and Venkatesh and Davis (2000). As a result, our research posits that the various constructs within the UTAUT2 model, namely performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation, collectively serve as predictors of BI. The correlation between an individual's behavioural intention and their internal evaluation is a significant aspect to consider. As a result, it can be observed that behavioural intention takes precedence over behavioural expectancy, thereby indicating that the level of behavioural expectancy is a reflection of the potency of behavioural intention in comparison to other intentions (Venkatesh et al., 2008).

2.8.2. Performance expectancy (PE)

Performance expectancy refers to the user's subjective belief that using a particular technology will help them achieve their goals. In this context, performance expectancy refers to the user's belief that using P2P energy trading will help them save money on their energy bills, reduce their carbon footprint, or gain other benefits. Performance expectancy is likely to be influenced by several factors, such as the user's understanding of P2P energy trading,

the user's trust in the technology, and the user's past experiences with energy trading. If the user understands P2P energy trading and trusts the technology, they are more likely to believe that it will help them achieve their goals. If the user has had positive experiences with energy trading in the past, they are also more likely to believe that P2P energy trading will be beneficial (Thomas et al., 2013; Oye et al., 2014).

As for the existing literature specifically on the blockchain, it has been found that performance expectancy has a significant positive impact on the behavioural intention to use blockchain technology. Motivation to embrace and use an upcoming technology is related to an individual's perception of the technology's benefits (Davis, 1989; Venkatesh et al., 2003). It has been demonstrated empirically that people frequently have inflated expectations regarding the potential advantages associated with blockchain-based applications. In addition, blockchain can utilise its decentralised nature to reduce process complexity and uncertainty, particularly for smart contract-based operations. Prior research (UTAUT2) indicates that there is a positive correlation between performance expectations and individuals' intention to use and employ a technology (Silinskyte, 2014, Queiroz & Fosso, 2019). Thus, I hypothesize that:

H1: Performance expectancy positively influences behavioural intention to use PEM.

The blockchain technology has been developed specifically to execute a large volume of transactions in a given amount of time (Ullah, 2021). This aspect is significant because it facilitates P2P energy trading, allowing a large number of participants to partake in real-time energy exchange (Kewell et al., 2017). Cloud-based solutions can also be used for peer-to-peer energy trading, but their performance is inferior to that of blockchain technology. Typically, cloud solutions are hosted on a single server or server cluster, making them more susceptible to intrusions and other disruptions. The inability of cloud solutions to effectively manage a high volume of transactions per second may cause performance issues during periods of increased trading activity. Since blockchain is a distributed ledger technology, it is scalable by adding more nodes to the network. In contrast, cloud-based

solutions are typically limited by the server or server cluster on which they are hosted. Blockchain is more secure than cloud solutions. Because blockchain is an immutable ledger, once a transaction is recorded, it cannot be altered or removed. Cloud solutions, on the other hand, are typically hosted on a single server or cluster of servers, making them more vulnerable to intrusions. Blockchain is seen to be more transparent than cloud solutions, which is because blockchain is a public ledger that permits anyone to view all recorded transactions. Cloud solutions, on the other hand, are typically hosted on private servers, so only authorised users can view the recorded transactions. Even though the characteristics of the two technologies make blockchain a more effective choice, recent studies have attributed better performance to cloud technology, while also attributing a stronger connection between PE and BIU (Erturk, 2019; Hahnel, 2020; Khan et al., 2021). Thus, I hypothesize that:

H1a: The strength of the relation between PE and BIU is bigger for the cloud technology in comparison to the blockchain technology.

2.8.3. Effort expectancy (EE)

Effort expectancy, according to Venkatesh et al. (2003), refers to the level of ease with which a system can be utilised. It is a personal measure that affects motivation and intention. People could be less motivated to complete a task if they believe it will take a lot of work. However, believing that a task requires little work increases motivation. Users' attitudes and intents towards embracing and using technology are influenced by effort expectancy in the context of technology. Users are more likely to adopt a technology if they expect it to be simple to use and to require little effort. To create intuitive user experiences that meet expectations and motivate users to engage in desired behaviours, designers and developers need to take into account consumers' views of effort expectancy. Effort expectancy is based on three different parts, perceived ease of use, complexity, and usability. In accordance with previous research, it is anticipated that effort anticipation will have a positive effect on the behavioural intention to use blockchain technology (Alazab et al., 2021; Venkatesh, 2003). Taking the current literature into consideration, it seems likely that users may be concerned about the learning curve associated with newer blockchain

technology, which may lead them to expect a high level of effort. However, it is important to note that both blockchain and cloud technologies are seen as similar, although cloud technologies are seen as having more potential due to their familiarity, which may outweigh concerns about ease of use and lead to a positive behavioral intention to adopt these technologies (Khechine, 2016). Thus I hypothesize the following:

H2: Effort expectancy positively influences behavioural intention to use PEM.

H2a: The strength of the relation between EE and BIU is bigger for the cloud technology in comparison to the blockchain technology.

2.8.4. Social influence (SI)

Social influence refers to the degree to which users allow themselves to be influenced by others (Venkatesh, 2012). In other words, the more important people from one's personal environment or influential people from the public believe that a new system should be used, the more likely one is to be convinced to use it oneself. The relationship between social influence and behavioural intention has been controversially discussed and rejected several times, especially in cross-cultural surveys (Alalwan et al. 2017, Boonsiritomachai & Pitchayadejanant, 2017). Consistent with blockchain-related research, it is anticipated that social influence will have a more favourable influence on the intention to adopt the blockchain technology than to adopt a cloud solution (Thomas et al., 2013; Martins et al., 2014), which is why we propose the following hypothesis:

H3: Social influence positively influences behavioural intention to use PEM.

H3a: The strength of the relation between SI and BIU is bigger for the blockchain technology in comparison to the cloud technology.

2.8.5. Facilitating conditions (FC)

The concept of facilitating conditions relates to the presence of supportive conditions. The extent to which individuals perceive that the efficacy of the novel system can be impacted by both organisational and technical infrastructures has been a subject of investigation (Venkatesh et al., 2003). The perception of uncertainty and ambiguity is commonly regarded as a hindrance to the acceptance and integration of novel technologies. Nevertheless, the primary objective of a novel technological advancement is to reduce these uncertainties. According to Venkatesh (2003), individuals who possess the means to access facilitating conditions are more inclined to develop the intention to utilise a particular technology. Therefore, it is anticipated that facilitating conditions will have an impact on the construct of behavioural intentions. Contrarily, the study conducted by Boonsiritomachai and Pitchayadejanant (2017), yielded inconclusive results regarding the existence of a direct correlation between FC and BI. Nevertheless, the aforementioned study has uncovered a noteworthy correlation between FC and hedonic motivation (HM), a phenomenon that will be thoroughly scrutinised in the subsequent section. By scholarly discourse, it can be posited that HM functions as an intermediary factor between FC and BI. Boonsiritomachai and Pitchayadejanant (2017) found a positive association between FC and BI, wherein FC exhibit a positive association with HM, subsequently leading to a positive impact on BI.

Several studies have shown, that people believe, blockchain technology may necessitate more specialised hardware and software, as well as more technical training and support (Golosova et al., 2018; Knauer et al., 2020; Laurence, 2023). This suggests that the perceived availability of facilitating conditions may be more crucial for blockchain technology than cloud technology. In contrast, cloud technology is more established and well-known, and it may be more likely to have the required resources and support. This suggests that the perceived availability of facilitating conditions may be less significant for cloud technology than blockchain technology (Tseng, 2010; Pieters, Kokkinou and Kollenburg, 2021; Saranya, 2023). Thus, the following hypotheses follow:

H4: Facilitating conditions positively influence behavioural intention to use PEM.

H4a: The strength of the relation between FC and BIU is bigger for the cloud technology in comparison to the blockchain technology.

2.8.6. Hedonic motivation (HM)

The UTAUT was extended to include the variables hedonic motivation (HM), price value (PV) and habit (HT) (Gunasinghe et al., 2020). Hedonic motivation (HM) refers to the pleasure or enjoyment of using a new technology. Users enjoy a system and take pleasure in using it if it works without problems and errors, there are ongoing updates, and it is easy to register (Boonsiritomachai & Pitchayadejanant, 2017). The construct of hedonic motivation is anticipated to exert a favourable impact on behavioural intention within the present context. Henceforth, it is postulated that the actions of individuals are subject to the sway of the amusement or gratification procured from engaging with a given technology (Knauer & Mann, 2020). Blockchain is described as the “most important invention since the internet” (Marc Andreessen) and is also seen as more transparent and secure than a cloud solution, which can give users security and satisfaction, increasing hedonistic motivation (Crosby et al., 2016; Juričić, Kučak & Đambić, 2022). It is also seen as more efficient, which can save users time and money. This can lead to a sense of empowerment, satisfaction, fulfilment and excitement (Saranya, 2023). Thus, I hypothesize that:

H5: Hedonic motivation positively influences behavioural intention to use PEM.

H5a: The strength of the relation between HM and BIU is bigger for the blockchain technology in comparison to the cloud technology.

2.8.7. Excluded constructs

Given the chosen technology, two constructs of the UTAUT2 model were omitted, as recommended (Venkatesh, Thong & Xu, 2012). The constructs of Price Value and Habit were not taken into consideration. Price value was not included because of its overly complex composition for specific prices participants pay or receive. Since the pricing is also individual and dependent on a large number of variables, the scale would have been too

difficult to explain to participants and it would have been impossible to analyse their intention to use or not use the technology based on the pricing. Habit was eliminated from the proposed research paradigm on the assumption that PEM are still in the early stage of its product life cycle (PLC) and developmental stages (Oliveira et al., 2016). Therefore, no statement can be made about the relationship between habit or price value and the use of PEM. Moreover, and importantly, since I cannot analyse and verify the actual usage behaviour of the new technology, as it is not yet applied in a general framework, I only analyse the BIU and not the usage behaviour (Soto et al., 2021).

2.9. Additional influencing factors in the context of PEM

As mentioned above, the UTAUT2 model is used as the basis for studying user acceptance of P2P energy trading. However, to analyse all important factors influencing technology acceptance, the model had to be modified and extended. Since the factors of risk and trust are particularly important in the area of energy and finance, the influence of these variables on the use of PEM is also examined (Queiroz & Fosso, 2019; Pieters et al., 2021). The additional proposed constructs, extending the UTAUT2 model are described in the following paragraphs.

2.9.1. Perceived privacy risk (PPR)

One of the key factors affecting the acceptance of PEM is perceived privacy risk. According to Monrat et al. (2019), there exists a positive correlation between the perceived level of privacy risk associated with an application and the likelihood of individuals opting out of utilising said technology. The relationship between perceived privacy risk and effort expectancy has been observed to exhibit a significant correlation. This implies that if users encounter difficulties in utilising the application of the service, they will subsequently assign a higher rating to the associated privacy risk, thereby exerting a detrimental influence on the adoption of the technology. In their seminal study, Laukkanen and Kiviniemi (2010) unearthed a noteworthy correlation between the variables of privacy risk and usage. By furnishing customers with comprehensive information, user manuals, and complimentary trial versions, companies have the potential to diminish the perception of risk. The study

conducted by Al-Jabri and Sohail (2012) further corroborated the previously mentioned theory, positing that the perception of privacy risk exerts a detrimental impact on the adoption and utilisation of upcoming technologies. Users' concern that their login credentials would end up in the wrong hands and that unauthorised people will have access to their personal and financial information is one reason why they perceive danger in PEM. According to the findings, PPR is a significant and dangerous factor that technology businesses should try to reduce for P2P energy trading communities (Wang et al., 2021).

As both blockchain and cloud technologies are both perceived as complex but users may have more data privacy concerns when utilising cloud solutions. Blockchain is seen as safer and even though cloud technologies are currently more adopted they pose security and privacy threats (Wang et al., 2021). Therefore, I suggest the following hypothesis:

H6: Perceived privacy risk negatively influences behavioural intention to use PEM.

H6a: The strength of the relation between PPR and BIU is bigger for the blockchain technology in comparison to the cloud technology.

2.9.2. Trust (TR)

The adoption of PEM is essentially influenced by trust in the technology. The importance of trust was illustrated by Smith's (2020) study, which discovered that a 10% increase in a country's trusting population can lead to an average 0.5% growth in real annual GDP per capita. However, Xu et al. (2014) noted that current research on trust in technology primarily focuses on individual user interactions, neglecting situations where users lack understanding of the system, thereby limiting their ability to mitigate risks. This highlights the significance of addressing user comprehension challenges to enhance trust and risk management in technology adoption.

The establishment of trust necessitates the presence of both structural assurance and comprehensive guidance regarding the utilisation of the application (Oliveira et al., 2014). The study conducted by Arcand et al. (2017) revealed that trust emerges as a significant

determinant in shaping the level of satisfaction experienced by users of mobile services. Hence, it can be posited that a positive correlation exists between the degree of trust placed in the application and the level of consumer satisfaction derived from the service. The basic principles of security and privacy hold a crucial role in the establishment of trust. To cultivate a sense of trust among users, it is imperative to uphold the utmost level of security in services. In summation, the augmentation of trust is achieved through the utmost prioritisation of security and privacy. As a result, it can be inferred that trust exerts a favourable influence on the level of satisfaction experienced by users of mobile applications. The more profound the customer's perception of security with the novel technology, the more substantial their trust in it becomes. The concept of low risk, as elucidated by Oliveira et al. (2014), also serves to explicate the intricate nature of trust.

The primary apprehension of customers with regard to blockchain technology pertains to the element of risk (which will be discussed in paragraph 2.9.4), thus necessitating a thorough examination of trust as well. Blockchain technology is inherently more trustworthy than cloud solutions because it is decentralized, transparent, and immutable. The fact that no single entity controls the blockchain makes it more resistant to attack and fraud, and the fact that all blockchain transactions are public makes it more difficult to conceal malicious activity. Once a transaction is added to the blockchain, it cannot be altered or removed, making it a trustworthy and tamper-proof log of all activity (Batwa & Norrman, 2021). To better use the trust scale, another scale about general trust was added as a moderator. Thus, I hypothesize that:

H7: Trust positively influences behavioural intention to use the PEM.

H7a: The strength of the relation between TR and BIU is bigger for the blockchain technology in comparison to the cloud technology.

2.9.3. Risk perception (RP)

The academic community has devoted considerable attention to investigating the intricate connection between risk and the acceptance of technology. Scholars have acknowledged that individuals commonly engage in a process of assessing potential risks before embracing novel technological advancements. Studies on the acceptability of new energy technologies revealed that attitudes towards the technologies are predicted by how these technologies are regarded in terms of risks and advantages (Huijts et al., 2012).

Risk, in the context of technological adoption or utilisation, can be precisely delineated as the probability or likelihood of unfavourable consequences or undesirable outcomes arising from said adoption or utilisation. The perception of risk stems from uncertainties surrounding the functionality, reliability, security, compatibility, and potential impact on current systems or processes associated with the technology in question. The presence of these uncertainties instils apprehension and unease within prospective users, resulting in reluctance or opposition towards embracing novel technologies (Benlian & Hess, 2011).

The contemporary scholarly discourse frequently references multiple rationales for the impact of risk on the acceptance of technology. The impact of perceived risk on an individual's confidence in the efficacy of a given technology cannot be understated. When the level of perceived risk is elevated, it engenders scepticism regarding the efficacy of the technology and may give rise to apprehensions regarding potential monetary setbacks or disruptions to business operations. Consequently, individuals may exhibit hesitancy in embracing technology. Furthermore, the perception of risk is influenced by the degree of familiarity and prior exposure to analogous technologies or innovations. The absence of acquaintance with novel technology can heighten the perception of risk, as both individuals and organisations may possess an incomplete comprehension of its functionality, potential obstacles, and ramifications for their operations. On the contrary, individuals who possess favourable encounters or knowledge about analogous technologies may exhibit a diminished perception of risk and an elevated inclination to embrace said technologies (Luo et al., 2010; Martins et al., 2014).

