Gordon Institute of Business Science
University of Pretoria

Variables influencing cryptocurrency adoption: An early majority user perspective

29249814

A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

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Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

29249814

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Abstract

As consumers demand faster, more flexible, convenient and efficient financial transitions, cryptocurrencies have emerged as a possible solution. South Africa is one of the top adopters of cryptocurrency and has moved into the early majority phase of the technology adoption lifecycle. Although many studies have been done on the early adopter phase, very little is known about the drivers of cryptocurrency adoption for early majority users. This study aims to fill this research gap by using the UTAUT2 technology adoption model theory, which was deemed to be the most applicable model because of its consumer focus. After a critical review of the literature, a conceptual model was built, incorporating multiple constructs relevant to cryptocurrency adoption. Primary survey data was collected, and multiple linear regression was used to analyse the data. The study found facilitating conditions to be the strongest predictor of behavioural intention, followed by performance expectancy, social influence, and finally habit. Habit was also the only and strongest predictor of actual usage. Interestingly, behavioural intention and facilitating conditions were found to be non-significant predictors of actual usage, contrary to many of the previous studies in cryptocurrency adoption. Finally, the study found performance expectancy, facilitating conditions and habit to significantly predict behavioural intention for both early adopters and early majority users.

Key terms: cryptocurrency, technology adoption, UTAUT2, user acceptance

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List of abbreviations and acronyms

ATM	automatic telling machine
BI	behavioural intention
DeFi	decentralised finance
EE	effort expectancy
FC	facilitating conditions
HM	hedonic motivation
HT	habit
IDT	Innovation Diffusion Theory
IS	information system
POS	point of sale
PE	performance expectancy
PEU	perceived ease of use
PTB	Planned Theory of Behaviour
PV	price value
SI	social influence
SME	small and medium-sized enterprise
SMS	short message service
SPSS	Statistical Package for Social Sciences
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Adoption and Use of Technology
VIF	Variance Inflation Factor

1. Introduction to the research problem

Most people with well-paying jobs make all their transactions digitally today and very seldom carry cash with them. For individuals privileged enough to transact digitally, it is easy to forget that roughly 30% of South Africans did not have a bank account in 2017, and there was almost no change from 2014 to 2017 (Demirguc-Kunt, Klapper, Singer, Ansar, & Hess, 2018). Financial exclusion can be broadly defined as shutting out less fortunate groups or individuals from access to mainstream money services. However, financial exclusion can more narrowly be defined as “the exclusion of individuals from particular sources of credit and financial services” such as interest-bearing savings and deposit accounts, insurance, the safe storage of money, cashless transactions and bill-payment services (Warsame, 2009).

Demirguc-Kunt et al. (2018) suggest that financial exclusion has a negative impact on a country’s economy, its small and medium-sized enterprises (SMEs), as well as the ability of the poor to contribute economically and to access the formal financial sector. The financially excluded and unbanked population deals in cash as a means of transacting. Despite the 70% banked population, in 2020 52% of all consumer transactions in South Africa were in cash (National Treasury Republic of South Africa, 2020).

A Mastercard study found that cash costs the South African consumer R23 billion a year, and that low-income earners suffer the highest cost of cash, losing roughly four percent of their earnings (Mastercard, 2017). The cost of capital can be broken down into two cost types, namely direct and indirect costs. Direct costs include automatic teller machine (ATM) costs, branch costs, point of sale (POS) costs, and remittance costs. Indirect costs include the maintenance costs of the machine itself, logistics and security costs to fill such machines, travel costs to get the cash access point, crime costs and interest forgone. Appendix A provides a full breakdown of the R23 billion cost of cash. It is important to note that Mastercard is not independent in this study, making the R23 billion questionable; however, it is fair to assume that the cost of capital to South African consumers is very high and that the lowest-earning individuals are paying the highest price for cash.

In an ever-growing digital world, users are demanding faster, more flexible, convenient and cost-efficient transaction capabilities (Fung & Halaburda, 2014). According to the International Migrant Stock data compiled by the United Nations (2020a), there are roughly 2.86 million legal migrants living South Africa, of which roughly 64% are from sub–Saharan Africa. The International Migration Report confirms that migration tends to take place within regions and this could explain the high migration factor from sub-Saharan Africa (United Nations, 2020b). Many migrants move to South Africa both legally and illegally, in search of better work opportunities. In many cases, migrants leave their families behind due to financial constraints. Once they start to generate income in South Africa, they need to send money home to support their families.

Table 1 shows the cost and time required to transfer fiat currency internationally from South Africa. More than 55% of South Africans live below the upper poverty line, which means that they receive less than R992 per person per month, making international payments expensive, or in some cases, unaffordable for financially excluded South Africans (StatsSA, 2017).

Table 1: 2021 International transfer fees and times of four major banks in SA. (Sources: ABSA, 2021; Nedbank, 2021; Standard Bank, 2021)

Bank	% Commission on transfer amount	Minimum fee	Maximum fee	Transfer time
ABSA	2.2%	R180.00	R800.00	2 – 5 days
Standard Bank	0.5%	R165.00	R650.00	At least 2 days
Nedbank	0.66%	R179.01	R900.93	At least 2 days

Conducting local transactions across different banks has its own challenges. There is a turnaround time of at least 24 hours before interbank transactions reflect in the receiver's account, as the transaction needs to be verified by a trusted third party like Visa, Mastercard or American Express. Such trusted third parties generate their revenue through commission for the transaction they process. The commission structure is a complicated one, as there are many different pricing models that banks and merchants need to consider. Having a trusted third party involved in validating each transaction in a resource-intensive, expensive and timely part of the transaction process.

In 2008, Satoshi Nakamoto published a white paper called *Bitcoin: A peer-to-peer electronic cash system*. Nakamoto proposed an electronic cash system that would eliminate the need for a trusted third party or a financial institution. Twelve years after the first bitcoin was mined, Bitcoin has grown to a market capitalization of $900 billion (CoinMarketCap, 2021a). Interest in cryptocurrency peaked in 2017 after the price of bitcoin increased by more than 1300%. The cryptocurrency market capitalization lost roughly 70% after the bitcoin price plummeted at the end of 2017, eroding trust in cryptocurrencies, and negatively impacting its adoption (CoinMarketCap, 2021b). Since early 2019, however, there has been renewed interest in cryptocurrencies in South Africa, as indicated in Figures 1 and 2, which indicate the cryptocurrency market capitalization and the Google search history respectively.

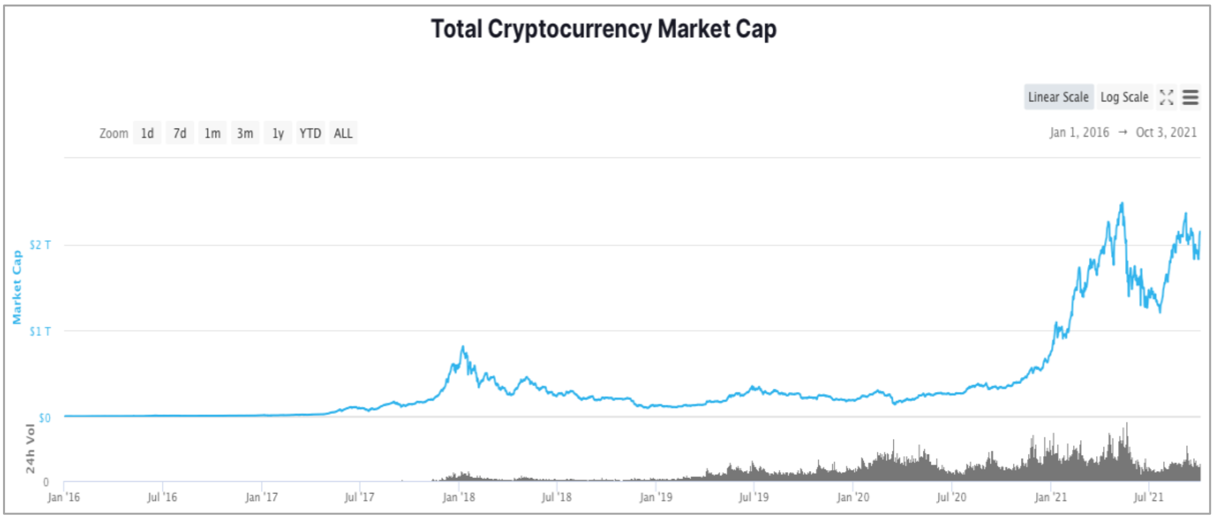

Figure 1: Total cryptocurrency market capitalization. (Source: CoinMarketCap, 2021b)

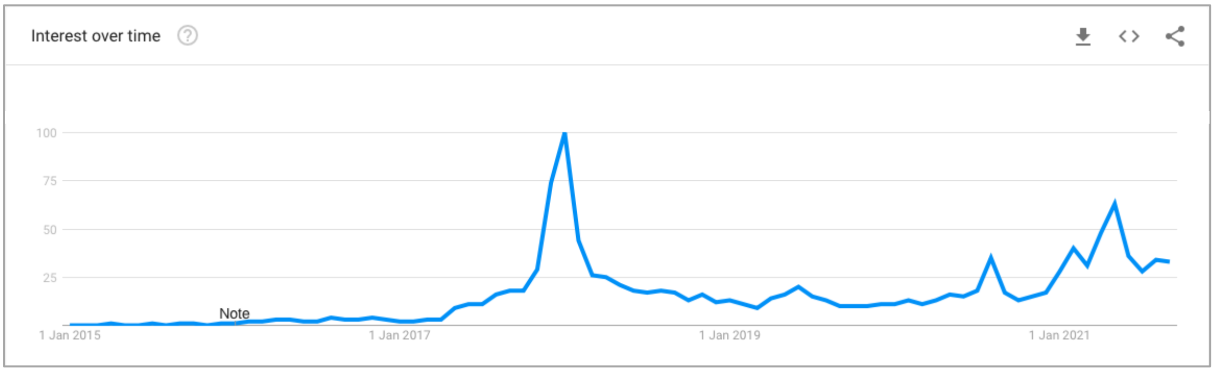

Figure 1: Cryptocurrency search trends from 2015 to 2021 (Source: Google, 2021)

The renewed interest, although not as high as in 2017, indicates a prolonged interest, suggesting that trust in cryptocurrencies is increasing. The market capitalization of cryptocurrencies has increased by 880% from October 2019 to October 2021, indicating an increased demand for cryptocurrencies and suggesting that adoption of cryptocurrencies is increasing as well (CoinMarketCap, 2021b).According to the Global Crypto Adoption Index report, South Africa ranked seventh out of 154 countries in terms of cryptocurrency adoption, indicating that South Africa is one of the early adopters of the technology (Chainalysis, 2020). Figure 3 provides a graphic representation of the innovation adoption curve as outlined in the Diffusion of Innovation theory by Everett Rogers in 1962 (Luu, 2018; Mora, 2019).