Recent literature consistently supports the hypothesis that risk perception is negatively correlated with the acceptance and usage of P2P energy trading. According to several

studies, people and organisations who perceive financial, technological, and regulatory risks as being larger are less likely to adopt and use P2P energy trading systems (Benlian et al., 2011; Erturk et al., 2019). These results highlight the necessity of resolving risk issues, increasing security precautions, and establishing clear regulatory frameworks to encourage widespread P2P energy trading adoption and realise its potential benefits in the move towards a sustainable energy future (Monrat et al., 2019; Soto et al., 2021). Current research indicates that cloud technologies pose higher security risks. Blockchain is more secure due to its decentralised structure, is considered tamper-proof and, unlike cloud solutions, cannot be tampered with by individuals providing the technology (Luo et al., 2010; Martins, et al., 2014; Erturk, et al., 2019). Thus, I hypothesize that:

H8: Risk perception negatively influences behavioural intention to use PEM.

H8a: The strength of the relation between RP and BIU is bigger for the blockchain technology in comparison to the cloud technology.

2.9.4. Technology savviness (TS)

An individual's knowledge, comfort, and competence with using technology are referred to as their level of technological savviness. It requires expertise, confidence, and the ability to operate a variety of hardware, software, and digital tools. It may be necessary to view familiarity from a different perspective, though, given that I am focusing our analysis on developing technologies, which are extremely complicated and necessitate a broad understanding of IT in general to understand the system. P2P energy trading technology has been the subject of substantial research on the relationship between technological aptitude and behavioural intention to use it. Technology savviness has a continuously beneficial impact on people's intentions to use P2P energy trading systems, according to research. Technologically savvy individuals possess a greater understanding and familiarity with technology, enabling them to navigate and utilize new platforms more effectively. They view P2P energy trading as a feasible and advantageous choice because of their higher levels of technological comfort and confidence. The potential benefits of P2P energy trading, such as

cost savings, improved energy efficiency, and environmental sustainability, are also more likely to be recognised by tech-savvy people. The likelihood that they will use P2P energy trading platforms rises as a result of their increased belief in the merits and advantages of the technology (Mutohhari, Sofyan & Nurtanto, 2021; Acur, Kandemir, de Weerd-Nederhof & Song, 2009). Additionally, studies have shown that tech-savvy people are more willing to put out the time and effort necessary to learn new technologies and are more receptive to adopting novel solutions. The same reasoning can be applied to blockchain technology, as opposed to cloud technology. This optimistic view of technology adoption increases the likelihood that people will adopt P2P energy trading services, which is why I expect a positive correlation and a stronger relationship for Blockchain (Danneels, 2007; Mutohhari et al., 2021). Thus, I hypothesize that:

H9: Technology savviness positively influences behavioural intention to use PEM.

H9a: The strength of the relation between TS and BIU is bigger for the blockchain technology in comparison to the cloud technology.

3. Methodology

3.1. Research design

The objective of this thesis is to identify factors that influence consumer adoption of blockchain technologies in the P2P energy marketplace. Therefore, the adapted UTAUT2 model was tested whether to verify the correlation of the constructs or not. Subsequently, the constructs are tested for differences with a multigroup analysis (MGA) to see if there is a significant difference between adopting the technology with a classic approach (in this case a cloud solution) and a blockchain solution. Thus, an experiment was conducted with the goal of testing all the subordinate hypotheses from the previous chapter to this overarching goal.

Several studies used the Technology Acceptance Model (TAM) with a qualitative approach consisting of interviews and case studies to delve into the constructs of the TAM and the perceived benefits and risks that influence blockchain technology adoption (Folkinshteyn & Lennon, 2016). However, qualitative studies with interviews do not allow to establish correlations of scales on the causality of model variables. Therefore a quantitative, cross-sectional approach with a controlled experimental design with a control and a "treatment" condition and randomized assignment of participants was followed. Cross-sectional studies are a type of observational research design that allows for the collection of data at a single point in time which is essential in this study. Apart from being a cost-effective option for researchers, cross-sectional studies can be useful for providing a snapshot of a particular population at a specific point in time, which can be helpful for descriptive analysis (MacDonald et al., 2019).

Since this is an analysis testing a theoretical framework from a predictive perspective and additionally the nature of the research is exploratory and the supporting theory is less developed, it is recommended to use partial least squared structural equation modelling (PLS-SEM). Other indications also support the use of the model. First, the structural model is seen as complex because it consists of many constructs, and second, because the research goal is to better understand the increasing complexity of acceptance of different technologies by exploring theoretical extensions of established theories (Hair et al, 2019).

The three causation factors that can help researchers determine causality in cross-sectional studies are temporal ordering, covariation, and non-spuriousness. Temporal ordering refers to the fact that the cause must come before the effect. Covariation refers to the fact that the cause and effect must vary together. Non-spuriousness refers to the fact that the relationship between the cause and effect cannot be explained by a third variable (Hill, 1965).

In order to assure this is the case this, the first step is to manipulate the independent variable (IV), which in this case was done by randomly assigning the participants to either the cloud solution video and thus the control group or the blockchain video and thus the treatment group. Afterwards, the survey was conducted and the DVs were recorded, meanwhile being moderated by age and gender.

Age and gender were specifically chosen as control variables as several works suggest they play an important role because researchers can enhance their comprehension of the intricate interplay between all the variables and the other factors inside the model, thereby elucidating their impact on the adoption and utilisation of technology (Khechine et al., 2016; Oye et al., 2014; Silinskyte, 2014). Studies have shown an effect of age on facilitating conditions: Individuals under 30 have facilitating conditions and social influence was found to be more important for younger individuals than for older individuals, whereas for effort expectancy the effect was reversed. In addition, a significant effect of gender on performance expectancy and facilitating conditions was found, such that men had higher expectations of a new technology than women and men. Similarly, facilitating conditions also had a higher effect on men (Yu, 2012).

Figure 1

Visual representation of the proposed research model for the hypotheses H1-H9

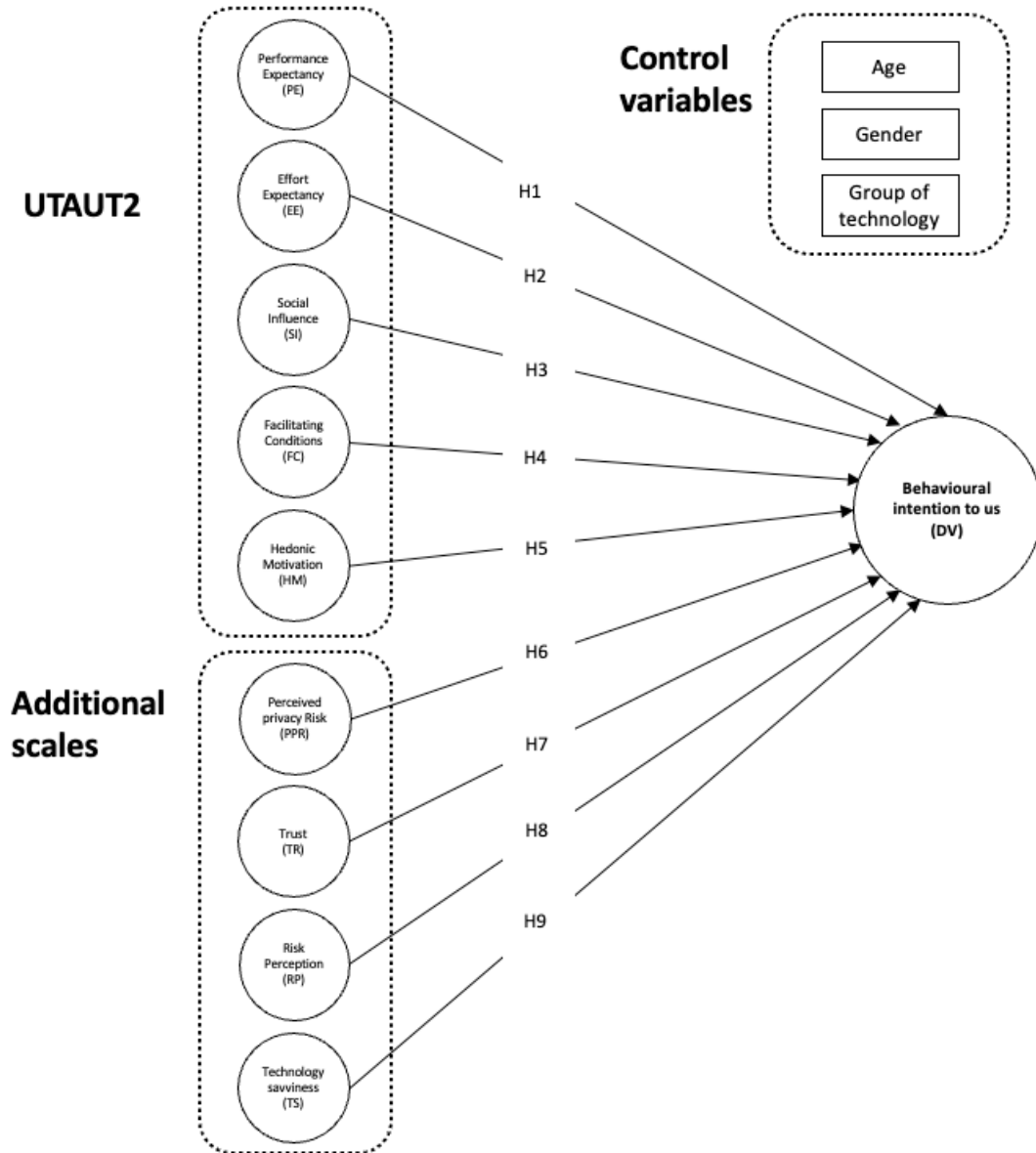
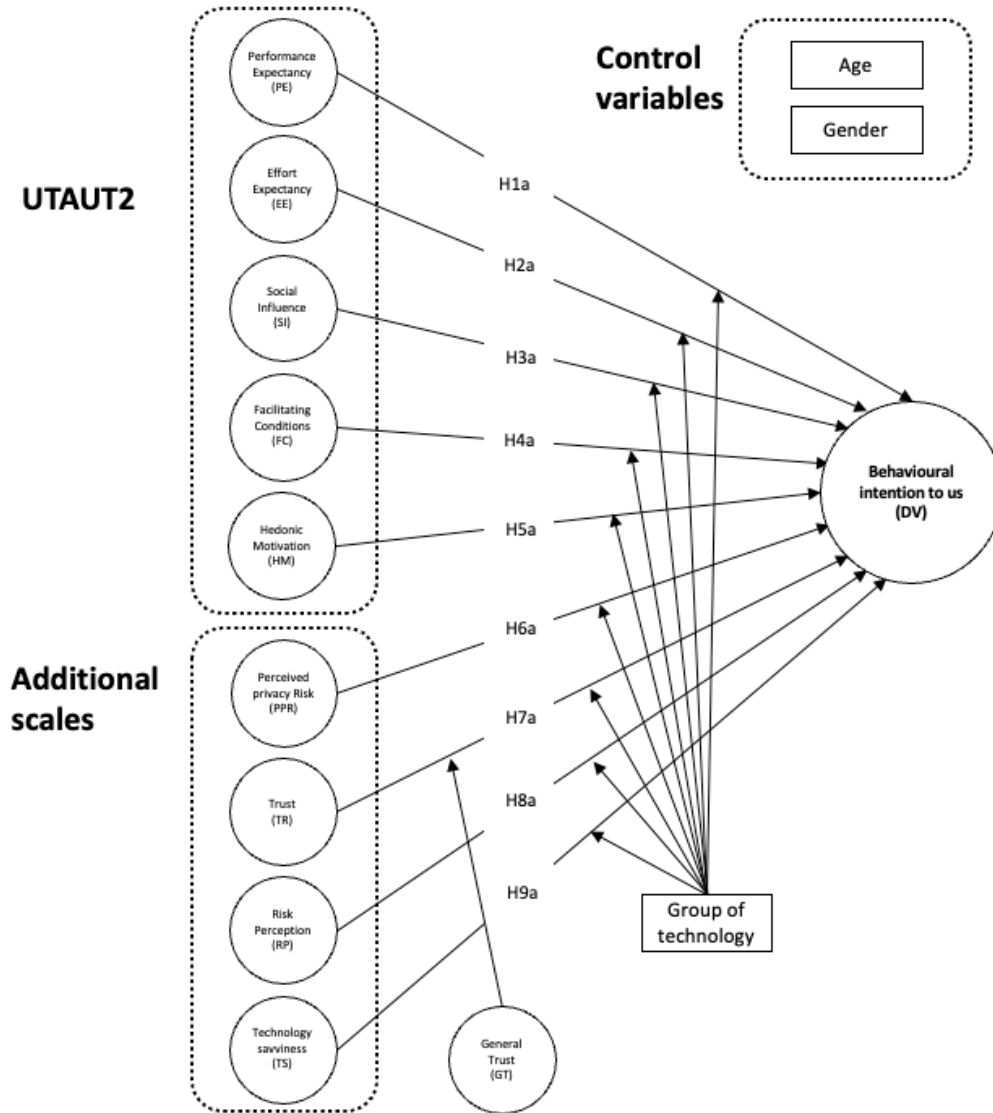


Figure 2

Visual representation of the proposed research model for the hypotheses H1a-H9a



3.2. Procedure

Participants were given information in the consent form about the research, which is part of the Masters' Psychology in Business and Economics, and that it is anonymous and voluntary. They also read other specific instructions about the survey and were required to confirm their participation and that they were over the age of 18. The full consent form is in Figure 6 in Appendix A.

For the socio-demographic data, eight parameters were examined, namely age, gender, education, marital status, employment status, household income (after taxes), number of people living with the participant, and political ideology. For all questions, there was an option not to disclose the information if the participant was uncomfortable with it. The answers of age and gender were later used as control variables.

To measure individual differences, a block of questions about trust was shown to every participant. It was divided into institutional trust and general trust. Then, two different versions of a video were created for the manipulation. In this section, a video about the technology was shown. The block of conditions - treatment group (blockchain technology) or control group (cloud solution) was randomly shown to participants. It was also ensured that each participant watched the video in its entirety. Through the platform, Qualtrics, on which the survey was created, it could be set that participants could only proceed with the survey if they watched the video completely. The survey itself was divided into three blocks, asking about the acceptance of the new technology. Participants could answer each question with a 1-7 Likert scales from “I Strongly disagree” to “I Strongly agree”. This allowed us to record the dependent variables (DV). The questions included the selected scales of the UTAUT2 model performance expectancy, effort expectancy, social influence, facilitation conditions, hedonic motivation, behavioural intention to use and the additional adding scales: perceived privacy risk, trust, risk perception and technology savviness (Gunasinghe et al., 2020; Venkatesh, 2012). To limit common method bias, several items were reverse-coded. For the scales items, see in Table 12 in Appendix L. A manipulation check and an attention check were also added. Participants who did not correctly answer this question were excluded from the data analysis.

The survey was created in Qualtrics (2023) and spread using the platform Prolific. Judged by the inverse square root method of minimal sample size calculation (Kock & Hadaya, 2016), considering a 5% significance level and an expected minimum path coefficient in a range of 0.11-0.2, it is recommended to analyze with more than 155 participants, to be able to use the power Analysis, One-way ANOVA of the PLS-SEM.

To ensure manipulation validity, in addition to the measure of asking whether the presented video was viewed correctly, a content question was also asked about the

clip. However, only one of the answers was correct. Since the content of the survey was not addressed before this question, participants could not arrive at the correct answer through information other than the video. Participants who did not pass the manipulation checks were excluded from the analysis.

3.2.1. Pre-tests

Due to the exploratory nature of the model's conceptualization and the essence of the current study, it was deemed necessary to conduct two pre-tests to identify any possible discrepancies or problems that participants might encounter with the survey. Initially, the questionnaire for the primary research was pre-tested with a convenience sample of eight people by conducting unstructured interviews. During this pre-test, participants were instructed to complete the comprehensive questionnaire under the supervision of the author. Comments and feedback from the participants were recorded. Since the survey consisted mostly of questions from the original literature of Venkatesh's UTAUT2 model, the individual questions are multiple-tested and validated technology acceptance scales, as expected, none of the questions was objected to and the survey questionnaire could be used in the same way in the final study.

The final pre-test ($N=20$) was conducted on a distinct convenience sample and unlike the first pre-test, followed a quantitative approach. Participants watched a clip, either about P2P energy trading using a blockchain technology or a cloud solution. Afterwards, the PANAS exam was conducted, also known as the Positive and Negative Affect Schedule, which is a self-administered questionnaire designed to assess an individual's present emotional condition (Watson, 1988). The reason for the procedure was, that I wanted to make sure that the two videos are seen as similar as possible (apart from the differences in the technology) and evoked the same emotional reactions in the participants, so that the results of the following study could not be attributed to differences in this regard.

The statistical analysis of the data was conducted through the utilisation of independent sample t-tests, which were performed in Microsoft Excel. The study found that there were no significant differences in the PANAS positive effect between the two groups, namely the blockchain group ($M = 2.9$, $SD = 0.68$) and the cloud solution group ($M = 3.1$,

$SD = 0.65$), as demonstrated by the t-test results ($t(18) = -0.23, p = .45$). The study found no statistically significant distinctions between the blockchain group ($M = 1.1, SD = .14$) and the cloud Solution group ($M = 1.7, SD = .45$) with regards to PANAS negative affect, $t(18) = -0.5, p = .01$. The findings indicate that the videos did not have statistically significant effects on participants across different conditions and did not influence their responses to specific questions at a 95% confidence level. This suggests that the study had strong internal validity. This permitted researchers to proceed with data acquisition for the study. To avoid carry-over effects, I made sure that participants from the initial pre-test couldn't be recruited for the second pre-test and the two main studies, as well as the participants of the second pre-test also did not participate in any of the studies.

3.3. Sample

In the initial study, a total of 423 participants were enlisted. The sample selection process was non-random due to the utilization of "Prolific" software for administering the questionnaire, which did not recruit the participants randomly from the population. The sample's inclusion criteria consisted of individuals who were English speakers from Western countries where English is the native language, and who were at least 18 years old. The final dataset did not contain any missing data. Furthermore, a total of 70 responses were excluded from the study on account of missing attention or manipulation checks, ultimately leaving a sample size of 352 distinct responses. The variance-based partial least squares (PLS) approach was chosen to assess the structural equation model presented in this study. The selection of this approach was based on its suitability in comparison to covariance-based approaches for assessing the impact of specific determinants on target constructs. Furthermore, it should be noted that the sample size of 352 participants in this study meets the recommended criteria for Partial Least Squares (PLS) analysis, as suggested by Chin (1998). According to Chin's "rule of thumb," which applies specifically to studies involving reflective constructs, the minimum number of cases required is determined by the highest number of structural paths that influence a construct. In the current scenario, the construct of meaningful use is shaped by eight distinct constructs. Based on the aforementioned heuristic, it is necessary to multiply this quantity by a factor of 10 to obtain the minimum number of instances of 80, a threshold that is significantly surpassed, also by the blockchain

group and the cloud solution group respectively. The allocation of responses across the conditions yielded 179 participants for blockchain and 173 participants for cloud solution.

39.9% of the participants were women, 58.1% were men, 1.4% were non-binary or third gender and 0.3% preferred not to answer the question. The 'highest education completed' by the 352 participants was 0.8% less than secondary education, 31.7% High School, 52.6% a Bachelor's degree, 15.0% a Master's Degree and 0.06% a Ph.D. Participants' age ranged from 21 to 50 years old ($M = 35.3$, $SD = 8.6$). Yearly income after tax ranked from 0 to 200000 EUR ($M = 50272$, $SD = 33214$). The number of people living with the person participating ranked from zero to seven ($M = 1.9$, $SD = 1.2$). The number of adults living with the person participating ranked from zero to 11 ($M = 1.9$, $SD = 1.2$). 51.3% were single, 39.9% were married or in a union of fact, 6.2% were divorced or separated and were 0.6% widowed. 51.6% were employed full-time (35+ hours a week), 18.7% employed part-time (less than 35 hours a week), 6.8% unemployed (currently looking for work), 8.5% unemployed (not currently looking for work), 7.1% student, 0.3% retired, 6.8% self-employed. The political ideology of the participants was 7.4% far-left, 28.6% left, 24.1% centre-left, 27.8% centre, 7.9% centre-right, 3.4% right and 0.6% far right.

3.4. Data analysis

The initial step involved exporting the unprocessed data from the Qualtrics platform into a Microsoft Excel format, specifically an XLMS file. Subsequently, the dataset underwent a cleaning process wherein duplicate entries, missing values, and test entries were eliminated. Before the import process, any inaccurate data present in the survey was systematically removed. The forthcoming chapter will encompass a discussion on this matter by the author. The data was subsequently processed to be imported into SMART PLS 4 software, which was employed for the analysis.

3.5. Manipulation test and validity

Out of the 423 respondents, three answered they had issues watching the video and one did not answer the question, which is why I cannot confirm that the person watched the

video. 53 people did not pass the manipulation test, which tested whether they paid attention while watching the video. Of these 53 people, 34 named a technology that belonged to neither group and 19 people answered the question incorrectly, inadvertently feeling they belonged to the wrong group without knowing it existed. The attention test was fielded by 19 participants and two people said they are currently already participating in an energy community. Altogether, 77 invalid unique answers were filled out by 71 people (some participants failed several tests).

In total, 352 valid answers resulted. 179 valid answers were collected from participants who watched the blockchain video and 173 valid answers for the cloud solution group. This is seen as an adequate number of respondents for statistical power and external validity of the PLS-SEM model.

3.6. Model fit

To calculate and estimate how well the model matches, the Standardized Mean Square Residual (SMSR) was chosen (Hair et al., 2019). According to Hu and Bentler (1999), a value below 0.10 is regarded as indicative of a good fit. Therefore, the obtained result of 0.052 can be interpreted as a very favourable fit.

4. Results

4.1. Construct validity and reliability

Construct validity and reliability were tested, before conducting the actual analysis. Cronbach's alpha is a statistical metric utilized to assess the degree of internal consistency within a questionnaire. It is a statistical measure employed to evaluate the internal consistency and construct validity of a questionnaire. The underlying premise of this approach is that the responses to questionnaire items are influenced by a shared latent factor. This method quantifies the extent to which the variability in responses can be attributed to this latent factor. A greater Cronbach's alpha coefficient indicates increased reliability and validity of the questionnaire, with a threshold of 0.7 or above generally regarded as acceptable and 0.8 and above as good. The constructs had the following results: BIU $\alpha = 0.962$, PE $\alpha = 0.916$, EE $\alpha = 0.956$, SI $\alpha = 0.945$, FC $\alpha = 0.761$, HM $\alpha = 0.955$, PPR $\alpha = 0.962$, TR $\alpha = 0.960$, RP $\alpha = 0.939$, TS $\alpha = 0.912$ and GT $\alpha = 0.542$. All constructs had a good value, apart from GT which was not acceptable and FC which was acceptable (Cronbach, 1951).

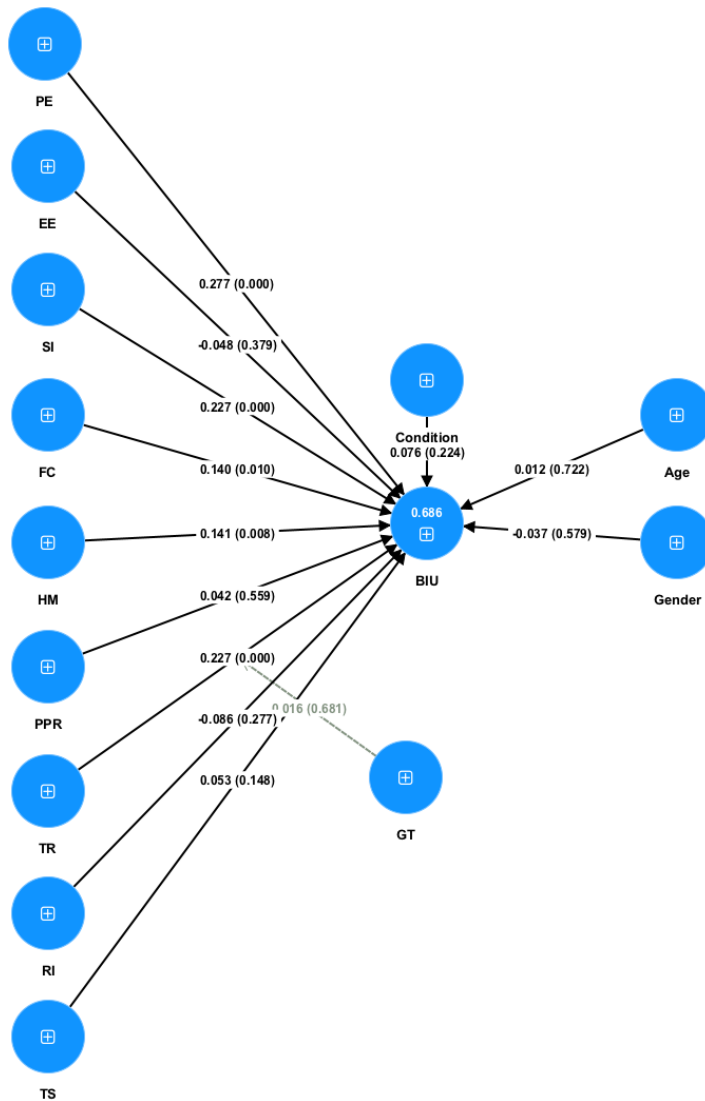
4.2. Assessment of the structural model

To evaluate the hypotheses H1, H2, H3, H4, H5, H6, H7, H8, H9, and H10 presented in Table 3 of Appendix F, a PLS-SEM analysis was performed, followed by the bootstrapping procedure, as described in the methods section. According to the recommendations put forth by Hair et al. (2014), the evaluation of a structural model will involve the examination of various factors, including the path coefficients, the level of R^2 for constructs, and the effect size, as quantified by Cohen's f^2 . Based on the synthesis of Chin (1998) and Hair et al. (2011), a comprehensive interpretation of R square values can be provided as follows: If the value of R square falls within the range of under 0.50, it indicates a model that is characterised as weak; a model can be classified as moderate if its R -squared value falls within the range of 0.50 to less than 0.67, R square indicates a moderate-strong model if it is between 0.67 and less than 0.75 and considered to be strong if R square is equal to or higher than 0.75. With an adjusted r^2 of 0.673, the model can be interpreted as moderate-strong. The outcomes of a bootstrapping technique, implemented on the structural

model in SMART PLS 4, are illustrated in Figure 3. The evaluation of path coefficients will be conducted in conjunction with the assessment of Cohen's f^2 effect size values. These effect size values quantify the influence of a construct by determining the extent to which the omission of the analysed construct from the analysis affects the R^2 of the predictive variables (Cohen, 1988). According to Cohen, the effects can be categorised as small, medium, and large, corresponding to f^2 values of 0.02, 0.15, and 0.35, respectively.

Figure 3

Path estimates of the structural model



Note: *p-values are displayed in the brackets after the respective path coefficients
 **Paths are highlighted using absolute path coefficient value strength

H1 predicted that performance expectancy positively influences behavioural intention to use PEM. Results suggested this relationship to be significant, with a path coefficient of 0.277, $p = .000$. The f^2 for the relation = 0.096 (small effect size by Cohen).

H2 predicted that effort expectancy positively influences behavioural intention to use PEM. Results suggested this relationship to be insignificant, with a path coefficient of -0.048, $p = .379$.

H3 predicted that social influence positively influences behavioural intention to use PEM. Results suggested this relationship to be significant, with a path coefficient of 0.227, $p = .000$. The f^2 for the relation = 0.075 (small effect size by Cohen).

H4 predicted that hedonic motivation positively influences behavioural intention to use PEM. Results suggested this relationship to be significant, with a path coefficient of 0.140, $p = .010$. The f^2 for the relation = 0.027 (small effect size by Cohen).

H5 predicted that hedonic motivation positively influences behavioural intention to use PEM. Results suggested this relationship to be significant, with a path coefficient of 0.141, $p = .008$. The f^2 for the relation = 0.037 (small effect size by Cohen).

H6 predicted that perceived privacy risk negatively influences behavioural intention to use PEM. Results suggested this relationship to be insignificant, with a path coefficient of 0.042, $p = .559$.

H7 predicted that trust positively influences behavioural intention to use PEM. Results suggested this relationship to be significant, with a path coefficient of 0.227, $p = .000$. The f^2 for the relation = 0.052 (small effect size by Cohen).

H8 predicted that risk perception negatively influences behavioural intention to use PEM. Results suggested this relationship to be insignificant, with a path coefficient of -0.086, $p = .277$.

H9 predicted that technology savviness positively influences behavioural intention to use PEM. Results suggested this relationship to be insignificant, with a path coefficient of 0.053, $p = .148$.

4.3. Multigroup analysis results

To examine the remaining hypotheses H1a, H2a, H3a, H4a, H5a, H6a, H7a, H8a and H9a related to differences between blockchain and the cloud solution group, a multigroup analysis (MGA) was performed. The study utilized 5000 bootstrap replications to estimate the results and calculated a 95% confidence interval. The path coefficients for the structural model obtained under blockchain technology and cloud solution conditions are depicted in Table 6 and presented in Appendix G. The results (also in Appendix G) show, that hypotheses H1a and H5a showed significant differences.

H1a predicted that the strength of the relation between performance expectancy and behavioural intention to use is bigger for the cloud technology in comparison to the blockchain technology. H1a is supported with a path coefficient of -0.232 , $p = .046$. The correlation of PE and BIU moderated by blockchain group ($.18$), $p = .039$ and moderated by the cloud solution group ($.41$, $p < .001$) had also each significant results.

H2a predicted that the strength of the relation between effort expectancy and behavioural intention to use is bigger for the cloud technology in comparison to the blockchain technology, which is not supported. H2a is rejected with, $p = .832$.

H3a predicted that the strength of the relation between social influence and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology, which is not supported. H3a is rejected with, $p = .661$.

H4a predicted that the strength of the relation between facilitating conditions and behavioural intention to use is bigger for the cloud technology in comparison to the blockchain technology, which is not supported. H4a is rejected with, $p = .370$.

H5a predicted that the strength of the relation between hedonic motivation and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology. H5a is supported with a path coefficient of 0.239 , $p = .015$. The correlation of HM and BIU moderated by blockchain group ($.26$, $p < .001$) had significant results whereas moderated by the cloud solution group ($.02$, $p = .784$) had not significant results.

H6a predicted that the strength of the relation between perceived privacy risk and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology, which is not supported. H6a is rejected with, $p = .081$.