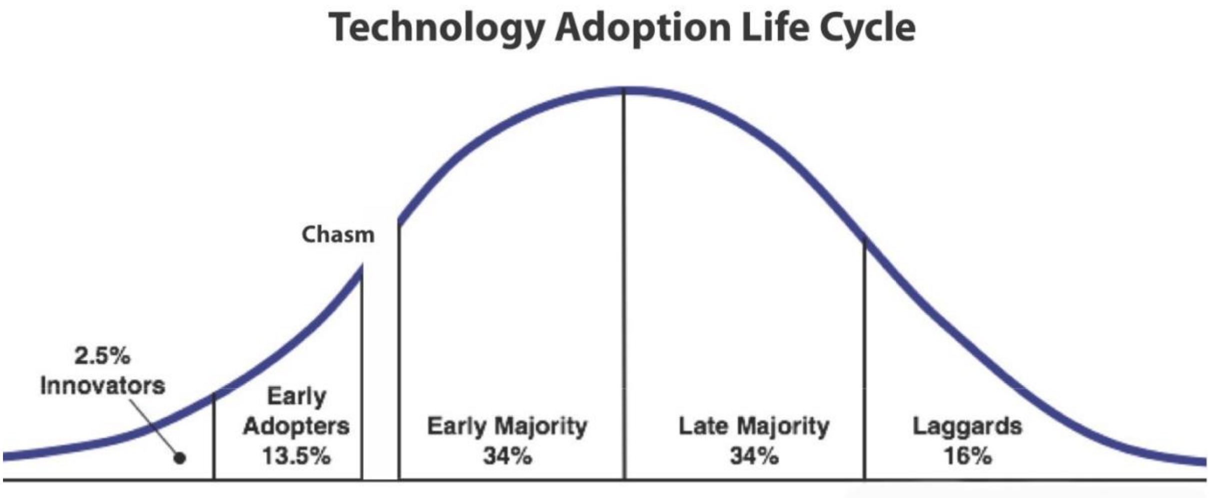

Figure 2: Innovation adoption curve based on Diffusion of Innovation Theory (Source: Mora, 2019)

The Innovation adoption curve suggests that the first 2.5% of users that adopt a new technology are referred to as innovators while the next 13.5% of adopters are referred to as the early adopters. A research paper focused on the state of cryptocurrency in Africa found that 13% of South African internet users between the ages of 16 and 64 had already adopted cryptocurrency by January 2020 (Arcane Research, 2020). Data from Statista (2021b) suggests that 17.8% of respondents in South Africa indicated that theyhad used or owned cryptocurrency by the end of 2020. By May 2021, the cryptocurrency market capitalization had grown ten times larger than it was in January 2020 (CoinMarketCap, 2021a). Institutional investment has flowed into the cryptocurrency market, with MicroStrategy and Greyscale leading the way in the USA (Maranz, 2020). From this data it can be concluded that cryptocurrency adoption has moved from the "early adopters" phase to the "early majority" phase on the innovation adoption curve. There have been no studies in a South African context that focus on drivers of cryptocurrency since moving into the “early adopters” phase of the innovation adoption curve. The literature is unclear when, exactly, the shift from “early adopters” to” early majority” happened, but this study assumes the shift happened during 2020, because in January 2020 the adoption rate was at 13% and at the end of 2020 the adoption rate was at 17.8% (Arcane Research, 2020; Statista, 2021b). The innovation adoption curve indicates that the early majority phase starts when roughly 16% of a population has adopted a new technology.

Literature studies on cryptocurrency adoption to date have focused mainly on the drivers from the perspective of innovators and early adopters, a small group of users. Sample sizes have been small due to the difficulty in identifying and connecting with early adopters, and especially innovators. Innovators, in the context of the cryptocurrency adoption lifecycle, refers to the technologists and programmers that did developmental work on the blockchain from 2009 to 2011.

1.1 Purpose statement

Many studies focus on identifying drivers of cryptocurrency adoption (Mazambani & Mutambara, 2019; Saiedi, Broström, & Ruiz, 2020; Walton & Johnston, 2018), but there is a lack of information relating to the adoption of cryptocurrency in South Africa from 2017 onwards. This study aims to fill this gap by identifying the drivers for cryptocurrency adoption in South Africa during the “early majority” phase and comparing those drivers to existing literature to determine whether drivers of adoption from “early majority” users are the same or different to drivers from “innovators” and “early adopters”. This research is intended to add to the theoretical body of knowledge by determining whether the drivers of cryptocurrency adoption are influenced by the life-cycle phase of the technological adoption. The outcome of this study will identify the drivers of cryptocurrency adoption in South Africa, including what the market segmentation looks like. This will help to identify target markets, which will allow businesses to create better products and services that cater for the needs of their customers.

1.2 Research questions

- **What factors influence the user’s behavioural intention to adopt cryptocurrencies?**

- **What factors influence a user's usage of cryptocurrency?**
- **Are the factors the same for early adopters and the early majority?**

1.3 Conclusion

At the end of 2017 nearly 70% of the South African population were still unbanked and performing transactions with cash. The cost of cash is estimated to be R23 billion per year, with the poorest people paying the highest price for it. Digital money has its own shortcomings in that transactions are expensive, and some transactions take days to clear. There has been a steady increase in interest in and market capitalization of cryptocurrencies over the last two years, indicating a growing interest in the technology.

Although cryptocurrencies rose to popularity in 2017, rapid growth, followed by the crash, had a negative impact on its adoption. However, over the past two years, from 2020 to 2021, there has been renewed interest in cryptocurrencies. The Diffusion of Innovation Theory has been used to indicate the cryptocurrency adoption phase in South Africa. The evidence suggests that South African has moved past the innovation and early majority phase and is currently in the early majority phase. This research has used quantitative rigour to understand what drives the early majority to adopt cryptocurrency, and whether those drivers are the same or different from the early adopters.

The following sections begin with a literature review relating to cryptocurrency adoption theory, followed by the presentation of a research model. The results are presented and conclusions are drawn from the findings; finally, the limitations of the study are presented and the implications for business are discussed.

2. Literature review

This section begins with an outline of the history of money, followed by a review of the factors that drive the adoption of alternative forms of money and a review of cryptocurrency. Sufficient detail is provided on the workings of the cryptocurrency system to justify why cryptocurrency can be considered a form of money.

Finally, to better understand consumer behaviour, the public perception of money is discussed, including the factors that drive its adoption, as well as a review of technology adoption and acceptance theory. This review of technology adoption includes the technology adoption lifecycle, as well as the drivers across the lifecycle of such technologies.

2.1 A history of money

The research is unclear about when money was first used. It could be argued that it began even before humans roamed the earth. Plants and animals such as bees and flowers have been bartering for millions of years as the flowers provide bees with nectar and, in exchange, bees spread the flowers' pollen to other flowers.

2.1.1 Barter

Barter, according to the Oxford Dictionary, is a system of exchange in which the parties in a transaction exchange goods or services directly for other goods or services, without using a medium of exchange such as money. It is an inefficient system because it requires the double coincidence of wants: this refers to the fact that a transaction can only occur if both parties want and need the exact item that the other party is trading. According to Ingham (2004), money was a consequence of individual rationality, as traders would hold stock of the most popular tradable commodities in order to maximize their trade options.

2.1.2 Definitions of money

Before money existed, the most traded commodities had three functions in common. First, they were used as a store of value, which means that they did not expire, break or disappear over time (Federal Reserve Bank of St Louis, n.d.). Second, the commodities were a unit of account (Federal Reserve Bank of St Louis, n.d.) and had to be measurable across a variety of different commodities, but also had to be stable in perceived value. The third common function the commodities resembled was to be a common medium of exchange, which meant that the commodities were widely accepted as a payment method (Federal Reserve Bank of St Louis, n.d.).

Ingham (2004) suggests that, to fulfil the three functions of money, six characteristics of money must be met. Table 2 lists the six characteristics, along with a short description of each.

Table 2: Six characteristics of money (Source: Ingham, 2004)

Characteristic	Definition
Durability	Must be able to withstand physical wear and tear;
Portability	Must be mobile and easy to move or transport;
Divisibility	Must be easily divided into smaller units of measure;
Uniformity	Must be uniform in its physical appearance and in value;
Limited Supply	Must be scarce or only a limit number of units available;
Acceptability	Must be easily accessible and accepted by as many people as possible.

Popular commodities such as shells or beads were portable and in limited supply, but lacked other characteristics, such as divisibility and uniformity.

2.1.3 Origins of coinage

Around 1000 BC, metal was used as a form of money because of its durability and scarcity. By 600 BC, early forms of coinage had been created in what is today known as Turkey. Amongst other things, coinage improved the uniformity characteristic of the metals to ensure a more stable form of money, which also led to more widespread acceptability or adoption of the commodity.

In around 800 AD, the Roman Empire issued a standard coin. It was not made from pure gold or silver, as was the case with the previous coins. Instead, the standard coins consisted of a mixture of metals and the coin's value was not linked to the value of the metals from which it was made. These coins were much smaller and lighter than previous coins, which improved the transferability of money (Sargent, Thomas; Velde, 2014).