H7a predicted that the strength of the relation between trust and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology, which is not supported. H7a is rejected with, $p = .285$.

H8a predicted that the strength of the relation between trust and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology, which is not supported. H8a is rejected with, $p = .334$.

H9a predicted that the strength of the relation between trust and behavioural intention to use is bigger for the blockchain technology in comparison to the cloud technology, which is not supported. H9a is rejected with, $p = .340$.

Table 1

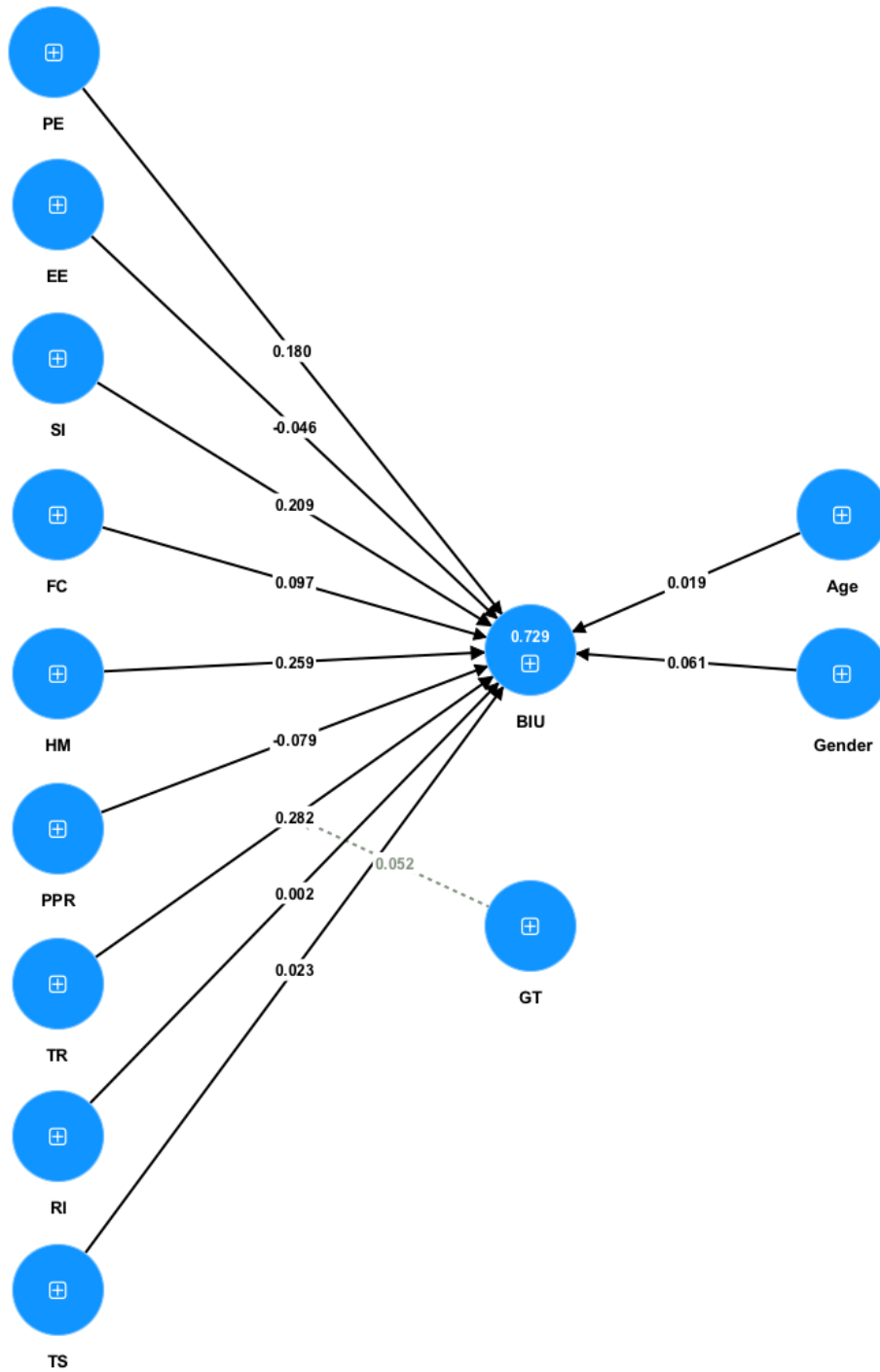
Support of hypotheses

Hypothesis	Supported?	F ² (effect size by Cohen)
H1: PE positively influences BIU of PEM.	✓	0.096
H2: EE positively influences BIU of PEM.	X	
H3: SI positively influences BIU of PEM.	✓	0.075
H4: FC positively influences BIU of PEM.	✓	0.027
H5: HM positively influences BIU of PEM.	✓	0.037
H6: PPR positively influences BIU of PEM.	X	
H7: TR positively influences BIU of PEM.	✓	0.052
H8: RP positively influences BIU of PEM.	X	
H9: TS positively influences BIU of PEM.	X	

Hypothesis	Supported?	Significant difference	Stronger for blockchain	Stronger for cloud solution
H1a: The strength of the relation between PE and BIU is bigger for the cloud technology in comparison to the blockchain technology	✓	✓	X	✓
H2a: The strength of the relation between EE and BIU is bigger for the cloud technology in comparison to the blockchain technology.	X	X	X	X
H3a: The strength of the relation between SI and BIU is bigger for the blockchain technology in comparison to the cloud technology.	X	X	X	X
H4a: The strength of the relation between FC and BIU is bigger for the cloud technology in comparison to the blockchain technology.	X	X	X	X
H5a: The strength of the relation between HM and BIU is bigger for the blockchain technology in comparison to the cloud technology.	✓	✓	✓	X
H6a: The strength of the relation between PPR and BIU is bigger for the blockchain technology in comparison to the cloud technology.	X	X	X	X
H7a: The strength of the relation between TR and BIU is bigger for the blockchain technology in comparison to the cloud technology.	X	X	X	X
H8a: The strength of the relation between RP and BIU is bigger for the blockchain technology in comparison to the cloud technology.	X	X	X	X
H9a: The strength of the relation between TS and BIU is bigger for the blockchain technology in comparison to the cloud technology.	X	X	X	X

Figure 4

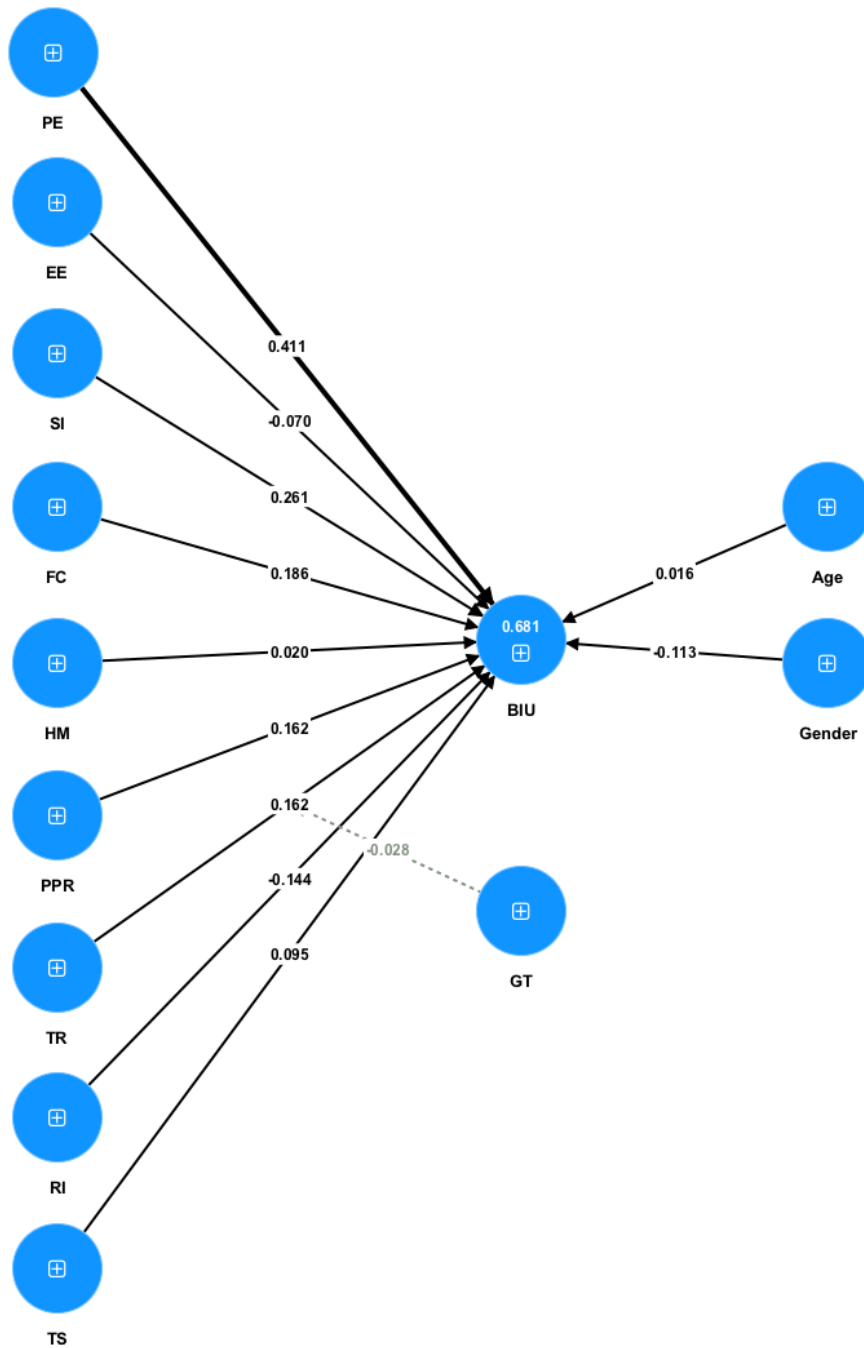
Individual paths estimates for structural model under blockchain condition



Note: value inside the construct circle represent respective R-squared

Figure 5

Individual paths estimate for structural model under cloud condition



Note: value inside the construct circle represent respective R-squared

5. Discussion

The research conducted aimed to assess the suitability of the adapted technology acceptance model UTAUT2 for the application of P2P energy trading with either a blockchain technology or a cloud solution. After establishing that the individual factors of the adapted UTAUT2 model are suitable to this application, and that five out of nine factors significantly impact BIU (performance expectations, social influence, facilitating conditions, hedonic motivation, and trust), it can be concluded that the behavioural intention to use this new technology can be explained by most of the proposed factors. Organisations conducting P2P energy trading and policymakers influencing the adoption of the technology can use this information to inform the development of policies, programs, marketing and sales strategies that promote the acceptance of P2P energy trading, such as subsidizing the installation of essential equipment and educating consumers about the benefits of P2P energy trading. Subsequently, an examination was conducted to determine if there are significant differences between conditions – blockchain and cloud. Such analysis allows to better understand how blockchain is understood vis-à-vis the more usual technology – the cloud – which allow policy makers to understand potential biases and to make an informed attempt at tackling them.

The analysis indicates that most of the constructs contribute similarly to adoption for both groups. Seven out of nine constructs contributed similarly. Only two factors, specifically performance expectancy and hedonic motivation, exhibited statistically significant differences in their relationship with BIU. Organizations offering blockchain-based software for energy trading can use this information to develop tailored to the specific needs of different consumer segments and pay special attention to the fields of performance expectancy and hedonic motivation.

Performance expectancy

Performance expectancy refers to the user's subjective belief that using a particular technology will help them achieve their goals. The study confirmed hypothesis H1 that there is a correlation between PE and BIU, and also supported H1a, that the strength of the relationship between PE and BIU is greater for cloud technology than for blockchain

technology. Prior research has indicated that the perception of enhanced productivity and performance resulting from the utilisation of technology, known as performance expectancy, has a significant impact on the inclination to adopt blockchain technology (Queiroz & Fosso, 2019). This finding aligns with the existing body of literature that emphasises the correlation between individuals' motivation to embrace novel technology and their perception of the advantages it offers. The decentralised nature of blockchain technology and its potential to streamline processes using smart contracts have generated significant anticipation (Silinskyte, 2014). The research highlights the significance of performance expectancy as a key determinant of individuals' inclination to adopt and employ technology. This finding is consistent with the outcomes of the UTAUT2 model (Davis, 1989; Venkatesh et al., 2012). The stronger association between PE and the BIU cloud solutions, as opposed to blockchain technology, can be attributed to various factors, including familiarity with cloud solutions, the presence of tangible benefits, ease of accessibility, lower barriers to entry, a wide range of use cases, and reduced technical complexity. The user-friendly characteristics, distinct benefits, extensive accessibility, and adaptable nature of cloud solutions collectively might enhance the perception of enhanced performance, thereby increasing the likelihood of user adoption (Agavanakis et al., 2018). On the contrary, the intricate and conceptual nature of blockchain may result in a diminished correlation between the anticipation of performance outcomes and the inclination to adopt it (Khan, 2021). Nevertheless, the significance of performance expectancy may differ depending on individual and contextual variables. It would be beneficial for further research to aim at understanding what leads to this difference.

Effort expectancy

Effort expectancy (EE), which refers to the level of ease with which a system can be utilised, seems to not directly affect the behavioural intention to use, contrary to H2. H2a is also rejected as no significant difference was measured between the cloud solutions and blockchain technology groups. The initial assumption that users are more likely to accept a technology if they believe it is easy to use and requires little effort, and vice versa, could therefore not be supported. To be more specific about EE, the three different parts on which the theory is based should be considered more in detail, namely perceived ease of use, complexity, and usability. The weak correlation between effort expectancy and behavioural

intention to use P2P energy trading can potentially be attributed to factors like complex technologies or lack of familiarity. Tseng (2010) found that early adopters were more influenced by social influence and facilitative conditions than potential adopters, despite having higher effort expectations on average, which is consistent with this study's findings. The findings indicate that individuals who have limited familiarity with a new technology, such as blockchain, may address their reservations regarding the effort needed to acquire knowledge about the technology. Instead, they may be influenced by their own and external motivation, specifically effort expectancy. Recent studies found similar results and only 45 out of 70 studies had significant results about EE (ref to the author who counted this). These factors interact and impact the link between perceived effort and the willingness to adopt (Khechine, 2016).

Social influence

Social influence (SI), which refers to the degree to which users allow themselves to be influenced by others (Venkatesh, 2012). As expected, social influence correlates with BIU and hypothesis H3 is supported. However, the strength of the relationship between SI and BIU is not greater for blockchain technology than for cloud technology, and no significant differences could be found between cloud and blockchain technology, thus H3a is rejected. The relationship between SI and BIU has been controversially discussed. While multiple academic investigations have substantiated the presence of significant effects created by social influence on behavioural intention, it is crucial to acknowledge that such influence is dependent upon the specific cultural or national context in question. For instance, while in country India has been found, for other countries like the US, there were no notable findings in the same investigations (Alazab et al. 2021; Queiroz & Fosso, 2019;). The fact that only English speakers from Western countries where English is the native language participated in the survey, could be one reason why there was a high congruency and correlation.