2.1.4 Paper money and digital money

The first form of paper money was introduced in China, where merchants and wholesalers issued notes to avoid heavy and bulk movement of coins for large transactions. The central bank quickly realised the value of paper money, which was much cheaper and faster to manufacture than coins. The introduction of paper money improved the transferability of money and allowed for even larger transactions (Headrick, 2009).

Although paper money and coins are still in circulation today, digital money, which was introduced in the late 1900s, has started to threaten the need for paper money and coins (Eveleth, 2015). When considering the characteristics of money, digital money is more durable, portable and divisible than paper money, while at the same time being equally uniform. It could, however, be argued that digital money is not as widely accepted as paper money in 2021.

2.1.5 Financial inclusion

Deloitte (2019) suggests that 20% of the South African population is still unbanked and for this reason does not have access to digital money and still transacts with paper money. Banking and transaction fees are expensive and it could take days for some transactions to clear. Transactions are verified by a trusted third-party company such as Visa, Mastercard, or American Express.

2.2 Enter cryptocurrency

Customers are continuously demanding faster, more flexible, convenient, time- and cost-efficient transactions. Through advances in technology and the rapid spread of the internet, a new form of digital currency, called cryptocurrency, has emerged (Fung & Halaburda, 2014). In 2009, the first decentralized digital currency, known as bitcoin, was created. Price Waterhouse Cooper defines cryptocurrency as "… a medium of exchange, such as the US dollar, but is digital and uses encryption techniques to control the creation of monetary units and to verify the transfer of funds" (Likens, 2021). Cryptocurrencies are virtual currencies that are considered an alternative architecture to fiat currency; just like fiat currency, it does not possess any nominal value. In other words, cryptocurrency uses computer cryptography and a decentralized network architecture to capture and store transactions on the blockchain, publicly distributed ledger (Fung & Halaburda, 2014).

2.2.1 Blockchain technology

Blockchain technology relating to peer-to-peer financial transactions was first proposed in a white paper by Nakamoto (2008). Blockchain is the underlying technology that uses cryptography to digitally encrypt all transactions. It also serves as a decentralized digital database of all transactions that take place on the blockchain, which is also referred to as a distributed ledger (Morkunas, Paschen, & Boon, 2019; Swan, 2015). The distributed leger is maintained by a network of computers that verify each transaction and only place the transaction in the ledger once it has been approved by most of the computer network.

The distributed ledger consists of two elements, namely, blocks and chains. A block comprises three elements: the data, the hash and the hash of the previous block. Data stored in the block depends on the type of blockchain. In the case of bitcoin, the data stored includes the sender identification (ID), receiver ID, and the transaction amount. The hash of a block can be explained as the fingerprint of the block. It is the unique identifier of the block and is used to determine the sequence of the blocks, which is important in ensuring that the transaction is traceable.

Figure 4 illustrates the six steps of exchanging an asset using blockchain technology:

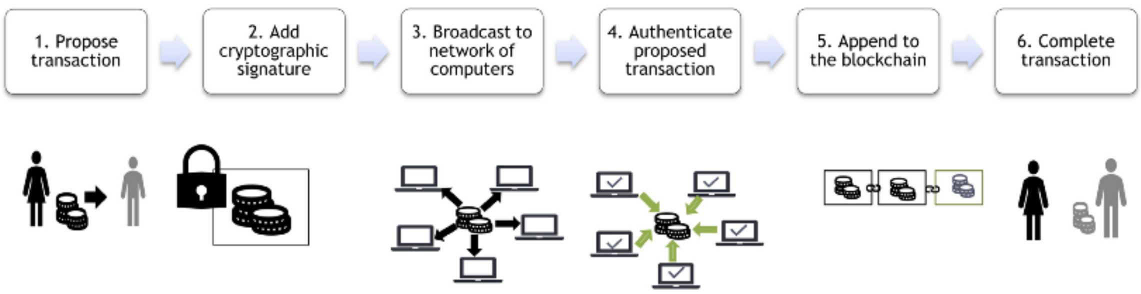

Figure 3: Six steps of transacting on a blockchain (Source: Morkunas et al., 2019)

As a transaction takes place, it is first converted into a hash transaction proposal and stored as a candidate (step 1), which means that the block is allocated the relevant data such as date, time, asset amount, sender information, receiver information. The data is programmable, depending on the purpose of the blockchain. The proposed transaction is then allocated a cryptographic signature (step 2), also known as a hash, for authenticity and integrity purposes. After that, the transaction is published to the distributed network

(Step 3) of computers to process and authenticate the transaction (Step 4). Once the transaction has been processed and authenticated, it is added to the distributed ledger (step 5), and this completes the asset transfer between entities (step 6). Each new transaction that occurs is linked to the previous transactions on the blockchain. This provides a complete, transparent and irreversible public history of all the transactions on the blockchain.

In the case of cryptocurrencies, digital currencies or coins are transferred between parties. The following section explains how digital currencies are created, how the decentralized network of computers operates, and why an entity would want to form part of the decentralized network.

2.2.2 Consensus mechanisms and the decentralized network

To help with the understanding of proof of stake, it is necessary to begin by explaining proof of work. Proof of work was first introduced, along with Bitcoin, by Nakamoto (2008). Proof of work and mining are closely linked. Proof of work blockchains are secured and authenticated by virtual miners, who are not geographically constrained and can connect to the network from anywhere in the world. The miners need to solve a mathematical puzzle to verify the block on a block chain. The first miner to solve the puzzle is rewarded with a predetermined number of tokens, also known as crypto. In the case of the bitcoin blockchain, the successful miner would receive bitcoin.

In summary, proof of work implies that all nodes or miners in the network need to process and authenticate the same transaction to maintain the security of the blockchain. (CoinBase, n.d.). The crypto rewards are what motivate and attract miners to the network as they are needed to authenticate transactions. As the value of the crypto increases, so does the value of the rewards, attracting more miners and making the blockchain more secure.

The process of mining is an incentive for miners to behave truthfully, as it is more profitable to generate crypto assets through powerful computing ability than to attack the network (Nakamoto, 2008). Initially, mining operations were completed by innovators and early adopters of the technology using their personal computers; however, as the popularity of cryptocurrency increased, so, too, did the competition for mining operations. Figure 5 shows the growth in the value of rewards for the bitcoin network just in the last year. The rewards have increased by 345%, to reach 47.6 million USD per day (YCharts, 2021).

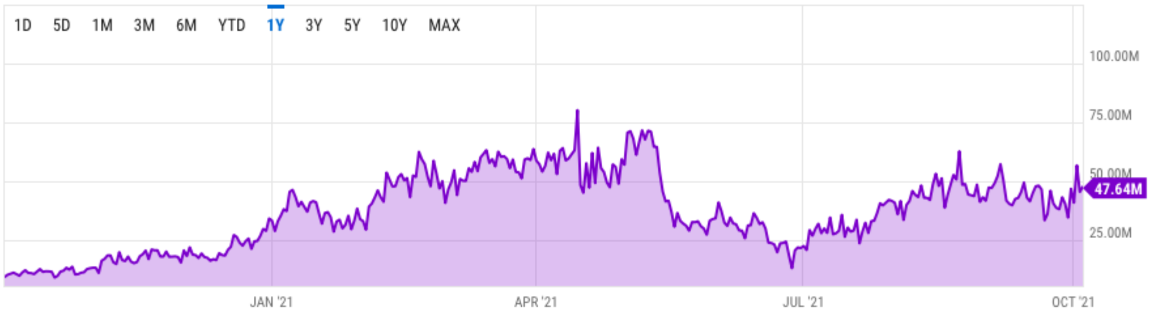

Figure 4: Bitcoin miner revenue per day (Source: YCharts 2021)

The advantage of proof of work consensus mechanisms is that the blockchain is robust, secure and decentralized. Some disadvantages are that the process is energy intensive, transactions take relatively long to process compared to other mechanisms, and scaling proof of work mechanisms is impractical due to the processing times.

Proof of stake was first introduced by the Ethereum developers, as they understood the limitations of the proof of work consensus mechanism. In the proof of stake blockchain, validators are employed to validate transactions. To become a validator, one must contribute or “stake” your own crypto for an opportunity to validate transactions, update the blockchain and earn rewards. The reward details vary according to the cryptocurrency project, but generally the network selects a validator to receive rewards based on the amount of crypto that the validators have contributed and the time the contribution has been in the system, effectively rewarding the most invested validators. Once the selected validator has verified the block, other validators can attest to the accuracy of the block and receive rewards in the form of crypto (CoinBase, n.d.).

Becoming a validator is a big responsibility. It requires a high degree of technical knowledge and the contribution that a validator needs to make is relatively high. For example, to become a validator on the Ethereum network, a validator must contribute 32 ETH, which equates to 115 175 USD at the current ETH price of 3 599 USD (Binance, 2021). Validators risk losing a share of their contribution should their node go offline, or if they validate a bad block of transactions.
The advantage of proof of work consensus mechanisms is that the process transactions

much faster and requires substantially less resources. One disadvantage to proof of stake mechanisms is that it becomes expensive for validators to join a network, limiting the number of validators and potentially pushing up transaction costs.

There are currently 5 840 different cryptocurrencies in existence. Cryptocurrencies vary in their consensus mechanisms, the value or nature of the rewards, the types of puzzles to be solved, privacy mechanisms, block authentication time and cryptographic algorithms. This has spurred regulators and scholars to classify cryptocurrencies based on their purpose. In the next section the different classifications of cryptocurrencies will be discussed, as well as current and future consumer usage and adoption trends.

2.3 Classification and uses of cryptocurrencies

When bitcoin was first introduced in 2009, it was merely a digital asset that could be transferred between network participants, who used it as a form of payment. Bitcoin was also referred to as a cryptocurrency, the only category for digital currencies at the time. Cryptocurrencies and their functions have since evolved, so that new classifications have been required. Giudici, Milne, & Vinogradov (2020) suggest that cryptocurrencies can be seen as part of the greater financial assets sub-class of “crypto assets”. Within crypto assets, Giudici et al. (2020) propose three subcategories, namely cryptocurrencies, crypto securities and crypto utilities. The three subcategories of crypto currencies can be defined as follows:

- **Cryptocurrency:** Crypto assets based on a blockchain, that can be exchanged or transferred between network peers and can be used as a means of payment, but has no other benefits to offer.

- **Crypto securities**: Crypto assets that, in addition to the benefits offered by cryptocurrencies, offer the possibility of future payments, such as profit-sharing.

- **Crypto utility assets**: Crypto assets that, in addition to the benefits offered by cryptocurrencies, “can be redeemed for or give access to some pre-specified products or services” (Giudici et al., 2020).

This research paper includes all forms of crypto assets under its definition of cryptocurrencies.

A Mastercard New Payments Index study indicates a growing interest in emerging payments, including cryptocurrencies (Priebe & Cozine, 2021). The Mastercard study canvassed over 15 000 individuals and was conducted across countries, including South Africa. South Africa contributed more than a thousand responses to the survey and the sample was nationally representative. It was found that there is a growing global interest in using cryptocurrencies as a payment method, and that 4 out of 10 people in Africa plan to use cryptocurrencies within the following year.

Millennials in Africa and the Middle East are especially engaged with cryptocurrencies, with 67% suggesting that they are more open to using cryptocurrencies than they were a year ago (Priebe & Cozine, 2021). This report provides further evidence of a mass interest in cryptocurrencies, especially as a means of payment. The next section will discuss the functions of money, and compare them to the functions of cryptocurrency, with the purpose of determining whether or not cryptocurrency can be considered money.

2.3.1 Can cryptocurrency be considered money?

As discussed previously, money is defined as having three functions namely to serve as a medium of exchange, a store of value, and a unit of account. Yermack (2013) argues that bitcoin, the largest cryptocurrency by market share, cannot be considered money. He draws this conclusion from an economic perspective, arguing that it does not function like other currencies, in that it is not widely accepted as a medium of exchange. A limited number of merchants accept bitcoin, and the worldwide commercial use of bitcoin is small. Yermack also argues that retailers will have to indicate the value of goods or services with four to five decimal places with leading zeros, a practice that is not common, and one which frustrates buyers and sellers alike. This leads Yermack to conclude that bitcoin is a poor unit of measure.

Finally, Yermack states that bitcoin is a poor store of value because of its volatility over time, as well as the difference in prices in different countries and on different exchanges. Kubát (2015) comes to the same conclusion as Yermack, based on the legal definition of money in the Czech Republic, Germany and other EU countries, that bitcoin cannot be categorized as money. He does, however, argue that bitcoin has a superior store of value to fiat currency.

Hazlett and Luther (2020) oppose Yermack's view that bitcoin cannot be considered money. They argue that the standard approach of defining money according to the three functions of money only applies if the item functions as a commonly accepted medium of exchange. Instead, Hazlett and Luther consider the definition of money (according to a leading textbook on money and banking) and from an economic perspective, as anything that is generally accepted as a form of payment for goods, services or the repayment of debts (Mishkin, 2019). Hazlett and Luther further argue that Yermack confuses the functions of money with the good characteristics of money, because although bitcoin is volatile and its value could decline within an isolated period, this simply means that bitcoin is a poor store of value, rather than not being a store of value at all (Hazlett & Luther, 2020).

When it comes to assessing whether an item should be classified as money, the definition of money, the common functions of money and the characteristics of good money are all relevant, not merely the functions of money, as Yumack (2013) argued. The final argument Hazlett and Luther (2020) present relates to the unit of measure: they argue that although goods and services would be denoted with multiple places with leading zeros, the same could be said of fiat currencies when looking at large purchases such as houses that cost more than six figures, or companies' accounting books, with seven or even eight digits.

It is important to note that both articles that considered bitcoin not to be a form of money were written in 2013 and 2015, in the early stages of cryptocurrency adoption. The cryptocurrency market has grown from $6 billion in 2015 to $2 432 billion in 2021 (CoinMarketCap, 2021a) and the number of cryptocurrency wallets increased from 2.8 million in 2015 to 73 million in 2021 (Statista, 2021a). The daily exchange trade volume for cryptocurrencies has increased from roughly $3 million in 2015 to $550 million, indicating that there is a growing demand for cryptocurrencies (Blockchain.com, 2021). These numbers indicate the rapid adoption of cryptocurrencies over the last five years, and their growing acceptance as a medium of exchange.

Based the fact that cryptocurrencies satisfy the three functions of money, as well as meeting the definition of money and have characteristics of good money such as improved durability, portability and limited supply compared to existing digital currencies, this researcher considers cryptocurrencies to be valid forms of money. Cryptocurrencies have improved durability because they can be removed from exchanges and held in personal, offline wallets, making the risk of hacking close to zero. Cryptocurrencies have improved portability because of the decentralized peer-to-peer network, making payments almost instant and costing a fraction of traditional digital currency transactions while removing the need for a trusted third party. Finally, cryptocurrencies create digital scarcity by limiting the supply, while traditional fiat currencies are devalued every year through the printing of more currency.

The next section will focus on the adoption of technology. The section starts by considering the drivers of mobile money adoption, a form of digital currency like cryptocurrencies. This is followed by a study of cryptocurrency adoption and the technology adoption lifecycle, in order to gain insight into the drivers for innovators and early adopters of cryptocurrency. Finally, this section will review adoption models in order to identify drivers of cryptocurrency for the early majority users.

2.4 Adoption of technology

2.4.1 Drivers of mobile money adoption in developing countries

Davis (1989) hypothesized that two variables, perceived ease of use and perceived usefulness, are fundamental elements in user acceptance of technology. This hypothesis was further supported by a literature review study by Shaikh and Karjaluoto (2015) of the adoption of mobile money, which is a form of digital currency. The review covered the period 2005 to 2009 (inclusive) and included 55 papers. The authors conducted a meta-analysis of consumer behaviour towards the adoption of mobile money. They found that from a total of 84 independent variables, perceived usefulness, compatibility and attitude were the most significant drivers that influenced user acceptance. Perceived ease of use, trust, social influence and perceived risk also had a significant impact on user acceptance.

Raza, Umer, and Shah (2017) studied the effects of four determinants on ease of use and perceived usefulness of mobile money in Pakistan, a developing country. The four determinants were resistance, perceived risk, compatibility and awareness. They concluded that resistance has a significant but negative effect on perceived ease of use, while perceived risk, compatibility and awareness has a significantly positive effect on both perceived ease of use and perceived usefulness.

Isaiah, Omwansa and Waema (2012) used the Technology Acceptance Model (TAM) to determine the drivers for mobile money adoption in Kenya, also a developing country, and found that perceived usefulness, perceived ease of use, self-efficacy and perceived credibility all influenced user's attitudes towards the adoption of mobile money. Raleting and Nel (2011) investigated the drivers for adoption of mobile money in South Africa among low-income users. They, too, concluded that ease of use, usefulness and self-efficacy significantly influenced user attitudes towards mobile money acceptance. Furthermore, they found that cost and facilitating conditions had a significant impact on user acceptance of mobile money.

Most studies relating to adoption of mobile money indicate that perceived usefulness, compatibility, social influence and perceived ease of use significantly influence the attitude towards adopting mobile money. Because cryptocurrency and mobile money are closely related, it can be hypothesized that the same variables will drive the adoption of cryptocurrencies.

2.4.2 Drivers of cryptocurrency adoption

Alzahrani and Daim (2019) compiled a meta-analysis of cryptocurrency adoption. Their review suggests that the main factors influencing adoption include investment opportunity, anonymity and privacy associated with transactions, technological curiosity, speed and cost of transactions and acceptance by business as a payment method. Acceptance by business is mostly related to studies conducted in North America rather than in developing countries.

Al-Amri, Zakaria, Habbal and Hassan (2019) also conducted a literature review focused on cryptocurrency adoption from 2014 to 2017; although their study only included 25 papers, ten of which were quantitative, they found that performance expectancy and effort expectancy had a significant influence on the adoption of cryptocurrency. There is a lack of research relating to the adoption of cryptocurrency from 2014 to 2017; this could be attributed to the fact that cryptocurrency was still in the early stages of adoption and finding adopters was proving difficult.

Gunawan and Novendra (2017) conducted an empirical study of bitcoin acceptance in Indonesia, a developing country. They used the Unified Theory of Adoption and Use of Technology (UTAUT) model and concluded that performance expectancy, social influence, and facilitating conditions were found to significantly influence the use of bitcoin. Nseke (2018) conducted a similar study to analyse the adoption of bitcoin by Africans. The study also used the UTAUT model but added hedonistic motivation, price and cost structure variables to the model. The study found that performance expectancy, effort expectations and social influence variables all significantly impact the adoption of bitcoin in Africa.

Walton and Johnston (2018) conducted a study using an integration between the Technology Acceptance Model (TAM) and Planned Theory of Behaviour (PTB). They found that perceived benefit, subjective norm and perceived behavioural control had a direct influence on a user's intention to use bitcoin, while perceived usefulness, perceived ease of use, and trust-related risk were found to have an indirect impact on the intention to adopt bitcoin.

Mahomed (2017) conducted a similar study in a South African context, using the UTAUT2 and found hedonic motivation, trust, social influence and facilitating conditions all had a significantly positive influence on cryptocurrency adoption, which correlated with the findings of the study done by Nseke (2018).

2.4.3 Cryptocurrency adoption in South Africa

The first cryptocurrency called bitcoin was introduced in 2009 by an anonymous entity known as Satoshi Nakomoto. Cryptocurrency adoption in South Africa has been high compared to other countries. Figure 7 shows the adoption level of cryptocurrency for all internet users between the ages of 16 and 64 in January 2020.