Facilitating conditions

The concept of facilitating conditions relates to the presence of supportive conditions, whereas the perception of uncertainty and ambiguity is viewed as an obstacle to the acceptance and integration of new technologies. However, the main objective of new technological progress is to reduce these uncertainties (Venkatesh et al., 2003). In line with H4, it was confirmed, that there is a correlation between FC and BIU. Since the blockchain technology is comparatively young compared to the cloud solution, differences in facilitating conditions were expected, but H4a could not be validated. One reason for this could be that both cloud solutions and blockchain require access to computers and internet connections, which are perceived comparatively similarly, even if the technology behind them is essentially different (Pieters et al., 2021). The technical know-how is also comparable, as both require a similar, moderate level of technical expertise. However, blockchain tends to be a little more complex to use than cloud solutions. Costs and support can vary for both, depending on the platform (Saranya, 2023). These facilitating conditions can all have an impact on the intention to use P2P energy trading. In general, however, it can be said that the construct of FC and BIU works well and the two constructs correlate, as Venkatesh has already demonstrated in another context. FC are more directly related to the user's perception of the usefulness of the technology, while other factors, such as hedonic motivation (HM), are more indirectly related to usefulness. FC affect usefulness by increasing the likelihood that the user will be able to use the technology effectively. In general, FC are more important for technologies that are complex or difficult to use. HM is more important for technologies that are perceived as enjoyable or entertaining (Juričić et al., 2022; Tseng, 2010). HM affects utility by increasing the likelihood that the user will want to use the technology. For the latter, however, the circumstance must be present. Because there were no significant differences between the two groups in the FC construct, differences in HM can be given even higher emphasis.

Hedonic motivation

The HM construct, which was tested for the pleasure or joy of using new technology, was well suited for multigroup analysis as it supported H5 and showed a high correlation with BIU, which was tested by Boonsiritomachai and Powitayadejanant with similar

approaches (2017). It was confirmed that individuals' actions are subject to the influence of pleasure or satisfaction derived from a particular technology. Using multi-group analysis, H5a is supported that the strength of the association between HM and BIU is greater for blockchain technology compared to cloud technology. Reasons for this could be that cloud solutions are typically seen as more traditional and less innovative than blockchain and associated with companies and organizations, while blockchain is more associated with innovative individuals and communities. Indeed, blockchain P2P energy trading is also seen as a more innovative and exciting technology, which can lead to greater hedonistic motivation. As a result of these factors, users may be more motivated to use blockchain P2P energy trading than a cloud solution because they perceive it as more exciting, innovative, personal, transparent, and accountable. This can lead to a stronger connection between hedonic motivation and behavioural intent to use.

Perceived privacy risk

Studies have shown a negative correlation between the perceived level of risk of an application and the likelihood that people will choose to use that technology (Al-Jabri & Sohail, 2012; Monrat et al., 2019). This study showed no correlation between PPR and BIU PEM and H6 had to be rejected, while also H6a could not be confirmed, as the strength of the relation between PPR and BIU is not bigger for the blockchain technology in comparison to the cloud technology. One possible explanation for this lack of relationship is that, due to its novelty, users may not be very concerned about privacy, as they are not aware of what kind of data they have to share to participate. On the other hand, well-informed study participants would know that the data protection is extremely secure and even higher than the data protection risk in online banking. As the video didn't inform perhaps enough about the privacy risks, and as the scale, PPR is a subjective measure, users may have different levels of concern about privacy when it comes to P2P energy trading. Some users may be more concerned about privacy than others, and this may affect their behavioural intention to use P2P energy trading (Wang et al., 2021). It is worth mentioning that while no highly significant correlation was shown under the condition blockchain, the p -value of $-.079$ shows a tendency towards a negative correlation, although this could also be a coincidence at the value mentioned. Overall, the relationship between perceived privacy risk and behavioural

intention to use P2P energy trading is complex and not fully understood. More research is needed to determine the factors that influence this relationship.

Trust

Trust is a key factor in the adoption of any new technology, as it has been shown that if users trust a technology, they are more likely to use it (Oliveira et al., 2014). Especially for P2P energy trading which is responsible for the power supply. Power supply is seen as an essential and critical necessity for our everyday life, which is why there are a few reasons for trust being important, including security, privacy, and reliability (Huijts et al., 2012). Blockchain technology can help to achieve these levels of trust, with an advantage compared to cloud solutions as it is a decentralized, transparent, and distributed ledger, which is seen as a key factor for trust (Eberhardt et al., 2020). Despite the high correlation between trust and intention to use the technology, no differences were found between the cloud and the blockchain, contrarily to expectations. This unexpected result warrants discussion. When building trust, the basic principles of security and privacy play a crucial role. Maintaining the highest level of security on the services is imperative to enhance user trust. According to Agavanakis et al., (2018), however, cloud solutions are more established, and consumers are more used to them, which can offset the technical trust benefits of blockchain technology. Erturk et al., (2019) state that trust in blockchain technology is caused by a lack of knowledge, problems with understanding and wrong critical conclusions that arise from cryptocurrencies. So, perhaps counteracting the expected positive effects of transparency, familiarity and knowledge with the cloud led to similar levels between groups.

Risk perception

In the context of technology adoption or use, RP can be accurately described as the likelihood or risk of unfavourable consequences or undesirable outcomes resulting from that adoption or use (Benlian & Hess, 2011). H8, which stated that risk perception negatively influences behavioural intention to use PEM is rejected. H8a could also be not confirmed, as the strength of the relation between RP and BIU is not bigger for the blockchain technology in comparison to the cloud technology. The risks associated with P2P energy

trading are known to be relatively low, the benefits are significant, the technology is becoming more secure and reliable, and users are becoming more aware of its features (Ableitner et al., 2020; Borges et al., 2022). However, risk perception does not always go hand in hand with actual risk and misperceptions and biases are abundant in this field (Erturk, et al., 2019). The decentralised nature, transparency, and tamper-proof characteristics of blockchain make it in theory a more secure platform for peer-to-peer energy trading compared to cloud solutions, which is why differences were expected.

Technology savviness

An individual's knowledge, comfort, and competence with using technology are referred to as their level of technological savviness (Mutohhari et al., 2021). Hypothesis H9, which stated a correlation TS and BIU PEM. The known thesis, that technological people value the PEM advantages more, like cost savings, improved energy efficiency and environmental care skills, could in this context not be proven (Mutohhari, 2021). There are a few possible explanations for this lack of correlation. It could be, because P2P energy trading is a relatively new technology, and there is no clear consensus on what level of technology savviness is required to use it. P2P energy trading can save users money on their energy bills and reduce their environmental impact. These benefits may be enough to motivate users to learn how to use P2P energy trading, even if they describe themselves as not very tech-savvy (Acur et al., 2009). Hypothesis H9a, which stated that the strength of the relation between TS and BIU is bigger for the blockchain technology in comparison to the cloud technology, could not be confirmed.

6. Limitations

The study has some limitations, which do not necessarily have a great influence on the results but should be mentioned nevertheless. It was conducted with an English-speaking sample from Western countries where English is the native tongue, so the results may not apply to other populations. Also, the study only examined one other form of peer-to-peer energy trading technologies which was compared to blockchain, namely cloud solution. This was the so-called control group, and it was chosen because it is the most prevalent comparable technology. However, it is not the only comparable technology, so the results may not apply to other technologies. Due to its recent emergence, the evaluation of this technology mostly focused on the intention to use, rather than its actual usage and acceptance. Despite these limitations, the study provides important insights into the factors that influence the behavioural intent to use P2P energy trading technologies.

7. Conclusions and Future Research Directions

This study aimed to determine the suitability of the UTAUT2 model in predicting individuals' behavioural intention to engage in peer-to-peer (P2P) energy trading, utilizing either blockchain or cloud solution technologies. The research revealed that a majority of the components in the UTAUT2 model, namely five out of nine, predicted the behavioural intention to use. These important predictors included performance expectancy, social influence, facilitating conditions, hedonic incentives and trust. The study also found that there were significant differences in the relationships between some of the factors and behavioural intention to use, depending on whether blockchain or cloud solution technology was used. For example, performance expectancy is a stronger predictor of behavioural intention to use cloud solution technology than blockchain technology. One possible explanation for this observance could be that cloud solution technology is more widely used, has been proven for a long time, and is perceived as more user-friendly compared to blockchain technology. The research also revealed that hedonic motivation exhibited a greater predictive capability in determining the behavioural intention to use blockchain technology compared to cloud solution technology. One possible explanation for this phenomenon could be the perception that blockchain technology has a higher degree of innovation and excitement compared to cloud solution technology. These findings have several implications for policymakers and organisations, conducting P2P energy trading. First, the study emphasises the significance of performance expectations, social influence, facilitating conditions, hedonic motivation, and trust in predicting individuals' behavioural intent to engage in P2P energy trading. Policymakers can use this information to develop policies and programmes that encourage the adoption of P2P energy trading.

For instance, policymakers could create public awareness campaigns to educate consumers on the advantages of P2P energy trading, e.g. about the facilitating conditions, perceived privacy risks and trust. Second, the study discovered that the relationships between certain factors and behavioural intention to use may vary depending on the technology employed. Organisations providing the hardware and or software can use this information to develop marketing and sales strategies tailored to the specific requirements of various consumer segments. For example, organisations could emphasise the performance expectancy and social influence of cloud solution technology to consumers who are new to

P2P energy trading. They could emphasise the innovation and hedonic motivation of blockchain technology to consumers who are more tech-savvy and interested in aspiring technologies. Recommendations for action resulting from the results of hedonic motivation can also be used specifically for customer contact, advertising or communication through emotional statements.

Future research should address the limitations of this study by taking part in a study with a larger and more varied sample size. It is recommended to conduct a longitudinal investigation to track the development of behavioural intentions and investigate the impact of additional variables, such as price. While the technology generally represents a financial advantage over traditional energy procurement, the financial advantage of the use of blockchain compared to other p2p energy trading technologies is small (Chen et al., 2022; Borges et al., 2022).

By addressing the mentioned limitations, future research can enhance our understanding of the factors that influence the adoption of P2P energy trading. This information can be applied to the design and implementation of user-friendly P2P energy trading systems. The successful distribution of P2P blockchain-based energy trading with the help of smart distribution networks and improved usage practices can make an essential contribution to a successful energy transition. This is predicted to make a significant contribution to achieving international climate goals and counteract climate change.

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Appendices

Appendix A

Figure 6

Consent form

Welcome to our studies on new energy solutions and workplace decisions. This research project is conducted by Professor Ian James Scott, Professor Filipa de Almeida, and Jakob Kungel.

In these studies you'll be asked to consider a couple of scenarios and answer about how you think you would act under such scenarios. You will also be asked to answer to questions on concepts related to such scenarios.

Your participation in this study is completely voluntary and you may withdraw from the questionnaire at any stage.

All information provided by you will be stored in a password protected electronic database, and it will only be viewed and analyzed by those conducting current research.

All responses will remain **anonymous**, meaning that there will be no identification required, be that names, e-mails or IP addresses. Thus, we kindly ask you to give sincere replies to the questions, also as there are no right or wrong answers.

If you have any further questions, associated with the study or its procedures, please contact us at the following e-mail address: filipadealmeida@ucp.pt.

The questionnaire will take you around 10 minutes in total.

We are very grateful for your participation.

Appendix B

Figure 7

Video script for blockchain version

The world is using more energy than ever before, and energy prices have hit record highs due to global events. This increases the need to transition to cleaner locally produced energy sources.

Up until now, we've relied on centralized power systems managed by traditional electricity providers to source our electricity. However, new opportunities have emerged for producing and selling electricity at a lower cost. One of these new methods is called peer-to-peer energy trading where people buy and sell electricity themselves with their neighbors in an energy community.

Peer to peer energy trading allows you to team up with other households in your area to create an electricity trading community. This community lets you trade and share privately generated electricity, like solar power, without needing an energy company as a middleman. You can sell any extra power you generate to other members in the community and they can benefit from purchasing cheaper locally and sustainably produced power.

Peer to peer energy trading has benefits for the national grid too, such as stabilizing the grid by balancing demand and reducing the risk of blackouts.

Even those who don't produce their own energy can join a power trading community, buying electricity from local renewable sources and supporting the shift to cleaner energy.

Financially, peer to peer energy trading is attractive for participants: community members pay less for the electricity they buy, while those who produce energy (prosumers) can sell it at a higher profit than selling it back to the grid. If participants are unhappy with current prices, they can always switch back to regular pricing plans available to everyone else.

Energy trading, including payments, is automatically handled on a secure, decentralized blockchain platform, ensuring that electricity is always sold and available when needed.

Blockchain is a decentralized database. This means there is no central party or company with access to your data, instead it is hosted on a secure but shared system that allows everyone to collaborate on an equal basis. On the blockchain data is stored in an unchangeable and transparent chain which is verified by all network participants.

The blockchain offers benefits like security, as the encrypted and decentralized data is protected against hacking and manipulation. This means, participants do not need to trust a company to maintain the privacy and security of our data. Trust is increased through consensus and collaboration among participants. High transparency means everyone has the same information, reducing inequalities and fraud. Blockchain can be faster and cheaper than traditional methods because it doesn't require intermediaries.

With its potential to transform industries, blockchain offers a secure, transparent, and efficient way to record and transfer data collaboratively as part of a community.

Figure 8

Video script cloud solution version

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Energy trading, including payments, is automatically handled on a secure, cloud solution platform, ensuring that electricity is always sold and available when needed.

The cloud system is a centralized database. This means all data is sent to a single company who will be in charge of maintaining security and privacy of our data. The data is stored without transparency so only the company in charge should have access to it and the ability to make any changes.

Cloud based systems offer benefits like security, as the data is encrypted to be protected against hacking and manipulation. Participants simply require the company running the system to maintain the privacy and security of our data. Trust is increased through the long history of cloud based platforms in many industries. The members of the cloud solution platform do not have transparent access to the information but they know that only a single company would be able to make changes to the information and it is in their interests to try to protect this information. Cloud based solutions can be faster and cheaper than traditional methods because it doesn't require on-premise servers.