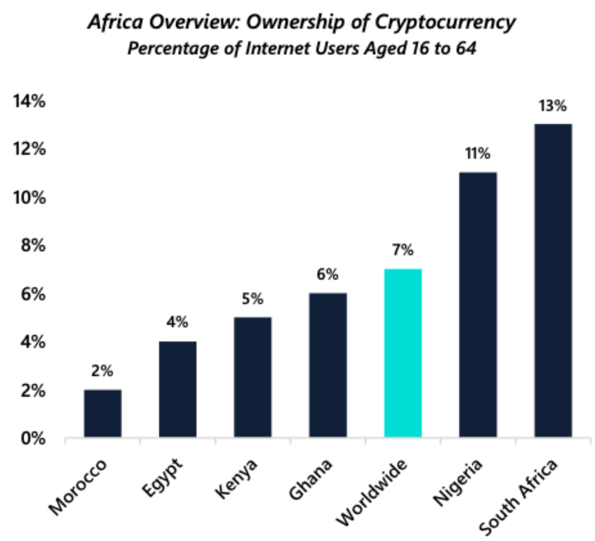

Figure 7: Adoption of cryptocurrencies by internet users (Source: Arcane Research, 2020)

South Africa has an adoption rate of 13%, almost double the worldwide average of 7% (Arcane Research, 2020). By the end of 2020 South Africa had reached an adoption level of 17.8%, indicating that South Africa's adoption of crypto has moved from the early adopter phase to the early majority phase (Statista, 2021b). The importance of a study period relating to the adoption life cycle, as proposed by Everett Rogers in 1962, cannot be understated (Mora, 2019). This study assumes all studies done in South Africa before 2021 are on innovators and early adopters.

The next section reviews existing models that study the adoption of new technology or innovations, also discussing their contexts and their limitations. Finally, an account is given of the selection of a model for purposes of this study, along with the relevant variables and hypotheses.

2.4.4 Innovation Diffusion Theory (IDT)

Diffusion theory describes the way innovations spread through a population (Straub, 2009). Diffusion theory considers factors such as social networks and time to explain the process of how a population adopts, adjusts, or even rejects an innovation (Straub, 2009). Diffusion theory looks thus at a macroeconomic perspective of the spread of an innovation over a period. Everett Rogers formulated a structure, known as the Innovation Diffusion Theory (IDT) for comprehending individual adoption and collective adoption, also termed diffusion. The IDT describes five stages of the adoption decision process:

1. **Awareness**: An individual aware of an innovation;
2. **Persuasion:** An individual has gathered information on the innovation and is able to make a personal judgement either for or against it;
3. **Decision:** An individual chooses to either accept or reject an innovation;
4. **Implementation:** An individual acts on their decision to either accept or reject the innovation;
5. **Confirmation:** An individual reflects on their choice and actions and re-evaluates whether to proceed with the innovation adoption.

Rogers identified five characteristics that influence the adoption of an innovation, namely, relative advantage, compatibility, observability, trialability and complexity (Straub, 2009). It is hypothesized that all these characteristics positively influence the adoption of an innovation. One of the main factors in the IDT is the context of time. Rogers categorized individuals together, based on the time it took to adopt an innovation. He found that early adopters tend to have a higher socio-economic status, more access to communication methods, and are more likely to be literate and intelligent, and to have more capacity for uncertainty (Straub, 2009).

Straub (2009) does, however, criticize the IDT and highlights concerns relating to it. The IDT is primarily descriptive rather than prescriptive, meaning that the framework does not explain how to facilitate adoption, instead, it explains why adoption occurs. Because the IDT framework considers adoption over time, IDT is process-focused rather than user-focused (Straub, 2009).

2.4.5 Technology Acceptance Model (TAM)

In contrast with the IDT model, which is time-dependent and process-focused, TAM refers to the user's behaviour and attitude to explain quantifiable factors that influence the adoption of a specific type of innovation. Davis (1989) hypothesized that two variables are fundamental determinants of user acceptance of information technology: these are perceived usefulness and perceived ease of use. Davis (1989) defines perceived usefulness as "the degree to which a person believes that using a particular system will enhance his or her job performance" and defines perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort" (p. 320). TAM predicts user behaviour from perceived usefulness and perceived ease of use, and although the two variables are important, TAM ignores many other variables that also influence user behaviour (Straub, 2009).

Venkatesh and Davis (2000) understood the shortcomings of TAM and developed TAM2. These researchers proposed two processes that influenced perceived usefulness, namely social influence and cognitive instrumental processes. Three social influence constructs (voluntariness, image, and subjective norm) and four cognitive instrumental constructs (output quality, result demonstrability, job relevance and perceived ease of use) were tested and were found not only to influence perceived usefulness, but also each other (Venkatesh & Davis, 2000).

TAM2 was later expanded by Venkatesh and Bala (2008) to include variables that influenced perceived ease of use, to formulate TAM 3. The variables identified by these authors are computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment and objective usability. TAM3 was found to be a slight improvement in determining behavioural intention compared to TAM2 (Venkatesh & Bala, 2008). However, Straub (2009) criticized all TAM models for not taking individual differences such as age, gender and experience into account. The Unified Theory of Acceptance and Usage of Technology (UTAUT) model was developed to address the shortcomings of the TAMs.

2.4.6 Unified Theory of Acceptance and Usage of Technology Model (UTAUT)

Venkatesh, Morris, Davis and Davis (2003) found that there were many competing individual acceptance models, each using different variables as acceptance measurements. They reviewed eight prominent acceptance models within user acceptance literature to formulate the UTAUT model with four core determinants of intention and usage and up to four moderators to determine key relationships (Venkatesh et al., 2003). The eight technology acceptance models have roots in sociology, psychology and information systems (ISs). Table 3 lists the eight models, with their set of variables used as acceptance measurements. The UTAUT model was specifically developed to explain employee technology acceptance and use behaviour (Thong, James Y. L. Xu, Xin. Venkatesh, 2012).

Table 3: Eight prominent technology acceptance models and their core concepts used as input to the UTAUT model

Acceptance model	**Acceptance measurements (core constructs)**
Theory of Reasoned Action (TRA) (Sheppard, Hartwick & Warshaw, 1988)	Attitude toward behaviour Subjective norm
Technology Acceptance Model (TAM) (Davis, 1989)	Perceived usefulness Perceived ease of use Subjective norm
Motivational Model (Vallerand, 1997)	Extrinsic motivation Intrinsic motivation

Theory of Planned Behaviour (TPB) (Ajzen, 1991)	Attitude toward behaviour Subjective norm Perceived behavioural control
Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995)	Attitude toward behaviour Subjective norm Perceived behavioural control Perceived usefulness
Model of PC Utilization (Thompson, Higgins, & Howell, 1991)	Job fit Complexity Long term consequences Affect towards use Social factors Facilitating conditions
Innovation Diffusion Theory (Straub, 2009)	Relative advantage Ease of use Image Visibility Compatibility Results demonstrability Voluntariness of use
Social Cognitive Theory (Heffernan, 1988)	Outcome expectations - performance Outcome expectations - personal Self-efficacy Affect Anxiety

Venkatesh et al. found four constructs to have a significant impact on user acceptance and usage behaviour. They were defined as follows:

- **Performance expectancy (PE):** “the degree to which an individual believes that using the system will help him or her attain gains in job performance” (Venkatesh et al., 2003).
- **Effort expectancy:** “the degree of ease associated with the use of the system” (Venkatesh et al., 2003)

- **Social influence:** “the degree to which an individual perceives that important others believe that he or she should use the new system” (Venkatesh et al., 2003)
- **Facilitating conditions:** “the degree to which an individual believes that an organisational and technical infrastructure exists to support the system” (Venkatesh et al., 2003)

The UTAUT study also found four moderators on the individual differences that affect the four core determinants; these were age, gender, experience, and voluntariness of use. Figure 8 displays the UTAUT model as proposed by Venkatesh et al. (2003).

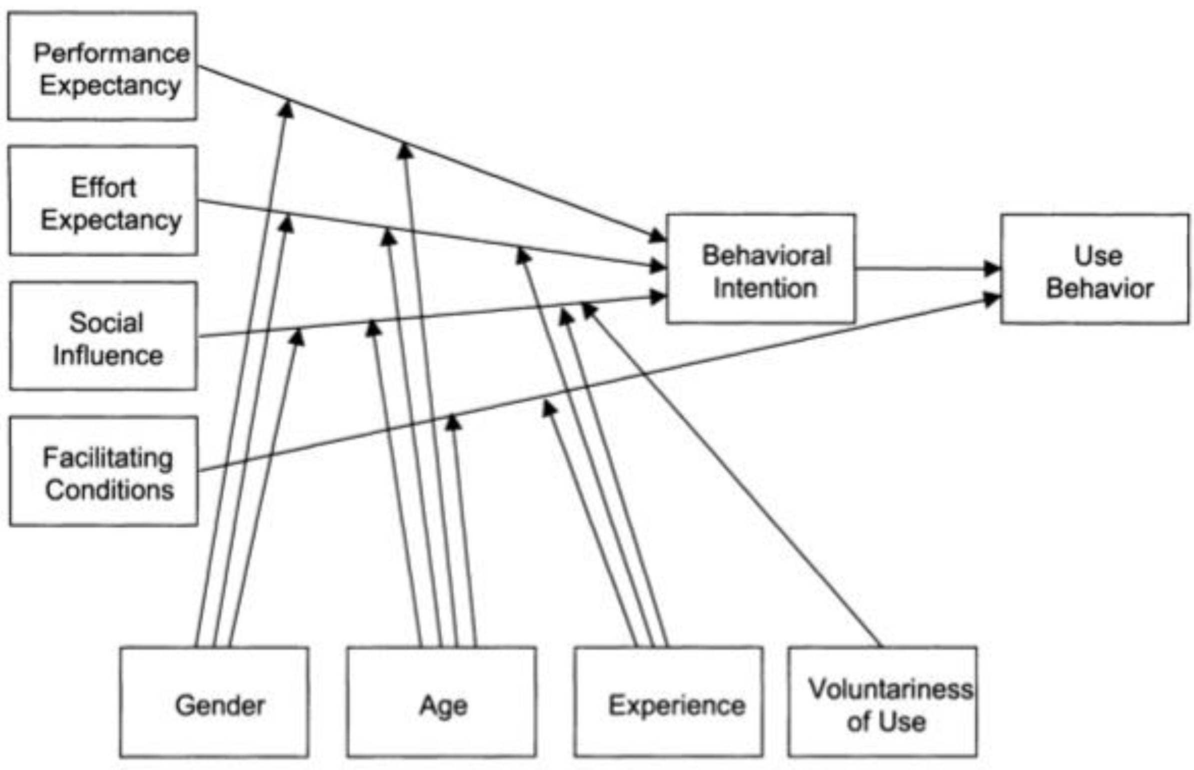

Figure 8: UTAUT model (Source: Venkatesh et al., 2003)

The UTAUT model was tested in four organisations over a period of six months and the results were compared with each of the eight prominent models. The eight models were found to explain between 17 percent and 53 percent of variance of intention to use a new technology, while the UTAUT model outperformed the eight models as it could explain 69 percent of the variance.

The UTAUT model was developed for an organizational and employee context, but in 2012 it was expanded to focus more on individuals and consumer intention and use. The result was the UTAUT2 model. The next section will explain the extension of the UTAUT2 model and why it is beneficial for studying consumer behaviour compared to the UTAUT model.

2.4.7 UTAUT2

Thong, Xu, and Venkatesh (2012) proposed UTAUT 2 to explicitly consider the consumer context. UTAUT2 was an extension of UTAUT. Hedonic motivation, cost or price value, and habit were added to address the consumer context specifically. Additionally, voluntariness of use was excluded from UTAUT since it was assumed consumers behave voluntarily. Figure 9 shows a summary of the concepts of UTAUT2.

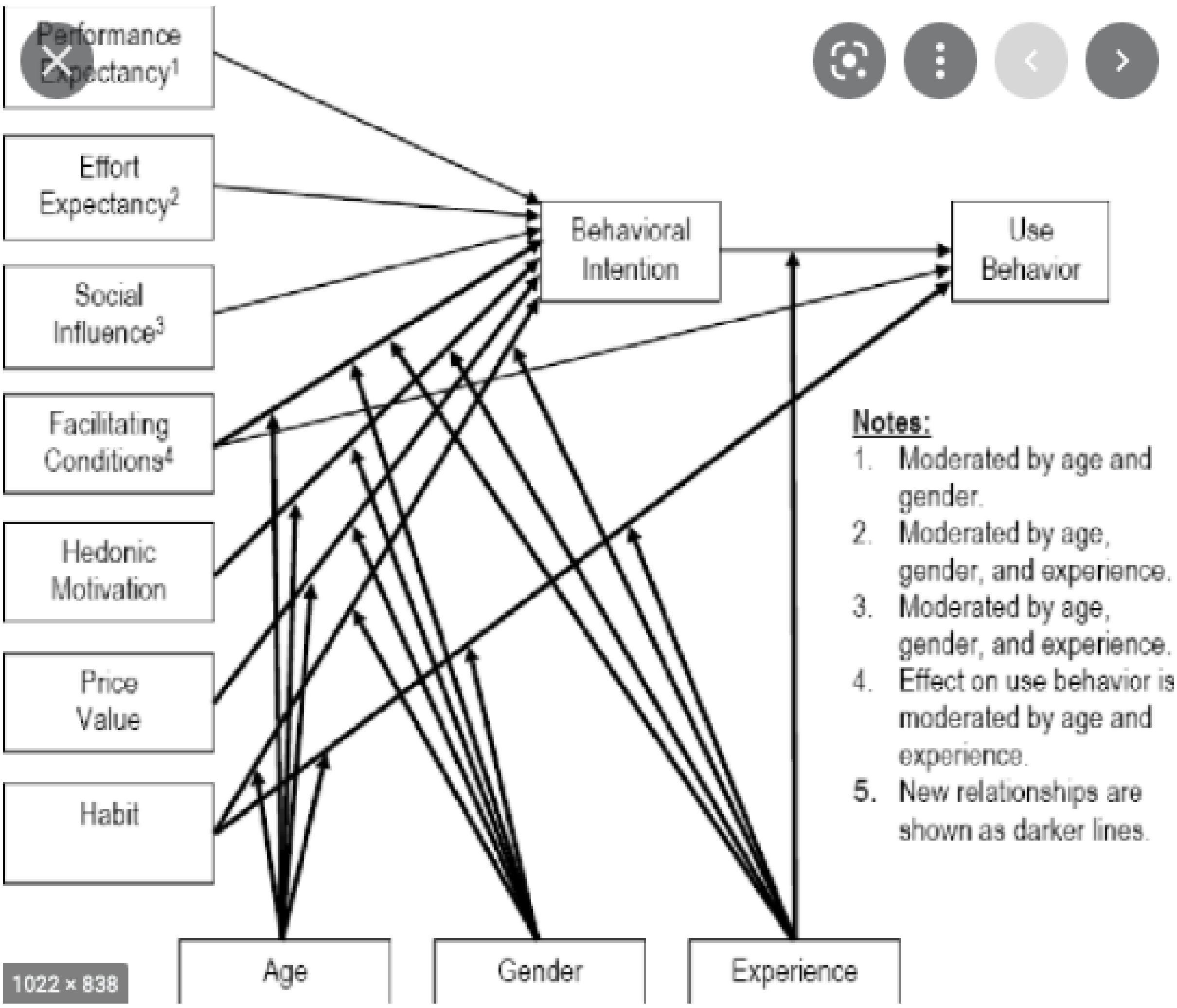

Figure 9: UTAUT 2 model. Source: (Thong, James Y. L. Xu, Xin. Venkatesh, 2012)

Hedonic motivation is defined as "the fun or pleasure derived from using a technology" (Thong et al., 2012). Hedonic motivation has been found to directly influence the acceptance and use of technology (J. Y. L. Thong, Hong, & Tam, 2006). For this reason, hedonic motivation was added to the UTAUT2 model.

Price value was the second variable added to address consumer acceptance and usage of technology. Price value is defined as "consumer's cognitive trade-off between the perceived benefits of the applications and the monetary cost of using them" (Thong, James Y. L. Xu, Xin. Venkatesh, 2012). Price value is important in the context of consumers because they usually bear the cost of adopting a new technology whereas in the context of employees, the company generally bears the cost. Marketing research regularly conceptualizes price and quality together (Zeithaml, 1988). For example, WhatsApp provides an alternative to short message service (SMS). It provides the same value, or service, but at a reduced cost to the consumer. The concept of cost and value sheds light on why consumers opt for WhatsApp as opposed to SMSs. For these reasons, price value was added to UTAUT2 model.

2.4.8 Model choice

IDT presents a viable choice; however, it is not intended specifically for technology adoption. Because it is focused on the adoption process over a longitudinal period of time, it might provide a broad overview of cryptocurrency adoption rather than on its drivers for consumers. On the other hand, TAM does not take consumer variables other than ease of use and usefulness into account. TAM was developed in an organizational context, questioning the outcomes of a study done in a consumer context (Thong, James Y. L. Xu, Xin. Venkatesh, 2012). UTAUT2 is, however, consumer-focused and has incorporated the best aspects of eight user acceptance models. For this reason, UTAUT2 was employed for this research.

2.5 Conclusion

The literature review began with a definition, overview and history of money, followed by an account of its characteristics and shortcomings. This was followed by a technical discussion of cryptocurrency: the blockchain process was discussed in detail, as well as the consensus mechanisms and the decentralized network. The chapter then provided an outline of the evolution of cryptocurrencies, leading to classification of different types of cryptocurrencies, including the underlying protocols governing cryptocurrencies, such as proof of work and proof of stake.

The chapter then compared the characteristics of money with those of cryptocurrencies to determine whether cryptocurrencies can be regarded as money. The literature is conflicting and there is no clear answer on this; however, this study has taken the position that cryptocurrency conforms to all the accepted characteristics of money. Finally, the literature review considers technology adoption models including IDT, TAM, TAM2, TAM3, UTAUT, and UTAUT2 and finds that UTAUT2 is considered the best model due to its emphasis and focus on consumer intention and application of technology.

3. Research propositions

A study of the relevant literature indicated that the most suitable approach for the research was based on the original concept of UTAUT2, formulated by Thong et al. (2012). The research propositions were adapted directly from this model; the reason for this was the lack of depth in the current understanding of cryptocurrency acceptance and usage by innovators and early majority adopters.

3.1 Hypotheses

Performance expectancy is the most common variable used to predict technology acceptance and usage. In the context of cryptocurrency, performance expectancy refers to how likely a consumer is to use cryptocurrencies because of their perception that their use will benefit them in their daily life. The literature clearly shows that performance expectancy has a positive and significant influence on a user's intention to use a new technology.

Studies have also been done in the context of the financial industry, including mobile banking (Alalwan, Dwivedi, & Rana, 2017), mobile payments ((Hussain, Mollik, Johns, & Rahman, 2019), and more recently, cryptocurrency (ter Ji-Xi, Salamzadeh, & Teoh, 2021); 20(Mahomed, 2017).

> **H1: <u>Performance expectancy</u> will positively influence a consumer's behavioural intention to use cryptocurrencies in South Africa**

Effort expectancy is expected to play a prominent role in the behavioural intention to use cryptocurrencies. Cryptocurrency is a technologically advanced concept that can be complex to understand, even for technologically savvy consumers. The are many types of cryptocurrencies, wallets and exchange platforms, as well as different blockchain and reward mechanisms; the consumer needs to take time and expend energy in order to understand these aspects. It has been widely suggested that effort expectancy has a positive influence on predicting behavioural intention in developing countries, specifically in the context of cryptocurrencies (Arias-Oliva, Pelegrín-Borondo, & Matías-Clavero, 2019; Shahzad, Xiu, Wang, & Shahbaz, 2018). Prior research also established that effort expectancy influences performance expectations (Alalwan et al., 2017); (Thong et al., 2012).