With its potential to transform industries, cloud base systems offer a secure, and efficient way to record and transfer data collaboratively as part of a community

Appendix C

Table 2

Heterotrait-montrait ratio (HTMT) analysis of constructs

	Age	BIU	EE	FC	GT	Gender	HM	PE	PPR	RI	SI	TR	TS	GT x TR
Age														
BIU	0.027													
EE	0.063	0.510												
FC	0.028	0.703	0.760											
GT	0.081	0.137	0.083	0.119										
Gender	0.077	0.016	0.087	0.070	0.088									
HM	0.099	0.615	0.485	0.536	0.106	0.017								
PE	0.039	0.766	0.486	0.686	0.217	0.061	0.615							
PPR	0.106	0.463	0.293	0.480	0.265	0.040	0.303	0.435						
RP	0.121	0.529	0.380	0.520	0.254	0.040	0.355	0.452	0.916					
SI	0.051	0.711	0.470	0.609	0.209	0.040	0.513	0.726	0.339	0.414				
TR	0.024	0.714	0.501	0.631	0.243	0.033	0.541	0.649	0.658	0.749	0.622			
TS	0.097	0.209	0.469	0.307	0.110	0.357	0.190	0.131	0.228	0.224	0.095	0.231		
GT x TR	0.015	0.007	0.012	0.071	0.205	0.137	0.019	0.020	0.028	0.034	0.038	0.081	0.136	

Appendix D

Table 3

Descriptive statistics and construct reliability

	Name	Mean	St.Dev.	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)	Collinearity statistics (VIF)
Performance Expectancy	PE_1	5.151	1.280	0.916	0.918	0.800	2.000
	PE_2	4.349	1.410				6.575
	PE_3	4.170	1.406				6.022
	PE_4	4.580	1.471				2.575
Effort Expectancy	EE_1	4.753	1.320	0.956	0.961	0.883	4.674
	EE_2	4.855	1.288				6.394
	EE_3	4.886	1.281				6.019
	EE_4	4.866	1.244				3.886
Social Influence	SI_1	4.710	1.336	0.945	0.948	0.901	4.138
	SI_2	4.693	1.298				5.073
	SI_3	4.770	1.328				4.798
Facilitating Condition	FC_1	5.750	0.929	0.761	0.779	0.675	1.501
	FC_2	5.062	1.237				1.588
	FC_3	5.267	1.093				1.537
Hedonic Motivation	HM_1	4.128	1.419	0.955	0.963	0.917	8.961
	HM_2	4.239	1.408				7.645
	HM_3	3.756	1.425				3.993
Perceived Privacy Risk	PPR_1	3.642	1.366	0.962	0.966	0.842	5.715
	PPR_2	3.719	1.358				6.683
	PPR_3	3.528	1.316				5.547
	PPR_4	3.429	1.317				4.529
	PPR_5	3.673	1.408				3.580
	PPR_6	3.486	1.286				5.469
Trust	TR_1	4.659	1.300	0.960	0.964	0.894	4.555
	TR_2	4.688	1.305				4.713
	TR_3	4.676	1.294				7.723
	TR_4	4.688	1.344				8.002
Risk	RP_1	3.915	1.358	0.939	0.943	0.700	2.568
	RP_2	2.983	1.204				2.710
	RP_3	3.472	1.344				3.307
	RP_4	3.668	1.323				3.855

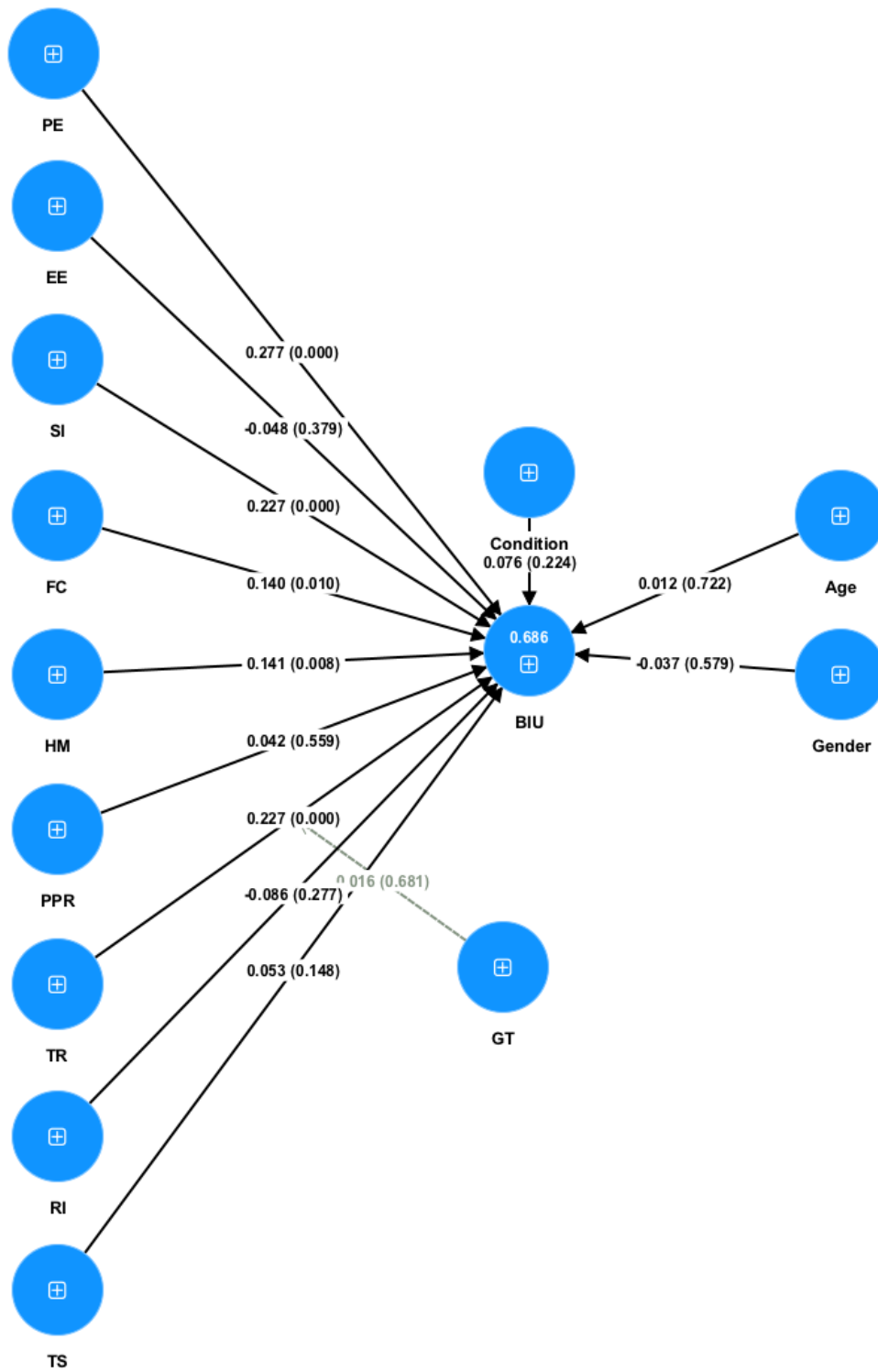
	RP_5	3.685	1.346				4.298
	RP_6	3.523	1.357				3.800
	RP_7	3.741	1.333				2.811
	RP_8	3.903	1.349				2.411
Technology Savviness	TS_1	4.284	1.715	0.912	0.933	0.564	2.747
	TS_2	4.452	1.393				1.348
	TS_3	3.514	1.650				2.223
	TS_4	5.389	1.316				2.980
	TS_5	4.528	1.520				2.797
	TS_6	4.577	1.618				3.120
	TS_7	4.929	1.413				3.006
	TS_8	5.361	1.443				1.907
	TS_9	5.500	1.208				2.530
	TS_10	4.543	1.544				1.571
Behavioural Intention to Use	BIU_1	5.165	1.304	0.962	0.962	0.929	5.985
	BIU_2	4.773	1.412				6.093
	BIU_3	4.972	1.392				7.801
General Trust	GT_1	4.688	1.396	0.542	0.817	0.497	2.554
	GT_2	4.511	1.498				1.965
	GT_3	5.304	1.093				1.598
	GT_4	3.699	1.116				1.206
	TR_others_1	3.989	1.170				3.427
	TR_others_2	6.006	1.053				1.434
	TR_others_3	4.477	1.241				2.013
	TR_others_4	3.656	1.198				3.261

*AVE > 0.5 bolded as significant, as per Mendes dos Santos & Cirillo (2021)
**Chronbach's Alphas > 0.6 bolded as significant, as per Nunally & Bernstein (1994)

Appendix E

Figure 9

Individual paths estimates for structural model



Note: *p-values are displayed in the brackets after the respective path coefficients
 **Paths are highlighted using absolute path coefficient value strength

Appendix F

Table 4

Initial factor cross-loading analysis of constructs

	PE	EE	SI	FC	HM	PPR	TR	RI	TS	BIU	GT	GTxTR	Age	Gender
PE_1	0.844	0.405	0.614	0.565	0.456	-0.389	0.521	-0.408	0.115	0.713	0.176	0.025	-0.061	0.101
PE_2	0.936	0.418	0.628	0.522	0.560	-0.349	0.549	-0.362	0.103	0.639	0.172	0.023	-0.056	0.009
PE_3	0.924	0.408	0.614	0.492	0.500	-0.343	0.535	-0.359	0.088	0.609	0.219	0.009	-0.010	0.013
PE_4	0.870	0.405	0.558	0.500	0.546	-0.384	0.577	-0.379	0.160	0.610	0.241	-0.011	-0.008	-0.088
EE_1	0.371	0.929	0.360	0.584	0.387	-0.235	0.403	-0.303	0.433	0.405	0.056	0.007	-0.045	-0.096
EE_2	0.465	0.954	0.462	0.621	0.444	-0.286	0.463	-0.371	0.383	0.485	0.056	0.025	-0.062	-0.096
EE_3	0.445	0.953	0.444	0.629	0.462	-0.277	0.488	-0.367	0.391	0.491	0.065	-0.000	-0.061	-0.063
EE_4	0.433	0.921	0.416	0.612	0.452	-0.268	0.450	-0.328	0.451	0.455	0.082	-0.011	-0.064	-0.064
SI_1	0.634	0.417	0.941	0.495	0.438	-0.307	0.556	-0.384	0.065	0.627	0.224	-0.036	-0.049	0.061
SI_2	0.658	0.414	0.952	0.479	0.484	-0.284	0.552	-0.339	0.073	0.620	0.226	-0.035	-0.054	0.048
SI_3	0.638	0.448	0.954	0.503	0.471	-0.334	0.581	-0.398	0.099	0.684	0.225	-0.035	-0.038	0.002
FC_1	0.406	0.586	0.400	0.796	0.334	-0.347	0.436	-0.383	0.358	0.450	0.093	-0.000	-0.017	-0.045
FC_2	0.567	0.576	0.460	0.863	0.430	-0.358	0.492	-0.370	0.232	0.582	0.072	0.057	-0.028	-0.001
FC_3	0.448	0.438	0.416	0.804	0.367	-0.317	0.406	-0.340	0.047	0.452	0.087	0.096	-0.015	0.104
HM_1	0.571	0.447	0.480	0.458	0.973	-0.288	0.500	-0.339	0.190	0.575	0.098	-0.033	-0.083	-0.024
HM_2	0.568	0.474	0.502	0.467	0.967	-0.310	0.538	-0.354	0.181	0.611	0.107	-0.009	-0.070	-0.010
HM_3	0.510	0.414	0.417	0.399	0.932	-0.239	0.454	-0.279	0.193	0.507	0.093	-0.011	-0.126	0.014
PPR_1	-0.412	-0.266	-0.326	-0.391	-0.272	0.930	-0.611	0.829	-0.213	-0.429	-0.237	-0.010	-0.124	0.032
PPR_2	-0.386	-0.267	-0.295	-0.377	-0.273	0.938	-0.589	0.817	-0.202	-0.422	-0.208	-0.023	-0.107	0.040
PPR_3	-0.379	-0.269	-0.296	-0.401	-0.270	0.924	-0.602	0.809	-0.219	-0.415	-0.203	-0.028	-0.083	0.024
PPR_4	-0.398	-0.306	-0.322	-0.434	-0.273	0.919	-0.612	0.801	-0.211	-0.448	-0.203	0.020	-0.116	-0.029
PPR_5	-0.321	-0.193	-0.265	-0.296	-0.235	0.868	-0.515	0.716	-0.187	-0.340	-0.240	0.036	-0.066	0.070
PPR_6	-0.359	-0.254	-0.283	-0.367	-0.289	0.924	-0.552	0.778	-0.205	-0.401	-0.244	0.035	-0.077	0.020
TR_1	0.588	0.472	0.555	0.517	0.469	-0.534	0.931	-0.652	0.218	0.669	0.235	-0.086	-0.029	-0.032
TR_2	0.524	0.434	0.524	0.479	0.451	-0.619	0.927	-0.665	0.211	0.595	0.219	-0.091	0.004	-0.045
TR_3	0.569	0.452	0.568	0.509	0.514	-0.606	0.958	-0.687	0.206	0.635	0.219	-0.041	0.034	-0.021
TR_4	0.620	0.464	0.594	0.547	0.532	-0.642	0.964	-0.709	0.217	0.698	0.259	-0.081	-0.021	-0.026
RP_1	-0.362	-0.315	-0.332	-0.330	-0.316	0.627	-0.655	0.821	-0.199	-0.460	-0.207	0.075	-0.084	0.064
RP_2	-0.352	-0.314	-0.344	-0.401	-0.274	0.652	-0.624	0.810	-0.177	-0.502	-0.190	0.025	-0.163	0.008
RP_3	-0.366	-0.337	-0.365	-0.390	-0.289	0.690	-0.626	0.857	-0.143	-0.470	-0.190	0.020	-0.083	-0.076
RP_4	-0.319	-0.259	-0.287	-0.336	-0.265	0.754	-0.553	0.854	-0.201	-0.389	-0.221	0.047	-0.093	0.031
RP_5	-0.341	-0.289	-0.335	-0.360	-0.291	0.773	-0.599	0.882	-0.160	-0.383	-0.215	-0.007	-0.140	-0.028
RP_6	-0.389	-0.316	-0.322	-0.407	-0.249	0.857	-0.578	0.863	-0.251	-0.415	-0.217	-0.010	-0.129	-0.006
RP_7	-0.296	-0.243	-0.267	-0.309	-0.224	0.801	-0.508	0.785	-0.199	-0.320	-0.149	0.023	-0.018	0.028

RP_8	-0.391	-0.350	-0.363	-0.404	-0.352	0.684	-0.621	0.815	-0.137	-0.427	-0.212	0.011	-0.072	-0.020
TS_1	0.079	0.299	0.053	0.152	0.089	-0.115	0.098	-0.098	0.800	0.123	0.132	-0.108	-0.133	-0.351
TS_2	0.053	0.279	0.010	0.115	0.088	-0.101	0.172	-0.076	0.520	0.101	0.006	-0.095	-0.051	-0.122
TS_3	0.135	0.371	0.138	0.166	0.235	-0.176	0.204	-0.165	0.749	0.177	0.025	-0.120	-0.060	-0.304
TS_4	0.032	0.334	-0.028	0.178	0.041	-0.093	0.079	-0.097	0.773	0.086	0.020	-0.092	-0.130	-0.260
TS_5	0.092	0.342	0.039	0.230	0.130	-0.221	0.187	-0.172	0.824	0.146	0.065	-0.056	-0.108	-0.349
TS_6	0.169	0.401	0.101	0.256	0.233	-0.179	0.208	-0.158	0.861	0.199	0.086	-0.104	-0.053	-0.336
TS_7	0.083	0.350	0.047	0.205	0.089	-0.133	0.142	-0.155	0.825	0.157	0.033	-0.058	-0.055	-0.279
TS_8	0.049	0.269	-0.032	0.188	0.061	-0.130	0.133	-0.143	0.635	0.095	0.041	-0.135	-0.057	-0.129
TS_9	0.101	0.354	0.064	0.245	0.193	-0.235	0.196	-0.241	0.811	0.217	0.064	-0.052	-0.044	-0.233
TS_10	0.101	0.257	0.122	0.157	0.156	-0.209	0.196	-0.234	0.640	0.164	0.042	-0.149	-0.002	-0.182
BIU_1	0.694	0.468	0.659	0.590	0.600	-0.420	0.662	-0.492	0.211	0.961	0.135	-0.001	-0.063	-0.012
BIU_2	0.714	0.479	0.641	0.585	0.529	-0.433	0.643	-0.477	0.178	0.960	0.150	0.015	0.002	-0.008
BIU_3	0.686	0.472	0.665	0.586	0.581	-0.443	0.687	-0.509	0.215	0.971	0.159	-0.003	-0.012	-0.025
GT_1	0.187	0.042	0.214	0.055	0.111	-0.130	0.181	-0.145	0.047	0.095	0.833	-0.161	-0.002	-0.038
GT_2	0.148	0.079	0.181	0.077	0.091	-0.257	0.218	-0.254	0.123	0.123	0.757	-0.183	0.000	-0.092
GT_3	-0.043	0.114	0.034	0.129	-0.032	0.095	-0.013	0.045	0.020	0.050	-0.474	0.138	-0.045	0.052
GT_4	-0.031	-0.048	-0.014	-0.047	-0.060	0.165	-0.157	0.179	-0.100	-0.011	-0.406	0.046	-0.090	0.060
TR_others_1	0.158	0.043	0.135	0.080	0.058	-0.126	0.183	-0.125	0.111	0.102	0.626	-0.111	0.068	-0.111
TR_others_2	0.175	0.067	0.188	0.098	0.105	-0.114	0.152	-0.107	-0.020	0.133	0.806	-0.172	0.077	0.015
TR_others_3	0.185	0.009	0.163	0.046	0.044	-0.251	0.189	-0.240	0.020	0.088	0.792	-0.155	0.087	-0.051
TR_others_4	0.171	-0.010	0.150	0.010	0.050	-0.233	0.168	-0.211	0.019	0.103	0.807	-0.126	0.061	-0.048
GT x TR	0.014	0.006	-0.037	0.063	-0.018	0.004	-0.079	0.028	-0.125	0.004	-0.194	1.000	-0.015	0.137
Age	-0.039	-0.062	-0.049	-0.025	-0.095	-0.105	-0.004	-0.121	-0.084	-0.025	0.062	-0.015	1.000	-0.077
Gender	0.014	-0.085	0.038	0.021	-0.008	0.026	-0.032	-0.001	-0.347	-0.016	-0.066	0.137	-0.077	1.000