H2: <u>Effort expectancy</u> has a positive and significant influence on behavioural intention in South Africa

H3: <u>Effort expectancy</u> has a positive and significant influence on performance expectancy of cryptocurrencies in South Africa.

Venkatesh et al. (2003) suggest that social influence facilitates individual trust in using new technologies, especially if the influencers are family or friends of the user. Previous research suggests that social influence has a positive effect on the intention to use a new technology. Studies ranging from mobile banking and payments to crowdfunding, all reveal the positive effect social influence has on the intention to use a new technology. There have, however, been contradictory results regarding the affect that social influence has on cryptocurrency use. Arias-Oliva et al. (2019) found that social influence was not a significant factor in explaining the behavioural intention to adopt cryptocurrencies in Spain, while Mahomed (2017) found that social influence had a positive and significant affect in explain behavioural intention to adopt cryptocurrencies in South Africa. Because of the overwhelming evidence that social influence has a positive effect on behavioural intention in the financial industry, as well as Mahomed's study in South Africa (2017), this research will adopt the following hypothesis:

H4: <u>Social influence</u> will have a positive and significant influence on a consumer's behavioural intention to use cryptocurrencies in South Africa

Hedonic motivation can be defined as "the fun or pleasure derived from using a technology" (Thong et al., 2012). Hedonic motivation has been shown to play a key role in predicting new technology adoption (Brown & Venkatesh, 2005). Due to the novelty, volatility and unpredictability associated with their adoption, it could be argued that cryptocurrencies create excitement and enjoyment, especially when gains are realized. For this reason, the following hypothesis is adopted:

H5: <u>Hedonic motivation</u> has a positive and significant impact on the consumer's behavioural intention to use cryptocurrencies in South Africa.

Cryptocurrencies are dependent on other systems such as exchange platforms, to buy and sell, for wallets to store the digital currency, for miners to validate transactions, and most importantly, for an internet connection and all its associated hardware and software. In the early days of cryptocurrencies, it was difficult to purchase them, but exchanges such as Luno in South Africa have simplified the transaction process and broken down barriers to accessing cryptocurrencies. Alalwan et al. (2017) and Arias-Oliva et al. (2019) found that facilitating conditions has a positive effect on predicting consumer behaviour relating to cryptocurrencies in Malaysia and Spain. Thong et al. (2012) suggest that facilitating conditions also influences the behavioural intention of a consumer to adopt a new technology. This hypothesis was supported in a study done by Mahomed (2017) in a cryptocurrency context in South Africa. Therefore:

> **H6: <u>Facilitating conditions</u> has a positive and significant impact on the consumer's use behaviour of cryptocurrencies in South Africa.**

> **H7: <u>Facilitating conditions</u> has a positive and significant impact on the consumer's behavioural intention to use cryptocurrencies in South Africa.**

Price value is defined as "the consumer's cognitive trade-off between the perceived benefits of the application and the monetary cost of using them" (Thong et al., 2012). Cryptocurrency wallets are free to use, transaction costs are lower and transaction times are faster than traditional banking systems. It could therefore be argued that cryptocurrencies provide better value for money. Alalwan et al. (2017) studied the adoption of mobile banking by a Jordanian bank and found that price value has a positive and significant effect on a consumer's behavioural intention to adopt mobile banking. Therefore:

> **H8: <u>Price value</u> has a positive and significant influence on the behavioural intention to adopt cryptocurrencies in South Africa.**

Due to the novelty of cryptocurrencies, there have been a limited number of studies on the effect that habit has on the intention to adopt them. Habit can be defined as the degree to which people behave automatically because of repetitiveness and learning (Thong et al., 2012). Arenas-Gaitán, Peral-Peral, & Ramón-Jerónimo (2015) found that habit positively influences both behavioural intention and the use of mobile banking in the elderly. Therefore:

H9: <u>Habit</u> has a positive influence on the behavioural intention to adopt cryptocurrencies in South Africa.

H10: <u>Habit</u> has a positive influence on the use of cryptocurrencies in South Africa.

The influence behavioural intention has on the adoption of a new technology has been widely studied and suggests that behavioural intention is a strong predictor of technological adoption (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Therefore, the following is hypothesized for this study:

H11: <u>Behavioural intention</u> has a positive and significant influence on the use of cryptocurrency in South Africa.

3.2 Conceptual model

From the above hypotheses, a conceptual model was proposed for this study. Figure 10 provides a summary of the one that was applied:

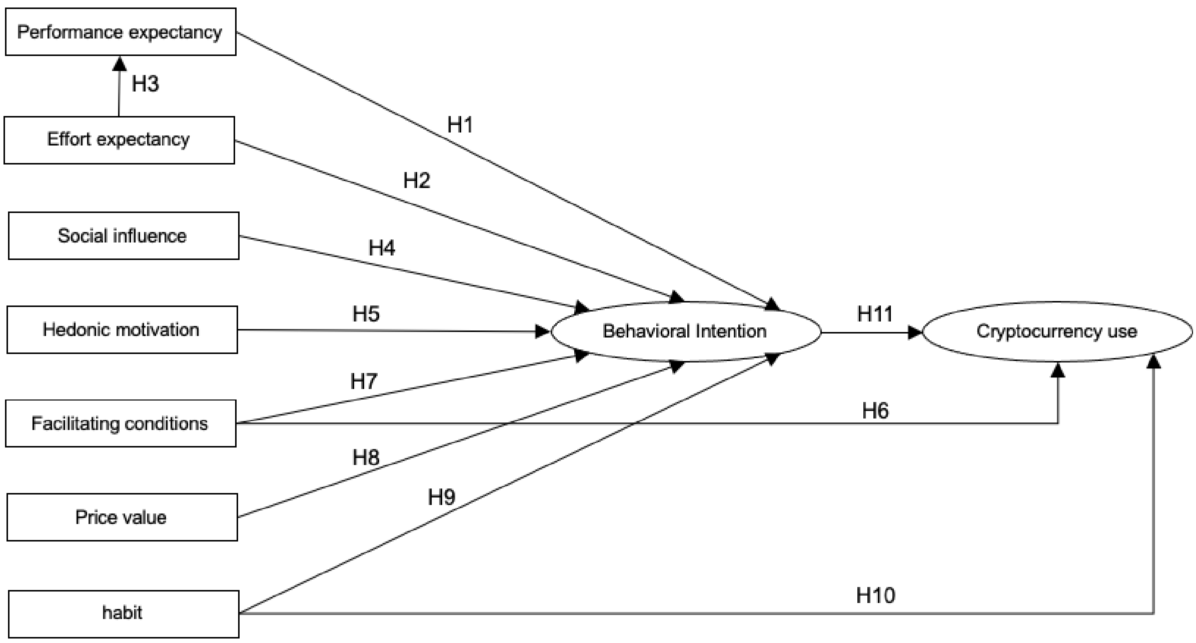

Figure 10: Conceptual model to study cryptocurrency adoption in South Africa

3.3 Conclusion

Based on the research outlined in Chapter 2, the UTAUT2 model was chosen as the best means of better understanding cryptocurrency adoption. The UTAUT2 model was used as a base to create a conceptual model comprising dependent and independent variables. The dependent variables included behavioural intention and actual use of cryptocurrency. The independent variables included performance and effort expectancy, social influence, hedonic motivation, facilitating conditions, price value and habit. The UTAUT2 model further proposes three moderating conditions that are hypothesized to have an influence on the independent variables, but this was outside the scope of this study.

The next chapter details the quantitative assessment of the conceptual model.

4. Research methodology and design

Cryptocurrency is a complex concept that is new to many people. Its complexity could affect the quality of the data collected, as some principles might not be easy to explain. Saunders and Lewis (2018) propose a framework for ensuring consistency and alignment of the research design. This framework is called the research onion and it encompasses all aspects of the philosophy of data collection and analysis.

4.1 Philosophy

When considering that the research questions are intended to identify the drivers of cryptocurrency adoption, it can be concluded that a positivist approach was followed. This study aimed to use and test an existing theory by observing reality from an objective viewpoint to discover relationships between variables. A highly-structured methodology was followed to ensure replication and generalization of the study (Saunders & Lewis, 2018). The focus was on quantifiable data that lends itself to statistical analysis. This research aims to identify causal relationships between the model variables and cryptocurrency acceptance behaviour.

4.2 Approach to theory development

The UTAUT2 model (Thong, James Y. L. Xu, Xin. Venkatesh, 2012) was used quantitatively and a deductive approach was followed by testing the model, using data collected in the manner described in the following sections.

4.3 Methodological choice and purpose of the research design

A mono method quantitative study was carried out using a modified questionnaire survey which was adopted from the UTAUT2 model (Thong, James Y. L. Xu, Xin. Venkatesh, 2012). The purpose of the research was to discover the major drivers of cryptocurrency adoption as an alternative currency among users. The research was also intended to search for new insights relating to drivers of cryptocurrency adoption, and can thus be considered exploratory in nature (Saunders & Lewis, 2018).

4.4 Strategy and time horizon

Because most cryptocurrency users are also internet users, the internet was used as a platform to distribute electronic questionnaire surveys. Surveys are easy to understand, widespread and useful for exploratory research (Saunders & Lewis, 2018). This survey was first piloted with a small group of cryptocurrency users to ensure that the length and difficulty of the survey did not impact the results. The surveys were completed online rather than face to face, to secure the anonymity of the participants; the questions were standardized to allow ease of comparison across different locations or times.

A cross-sectional study was the most practical research strategy, as a comparison of the cryptocurrency drivers in this study was compared with studies done before 2018, in order to determine whether there was a difference in drivers between for early adopters and early majority users. It is important to note that acceptance models consider socio-cognitive aspects, so although the adoption rate of cryptocurrency might be high, the socio-cognitive aspects might not change significantly over a period. For this reason, a cross-sectional study would also have been appropriate.

4.5 Population and unit of analysis

Cryptocurrency is considered an internet technology, since an internet connection is required to access it. For this reason, in South Africa, the population is limited to internet users, including smartphone users. This equates to 64% of the total South African population, or 38 million people (Hootsuite, 2021). It could be argued that offline users could also adopt cryptocurrency; however, without internet access or a smartphone this is highly unlikely.