*Factor loadings 0.55 and above are bolded as significant, as per Hair et al. (2015)

Table 5

Factor cross-loadings analysis of constructs after model alteration

	PE	EE	SI	FC	HM	PPR	TR	RI	TS	BIU	GT	GTxTR	Age	Gender
PE_1	0.844	0.405	0.614	0.565	0.456	-0.389	0.521	-0.408	0.115	0.713	0.168	0.025	-0.061	0.101
PE_2	0.936	0.418	0.628	0.522	0.560	-0.349	0.549	-0.362	0.104	0.639	0.167	0.023	-0.056	0.009
PE_3	0.924	0.408	0.614	0.492	0.500	-0.343	0.535	-0.359	0.089	0.609	0.216	0.009	-0.010	0.013
PE_4	0.870	0.405	0.558	0.500	0.546	-0.384	0.577	-0.379	0.161	0.610	0.236	-0.011	-0.008	-0.088
EE_1	0.371	0.929	0.360	0.584	0.387	-0.235	0.403	-0.303	0.426	0.405	0.043	0.007	-0.045	-0.096
EE_2	0.465	0.954	0.462	0.621	0.444	-0.286	0.463	-0.371	0.377	0.485	0.041	0.025	-0.062	-0.096
EE_3	0.445	0.953	0.444	0.629	0.462	-0.277	0.488	-0.367	0.384	0.491	0.048	-0.000	-0.061	-0.063

EE_4	0.433	0.921	0.416	0.612	0.452	-0.268	0.450	-0.328	0.447	0.455	0.069	-0.011	-0.064	-0.064
SI_1	0.634	0.417	0.941	0.495	0.438	-0.307	0.556	-0.384	0.071	0.627	0.210	-0.036	-0.049	0.061
SI_2	0.658	0.414	0.952	0.479	0.484	-0.284	0.552	-0.339	0.076	0.620	0.213	-0.035	-0.054	0.048
SI_3	0.638	0.448	0.954	0.503	0.471	-0.334	0.581	-0.398	0.098	0.684	0.212	-0.035	-0.038	0.002
FC_1	0.406	0.586	0.400	0.796	0.334	-0.347	0.436	-0.383	0.359	0.450	0.080	-0.000	-0.017	-0.045
FC_2	0.567	0.576	0.460	0.863	0.430	-0.358	0.492	-0.370	0.231	0.582	0.052	0.057	-0.028	-0.001
FC_3	0.448	0.438	0.416	0.804	0.367	-0.317	0.406	-0.340	0.050	0.452	0.075	0.096	-0.015	0.104
HM_1	0.571	0.447	0.480	0.458	0.973	-0.288	0.500	-0.339	0.191	0.575	0.097	-0.033	-0.083	-0.024
HM_2	0.568	0.474	0.502	0.467	0.967	-0.310	0.538	-0.354	0.183	0.611	0.102	-0.009	-0.070	-0.010
HM_3	0.510	0.414	0.417	0.399	0.932	-0.239	0.454	-0.279	0.191	0.507	0.092	-0.011	-0.126	0.014
PPR_1	-0.412	-0.266	-0.326	-0.391	-0.272	0.930	-0.611	0.829	-0.212	-0.429	-0.236	-0.010	-0.124	0.032
PPR_2	-0.386	-0.267	-0.295	-0.377	-0.273	0.938	-0.589	0.817	-0.202	-0.422	-0.203	-0.023	-0.107	0.040
PPR_3	-0.379	-0.269	-0.296	-0.401	-0.270	0.924	-0.602	0.809	-0.220	-0.415	-0.194	-0.028	-0.083	0.024
PPR_4	-0.398	-0.306	-0.322	-0.434	-0.273	0.919	-0.612	0.801	-0.209	-0.448	-0.197	0.020	-0.116	-0.029
PPR_5	-0.321	-0.193	-0.265	-0.296	-0.235	0.868	-0.515	0.716	-0.190	-0.340	-0.241	0.036	-0.066	0.070
PPR_6	-0.359	-0.254	-0.283	-0.367	-0.289	0.924	-0.552	0.778	-0.208	-0.401	-0.242	0.035	-0.077	0.020
TR_1	0.588	0.472	0.555	0.517	0.469	-0.534	0.931	-0.652	0.212	0.669	0.222	-0.086	-0.029	-0.032
TR_2	0.524	0.434	0.524	0.479	0.451	-0.619	0.927	-0.665	0.205	0.595	0.209	-0.091	0.004	-0.045
TR_3	0.569	0.452	0.568	0.509	0.514	-0.606	0.958	-0.687	0.202	0.635	0.204	-0.041	0.034	-0.021
TR_4	0.620	0.464	0.594	0.547	0.532	-0.642	0.964	-0.709	0.211	0.698	0.248	-0.081	-0.021	-0.026
RP_1	-0.362	-0.315	-0.332	-0.330	-0.316	0.627	-0.655	0.821	-0.199	-0.460	-0.198	0.075	-0.084	0.064
RP_2	-0.352	-0.314	-0.344	-0.401	-0.274	0.652	-0.624	0.810	-0.179	-0.502	-0.181	0.025	-0.163	0.008
RP_3	-0.366	-0.337	-0.365	-0.390	-0.289	0.690	-0.626	0.857	-0.144	-0.470	-0.179	0.020	-0.083	-0.076
RP_4	-0.319	-0.259	-0.287	-0.336	-0.265	0.754	-0.553	0.854	-0.210	-0.389	-0.213	0.047	-0.093	0.031
RP_5	-0.341	-0.289	-0.335	-0.360	-0.291	0.773	-0.599	0.882	-0.164	-0.383	-0.205	-0.007	-0.140	-0.028
RP_6	-0.389	-0.316	-0.322	-0.407	-0.249	0.857	-0.578	0.863	-0.255	-0.415	-0.207	-0.010	-0.129	-0.006
RP_7	-0.296	-0.243	-0.267	-0.309	-0.224	0.801	-0.508	0.785	-0.203	-0.320	-0.143	0.023	-0.018	0.028
RP_8	-0.391	-0.350	-0.363	-0.404	-0.352	0.684	-0.621	0.815	-0.133	-0.427	-0.210	0.011	-0.072	-0.020
TS_1	0.079	0.299	0.053	0.152	0.089	-0.115	0.098	-0.098	0.800	0.123	0.132	-0.111	-0.133	-0.351
TS_3	0.135	0.371	0.138	0.166	0.235	-0.176	0.204	-0.165	0.745	0.177	0.026	-0.121	-0.060	-0.304
TS_4	0.032	0.334	-0.028	0.178	0.041	-0.093	0.079	-0.097	0.780	0.086	0.012	-0.095	-0.130	-0.260
TS_5	0.092	0.342	0.039	0.230	0.130	-0.221	0.187	-0.172	0.823	0.146	0.060	-0.059	-0.108	-0.349
TS_6	0.169	0.401	0.101	0.256	0.233	-0.179	0.208	-0.158	0.866	0.199	0.073	-0.107	-0.053	-0.336
TS_7	0.083	0.350	0.047	0.205	0.089	-0.133	0.142	-0.155	0.830	0.157	0.024	-0.057	-0.055	-0.279
TS_8	0.049	0.269	-0.032	0.188	0.061	-0.130	0.133	-0.143	0.632	0.095	0.034	-0.131	-0.057	-0.129
TS_9	0.101	0.354	0.064	0.245	0.193	-0.235	0.196	-0.241	0.823	0.217	0.053	-0.052	-0.044	-0.233
TS_10	0.101	0.257	0.122	0.157	0.156	-0.209	0.196	-0.234	0.636	0.164	0.039	-0.151	-0.002	-0.182
BIU_1	0.694	0.468	0.659	0.590	0.600	-0.420	0.662	-0.492	0.212	0.961	0.124	-0.001	-0.063	-0.012
BIU_2	0.714	0.479	0.641	0.585	0.529	-0.433	0.643	-0.477	0.178	0.960	0.139	0.015	0.002	-0.008
BIU_3	0.686	0.472	0.665	0.586	0.581	-0.443	0.687	-0.509	0.215	0.971	0.147	-0.003	-0.012	-0.025
GT_1	0.187	0.042	0.214	0.055	0.111	-0.130	0.181	-0.145	0.046	0.095	0.835	-0.165	-0.002	-0.038

GT_2	0.148	0.079	0.181	0.077	0.091	-0.257	0.218	-0.254	0.122	0.123	0.767	-0.188	0.000	-0.092
TR_others_1	0.158	0.043	0.135	0.080	0.058	-0.126	0.183	-0.125	0.119	0.102	0.615	-0.117	0.068	-0.111
TR_others_2	0.175	0.067	0.188	0.098	0.105	-0.114	0.152	-0.107	-0.016	0.133	0.801	-0.174	0.077	0.015
TR_others_3	0.185	0.009	0.163	0.046	0.044	-0.251	0.189	-0.240	0.017	0.088	0.803	-0.152	0.087	-0.051
TR_others_4	0.171	-0.010	0.150	0.010	0.050	-0.233	0.168	-0.211	0.019	0.103	0.821	-0.129	0.061	-0.048
GT x TR	0.014	0.006	-0.037	0.063	-0.018	0.004	-0.079	0.028	-0.123	0.004	-0.202	1.000	-0.015	0.137
Age	-0.039	-0.062	-0.049	-0.025	-0.095	-0.105	-0.004	-0.121	-0.083	-0.025	0.062	-0.015	1.000	-0.077
Gender	0.014	-0.085	0.038	0.021	-0.008	0.026	-0.032	-0.001	-0.351	-0.016	-0.067	0.137	-0.077	1.000

*Factor loadings 0.55 and above are bolded as significant, as per Hair et al. (2015)

Appendix G

Table 6

Path coefficients – confidence intervals (bias-corrected) between conditions

	Difference (Blockchain - Cloud)	1-tailed (Blockchain vs. Cloud) p-value	2-tailed (Blockchain vs. Cloud) p-value
PE -> BIU	-0.232	0.977	0.046
EE -> BIU	0.024	0.416	0.832
SI -> BIU	-0.052	0.670	0.661
FC -> BIU	-0.089	0.815	0.370
HM -> BIU	0.239	0.007	0.015
PPR -> BIU	-0.240	0.960	0.081
TR -> BIU	0.120	0.143	0.285
RI -> BIU	0.146	0.167	0.334
TS -> BIU	-0.072	0.830	0.340
GT -> BIU	0.062	0.223	0.446
GT x TR -> BIU	0.079	0.137	0.273
Age -> BIU	0.003	0.488	0.976
Gender -> BIU	0.174	0.096	0.193

Note: significantly different paths are highlighted in grey

Appendix H

Table 7

Bootstrapping results for individual paths estimates between conditions

	Original (Blockchain)	Original (Cloud)	Mean (Blockchain)	Mean (Cloud)	STDEV (Blockchain)	STDEV (Cloud)	t value (Blockchain)	t value (Cloud)	p-value (Blockchain)	p-value (Cloud)
PE -> BIU	0.180	0.411	0.177	0.412	0.087	0.076	2.067	5.409	0.039	0.000
EE -> BIU	-0.046	-0.070	-0.039	-0.075	0.072	0.085	0.641	0.823	0.522	0.410
SI -> BIU	0.209	0.261	0.202	0.259	0.086	0.079	2.434	3.310	0.015	0.001
FC -> BIU	0.097	0.186	0.114	0.175	0.064	0.077	1.514	2.413	0.130	0.016
HM -> BIU	0.259	0.020	0.251	0.021	0.066	0.073	3.909	0.274	0.000	0.784
PPR -> BIU	-0.079	0.162	-0.073	0.153	0.100	0.094	0.790	1.724	0.430	0.085
TR -> BIU	0.282	0.162	0.277	0.168	0.079	0.080	3.558	2.010	0.000	0.044
RP -> BIU	0.002	-0.144	0.004	-0.134	0.119	0.093	0.020	1.537	0.984	0.124
TS -> BIU	0.023	0.095	0.031	0.101	0.053	0.054	0.426	1.748	0.670	0.080
GT -> BIU	-0.016	-0.078	0.005	-0.042	0.055	0.078	0.300	1.002	0.765	0.316
GT x TR -> BIU	0.052	-0.028	0.037	-0.037	0.055	0.048	0.935	0.577	0.350	0.564
Age -> BIU	0.019	0.016	0.021	0.013	0.048	0.047	0.402	0.348	0.688	0.728
Gender -> BIU	0.061	-0.113	0.067	-0.108	0.083	0.104	0.738	1.083	0.460	0.279

Note: significant differences are highlighted in grey

Table 8

Bootstrapping results for paths estimates differences with moderation of age

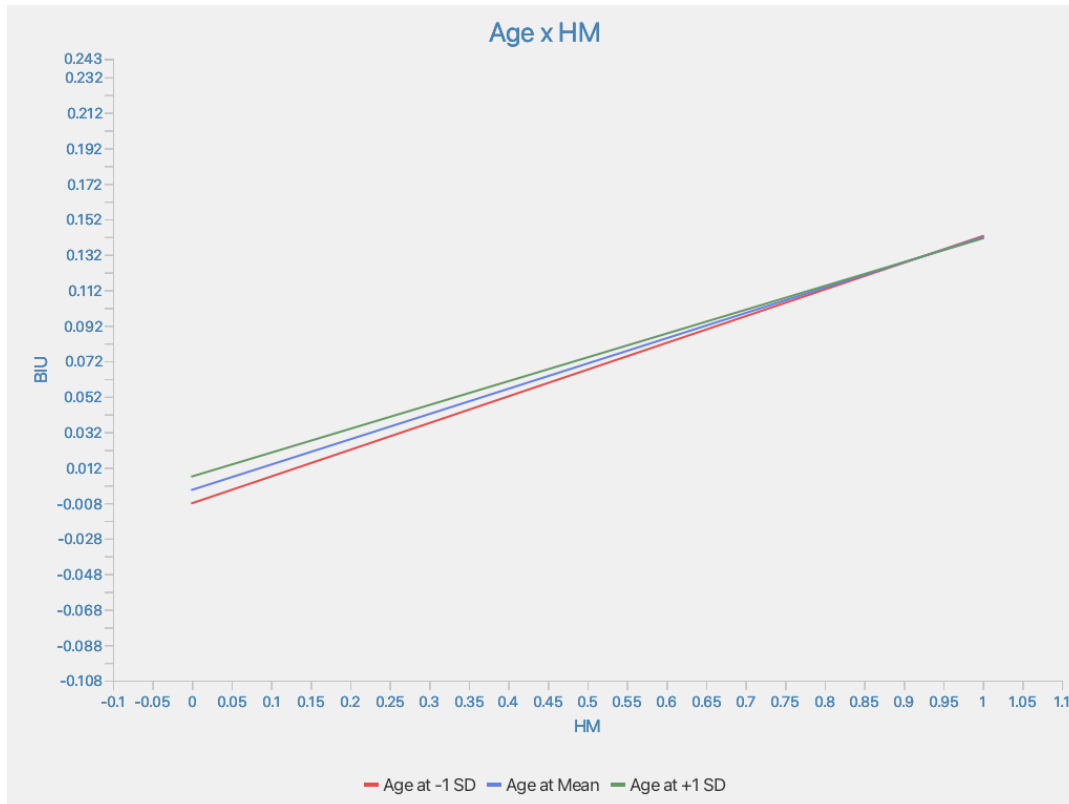
	Difference (Blockchain - Cloud)	1-tailed (Blockchain vs. Cloud) p-value	2-tailed (Blockchain vs. Cloud) p-value
Age -> BIU	0.029	0.342	0.683
PE -> BIU	-0.214	0.955	0.090
EE -> BIU	0.036	0.385	0.771
SI -> BIU	-0.056	0.688	0.624
FC -> BIU	-0.105	0.831	0.337
HM -> BIU	0.234	0.016	0.033
PPR -> BIU	-0.159	0.849	0.302
TR -> BIU	0.079	0.252	0.504
RP -> BIU	0.026	0.436	0.873

TS -> BIU	-0.076	0.839	0.321
GT -> BIU	0.033	0.337	0.674
Gender -> BIU	0.138	0.158	0.317
GT x TR -> BIU	0.091	0.110	0.220
Age x PE -> BIU	0.068	0.321	0.641
Age x EE -> BIU	0.085	0.242	0.484
Age x SI -> BIU	-0.118	0.821	0.357
Age x FC -> BIU	-0.014	0.552	0.896
Age x HM -> BIU	0.025	0.401	0.802
Age x PPR -> BIU	0.094	0.280	0.559
Age x RI -> BIU	-0.171	0.849	0.302
Age x TR -> BIU	-0.085	0.735	0.530
Age x TS -> BIU	0.062	0.202	0.403

Note: significantly different paths are highlighted in grey

Figure 10

Simple slope analysis for HM -> BIU under the moderation of age



Appendix I

Table 9

Bootstrapping results for paths estimates differences

	Difference (Blockchain - Cloud)	t value (Blockchain vs Cloud)	pp-value(Blockchain vs.Cloud)
PE -> BIU	-0.232	2.006	0.046
EE -> BIU	0.024	0.217	0.828
SI -> BIU	-0.052	0.442	0.659
FC -> BIU	-0.089	0.895	0.372
HM -> BIU	0.239	2.431	0.016
PPR -> BIU	0.062	0.654	0.513
TR -> BIU	0.146	0.962	0.337
RP -> BIU	-0.240	1.760	0.079
TS -> BIU	0.120	1.068	0.286
GTxTR -> BIU	-0.072	0.953	0.341
GT -> BIU	0.079	1.085	0.279
Age -> BIU	0.003	0.044	0.965
Gender -> BIU	0.174	1.316	0.189

Note: significantly different paths are highlighted in grey

Appendix J

Table 10

Path coefficients – confidence intervals (bias-corrected)

	2.5% (Blockchain)	97.5% (Blockchain)	2.5% (Cloud)	97.5% (Cloud)
PE -> BIU	0.007	0.347	0.249	0.547
EE -> BIU	-0.188	0.091	-0.237	0.103
SI -> BIU	0.048	0.380	0.102	0.413
FC -> BIU	-0.029	0.218	0.045	0.349
HM -> BIU	0.139	0.397	-0.116	0.167
PPR -> BIU	-0.271	0.120	-0.007	0.365
TR -> BIU	0.139	0.454	-0.004	0.310

RP -> BIU	-0.234	0.233	-0.352	0.021
TS -> BIU	-0.092	0.117	-0.013	0.198
GT x TR -> BIU	-0.050	0.155	-0.111	0.081
GT -> BIU	-0.148	0.068	-0.207	0.032
Age -> BIU	-0.073	0.117	-0.078	0.105
Gender -> BIU	-0.107	0.216	-0.315	0.094

Note: significantly different paths are highlighted in grey

Appendix L

Figure 11

Individual paths estimates for structural model under blockchain condition (values inside the construct circles represent respective R-squared)

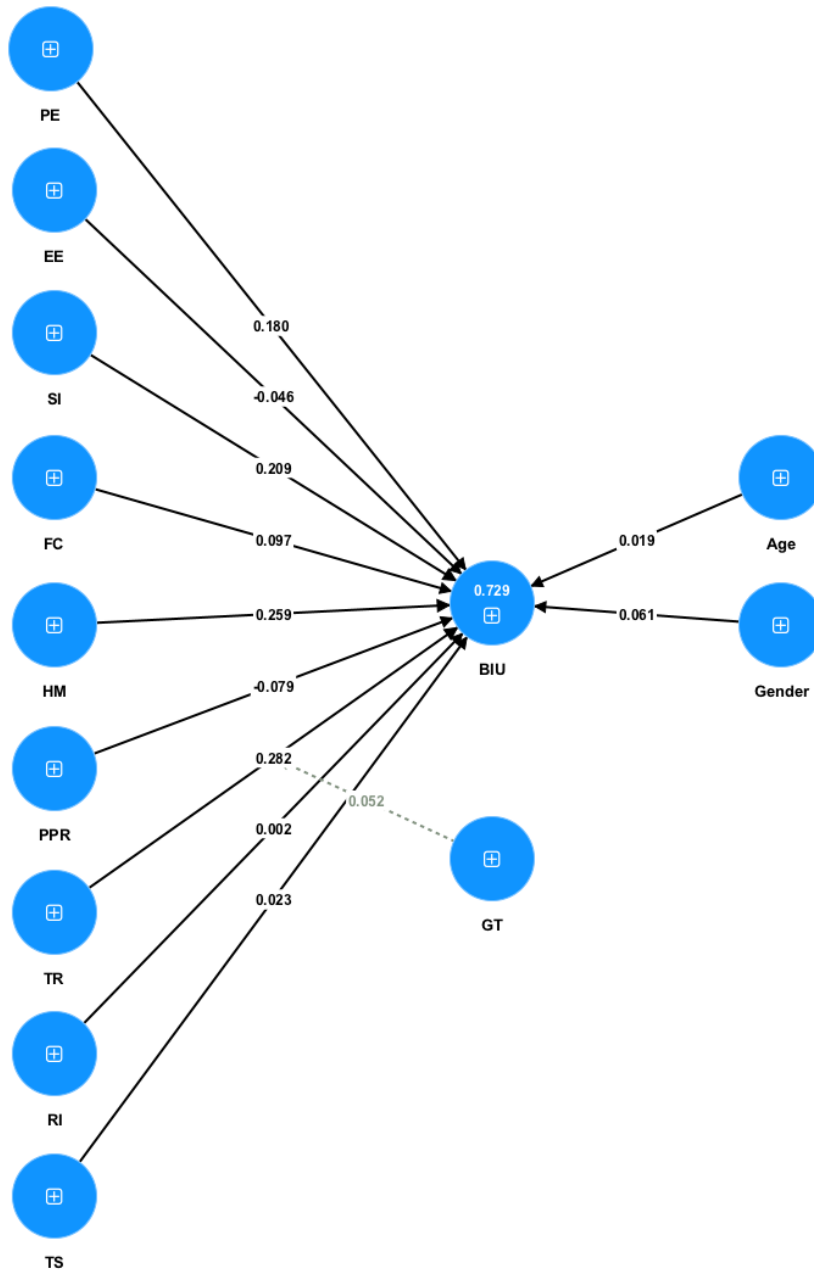
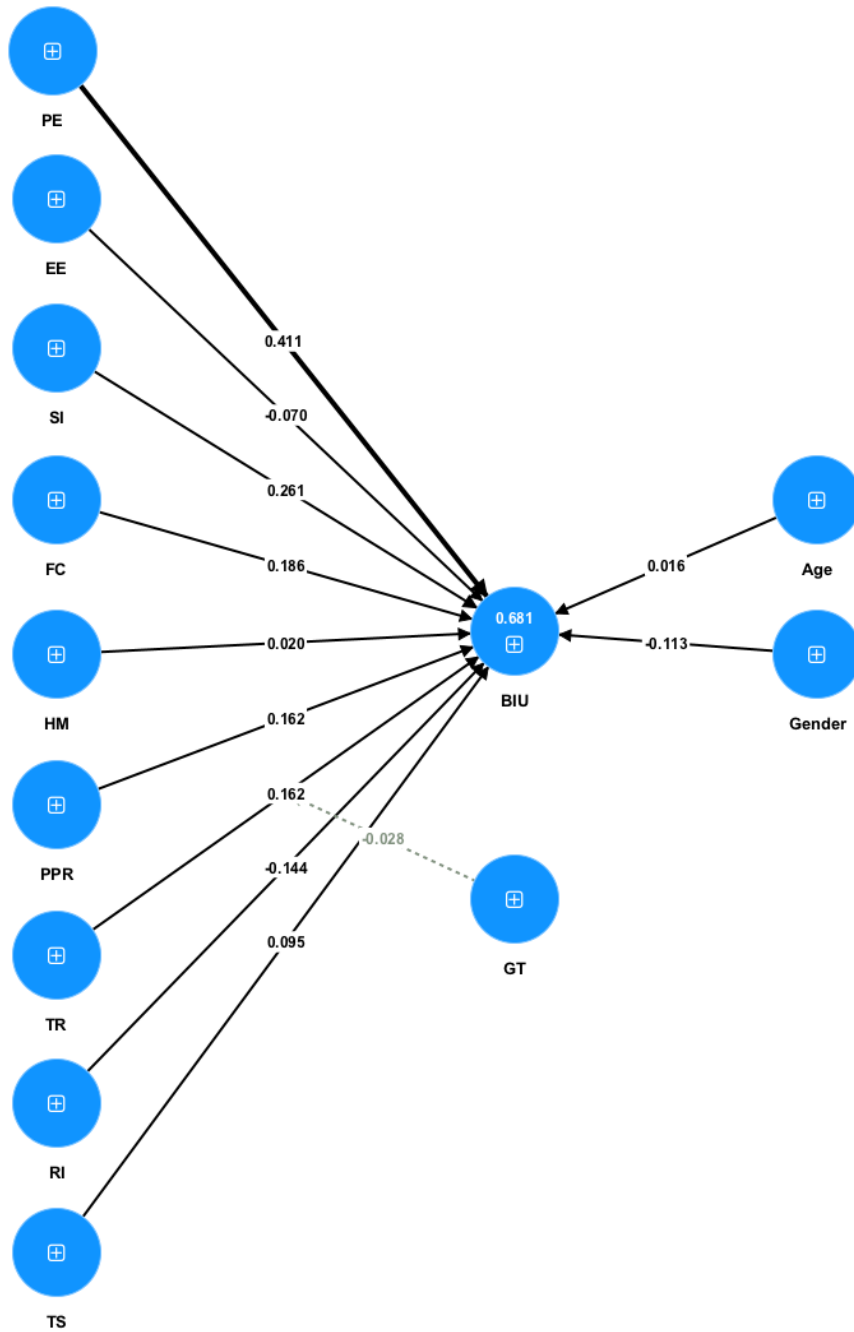


Figure 12

Individual paths estimates for structural model under cloud condition (values inside the construct circles represent respective R-squared)



Appendix M

Table 12

Adopted UTAUT2 model with scales

Variable	Scale	Adopted from
UTAUT2 model		
PE. Performance Expectancy	PE1: This Technology would be useful in my daily life. PE2: Using this Technology increases my chances of achieving things that are important to me. PE3: Using this technology helps me accomplish my goals PE4. Using this technology increases my independence.	Venkatesh et al., 2012
EE. (Effort Expectancy	EE1. Learning how to use this technology looks easy to me EE2. This technology looks clear and understandable EE3. I feel this technology will be easy to use EE4. It will be easy for me to become skillful at using this technology.	Venkatesh et al., 2012
SI. Social Influence	SI1: People who are important to me think that I should use this technology. SI2: People who influence my behavior think that I should use this technology.	Venkatesh et al., 2012

	SI3: People whose opinions I value prefer that I use this technology.	
FC. Facilitating Conditions	FC1: I can gain the necessary knowledge to use this technology. FC2: This technology is compatible with other technologies I use FC3: I can get help from others when I have difficulties in using this technology	Venkatesh et al., 2012
HM. Hedonic motivation	HM1: Using this technology is fun HM2: Using this technology is enjoyable HM3: Using this technology is very entertaining	Venkatesh et al., 2012
BI. Behavioral intention	BI1: If I had the opportunity, I would use this technology in the future. BI2: If I had the opportunity, I would always try to use this technology. BI3: If I had the opportunity, I would use this technology frequently.	Venkatesh (2012)
Additional Scales		
GT. General Trust	GT1: In general, you can trust people. GT2: Nowadays, you can't rely on anybody. GT3: How much do you trust strangers you meet for the first time? GT4: When dealing with strangers, it's better to be cautious before trusting them.	Yamagishi, 1994 Naef, M.; Schupp, J. (2009): Measuring Trust: Experiments and Surveys in Contrast and Combination

	<p>GT5: Most people are trustful of others.</p> <p>GT6: I trust people in my family.</p> <p>GT7: I trust people in my neighbourhood.</p> <p>GT8: I trust people in my strangers.</p>	
RI. Risk	<p>RI1: Overall, using this technology as a way of buying and selling energy would be risky.</p> <p>RI2: Overall, this technology would be dangerous to use.</p> <p>RI3: Using this technology would expose me to an overall risk.</p> <p>RI4: Using this technology subjects my energy account to potential fraud.</p> <p>RI5: Using this technology subjects my energy account to financial risk.</p> <p>RI6: I think using this technology puts my privacy at risk.</p> <p>RI7: Hackers might take control of my energy account if I use this technology.</p> <p>RI8: Using this technology might not perform well and will create problems with my energy account.</p>	Featherman and Pavlou, 2003
TS. Technology savviness	<p>TS1: Other people come to you for advice on new technologies.</p> <p>TS2: It seems your friends are learning more about the newest technologies than you are [reverse coded]*</p> <p>TS3: In general, you are among the first in your circle of friends to acquire new technology when it appears *</p>	Parasuraman , 2000

	<p>TS4: You can usually figure out new high-tech products and services without help from others *</p> <p>TS5: You keep up with the latest technological developments in your areas of interest *</p> <p>TS6: You enjoy the challenge of figuring out high-tech gadgets.</p> <p>TS7: You find you have fewer problems than other people in making technology work for you.</p> <p>TS8: You have avoided trying new high-tech things because of the time it takes to learn them [reverse coded]</p> <p>TS9: You are always open to learning about new and different technologies *</p> <p>TS10: There is no sense trying out new high-tech products when what you have already is working fine [reverse coded]</p>	
<p>PR. Perceived Privacy Risk</p>	<p>PPR1: There is a considerable privacy risk involved in using this technology.</p> <p>PPR2: My decision to use this technology exposes me to privacy risks.</p> <p>PPR3: Using this technology service would lead to a loss of privacy.</p>	<p>Hsu and Lin, 2018</p>
	<p>PPR4: What are the chances that using this technology will cause you to lose control over the privacy of your payment information?</p> <p>PPR5: My signing up for and using this technology would lead to a loss of privacy for me because my personal information would be used without my knowledge.</p>	<p>Featherman and Pavlou, 2003</p>

	PPR6: Internet hackers (criminals) might take control of my energy trading account if I used this technology.	
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