The study population was further limited to internet users over the age of 18, who are considered adults under South African law. The unit of analysis is the individual respondent, since this research aims to predict consumer adoption of cryptocurrency.

4.6 Sampling method and size

Because the exact population is not known and a sampling frame does not exist, a non-probability sampling technique was used to generate a sample. Saunders and Lewis (2018) suggest using volunteer sampling to enlist participants who are not easy to identify or communicate with. Internet users might be easy to reach, but they are not always easy to identify. For this reason, volunteer sampling was used to reach potential sample members.

As a backup plan, if the volunteer sampling technique did not provide a sufficient sample size, self-selection sampling and snowball sampling would have been used to increase the sample size. Saunders and Lewis (2018) point out that self-selection sampling runs the risk of attracting participants with strong feelings or opinions about the research, who might be different from the group who do not offer to take part and might not be representative of the population. The risk of snowball sampling is that of selection bias, which could result in a homogenous sample.

Saunders and Lewis (2018) suggest that for a population greater than 100 000, when a non-probabilistic sampling technique is used, a sample size of 385 is sufficient. To allow for ineffectual responses, the sample size for this study was increased to 400. SurveyMonkey (2021) suggests that the online survey response rate varies from 20% to 30%. Based on a 20% response rate, 1925 members were targeted for this research.

4.7 Measurement instrument

The UTAUT2 model was selected as the best fit to predict cryptocurrency adoption by consumers. Thong et al. (2012) propose that a survey instrument accompanies the model. This survey was used to measure nine constructs, as proposed by the model, along with demographic variables, as outlined in Table 4.

Table 4: Demographic variables and data types to be measured in the survey

Variable	**Data type**
Age	Ordinal
Race	Nominal
Gender	Nominal
Income	Ordinal
Education level	Nominal
Current knowledge	Likert scale, ordinal

The survey instrument initially proposed was tested with mobile internet, but the survey was easily adjusted to fit the context of this research, which related to cryptocurrency. It is important to note that the literature review could have included subsequent constructs and variables at a later stage, should the theory have justified their inclusion in the research. The full questionnaire used in this study which was based on the UTAUT2 model questionnaire, can be viewed in appendix C.

Although the variables in Table 4 do not form part of the UTAUT2 model, they are relevant to this research and were therefore included in the first part of the survey, followed by part two, which related to the UTAUT2 model. Age was the first variable, in order to check that participants were over the age of 18. Questions about income and race seemed personal and were therefore optional. Age was divided into seven brackets, namely: under 18, 18 – 24, 25 – 34, 35 – 44, 45 – 54, 55 – 64, 65 and over. If the respondent selected the under-18 bracket, the survey ended automatically.

Questions relating to each of the nine constructs from the UTAUT2 model were based on a five-point Likert scale, coded from one to five, where one was "Strongly disagree" and five was "Strongly agree". There were 29 questions in total, relating to the nine constructs. It is possible that the literature review could have proposed additional questions that were relevant but were not included in the UTAUT2 model. The UTAUT2 model considered use behaviour to be the dependent variable which each of the nine constructs influenced. To measure the dependent variable, use behaviour, a seven-point time-scale was used, ranging from "never" to "many times a day", as proposed in the original model (Thong, James Y. L. Xu, Xin. Venkatesh, 2012).

Saunders & Lewis (2018) highlight the importance testing the survey. Because the original questions were adapted to predict cryptocurrency adoption, a pilot test had to be done to ensure that the questions were clear, understandable and not leading.

4.8 Data gathering process

As previously mentioned, a survey questionnaire was distributed online, since the population was assumed to be internet users. The survey was created on SurveyMonkey and distributed using social media channels as part of the volunteer sampling approach.

Appendix B illustrates the survey disclaimer that respondents needed to accept in order to complete the survey. Before any data could be collected however, ethical clearance was required. Appendix E illustrates the ethical clearance received by the GIBS ethical clearance committee. This survey ran for roughly six weeks. Should this process alone not generate a large enough sample, the survey will would have been emailed to a selected group of members that fit the population criteria, being over 18, being an internet user, and having adopted cryptocurrency after December 2019. This was to make sure that only early majority users were included in the study, and not early adopters. The research further depended on the selected members to share the survey with other members that fit the population criteria. A further two weeks were allowed for the self-selection and snowball sampling techniques.

4.9 Data analysis approach

The data was analysed using the Statistical Package for Social Sciences (SPSS) a statistics software package. This study generated categorical data. Firstly, descriptive data analysis was applied to the ordinal data to determine its statistical validity. A breakdown of all demographic data was presented. Further to the descriptive data analysis, there was a need to identify the relationships, if any, between the dependent and independent variables (Wegner, 2018).

Wegner (2018) proposes multiple linear regression analysis, which is a widely-used and very robust statistical prediction model, commonly used because of its simplicity and the ease with which conclusions can be drawn. To use multiple linear regression, the following assumptions must be made (Montgomery and Runger, 2011):

- **A linear relationship** exists between the dependent and independent variables. To test for linearity, scatter plots were utilized in this study;
- **Multivariate normality**: the errors between the predicted and observed values are normally and independently distributed;
- **There is no collinearity** within the data. Collinearity can be tested by using Variance Inflation Factor (VIF). Any VIF value above ten indicates that collinearity could be a problem.
- **Homoscedasticity**.

In its simplest form, linear regression involves fitting a linear curve to determine the formula of the line. The formula is y = mx + c, where y is the independent variable, x the dependent variable, and m the change in the independent variable caused by the change in the dependent variable.

The first step in the data analysis process was to make sure the inputs from the survey were in the correct format and to manually manipulate any data that needs to be converted to the correct format. Thereafter, an analysis of descriptive statistics was done, highlighting the demographics of respondents. Step three involved testing the assumptions of multiple linear regression, including linearity, normality, collinearity and homoscedasticity. Step four included the multiple linear regression analysis of the contextual model.

4.10 Quality controls

To ensure the credibility of the research, finding and conclusion, validity and reliability needed to be tested. Saunders & Lewis (2018) point to five principal factors to consider when testing validity. To ensure that subject selection was not an issue, volunteer sampling was used as a first choice: this was also to avoid selection bias, which can result in an unrepresentative sample of the population. History did not play a role in this study, as a cross-sectional study was done. Testing was also done on the data before commencement of the Multiple Regression Analysis. Outliers, normality, collinearity and homoscedasticity were all tested to confirm that assumptions were valid for Multiple Regression Analysis.

4.11 Limitations

One limitation was the fact that self-selection and snowball sampling techniques might be used. These techniques could attract selection bias and risk a homogenous sample. The sample would thus not be generalizable to the population. This research was not conducted by a person with expertise in modifying questions for surveys or in analysing data, and this could also have impacted the output of this research (Agee, 2009). There were also possible limitations to the UTAUT2 model employed in this research, since it made use of a questionnaire that relied on self-reported rather than actual usage. Due to time constraints, the study was cross-sectional; however, a longitudinal study over a period could yield different results as early adopters and mass adopters of cryptocurrency would all be included in the study. This cross-sectional study captured only early majority adopters and will relied on other studies for comparative purposes.

4.12 Conclusion

This chapter has given an account of the general approach and the methods used in this study, based mainly on the UTAUT2 model, which was identified as the most suitable for application in this context. The quality controls applied, as well as the limitations of the study were also discussed.

5. Results

The statistical analysis was performed through a combination of Microsoft Excel and statistics software from IBM called Statistical Package for Social Sciences (SPSS). The data manipulation and descriptive statistics were completed in Microsoft Excel, while the multiple linear regression analysis and all associated calculations and analytics were completed in SPSS. This chapter begins by presenting the descriptive statistics of the data collected, followed by a test on the data for reliability and validity. Finally, three multiple linear regressions are presented for the three dependent variables (behavioural intention, consumer use and performance expectancy) as per the conceptual model.

5.1 Data transformations

The only data transformations needed was to convert some text inputs from the education level. All text inputs could be categorized into the existing categories. There was a total of 4 text inputs from 147 responses that were transformed to fit the existing education level categories.

5.1.1 Descriptive statistics

From a total of 147 responses, 42 respondents indicated that they had engaged with cryptocurrencies before the start of January 2020. Those 42 responses were therefore excluded from the study, as they did not form part of the population of interest. One response had only partially completed data and was also excluded. The total sample size for this study was 104: Table 5 shows a summary of the sample demographics. The field “Frequency” refers to the number of times a respondent selected an option in the question, while “Contribution” refers to the percentage contribution per option from total responses.

Table 5: Summary of respondent demographics

	Frequency	Contribution
Cryptocurrency Usage		
Yes	25	24%
No	79	76%
Grand Total	104	100%
Cryptocurrency Usage Frequency		
Less than once per year	1	1%
Once per year	1	1%
Once per month	11	11%
Once per week	8	8%
Once per day	6	6%
More than once per day	1	1%
Never	76	73%
Total	104	100%
Cryptocurrency Knowledge		
Expert understanding	0	0%
Deep understanding	8	8%
Basic understanding	67	64%
No understanding	29	28%
Total	104	100%
Mobile Banking Comfort Level		
Very comfortable	60	58%
Comfortable	29	28%
Neutral	9	9%
Uncomfortable	2	2%
Very uncomfortable	4	4%
Total	104	100%
Age		
18 - 24	4	4%
25 - 34	48	46%
35 - 44	26	25%
45 - 54	20	19%
55 - 65	4	4%
65 and over	1	1%
Prefer not to say	1	1%

Total	104	100%

Gender		
Male	51	49%
Female	53	51%
Grand Total	104	100%

Level of Education		
High School not completed	1	1%
High School graduate	20	19%
Tertiary Institution (college)	21	20%
Tertiary Institution (university)	40	38%
Post Graduate qualification	22	21%
Grand Total	104	100%

5.1.2 Cryptocurrency usage and gender

From 104 responses, only 24% or 25 respondents said that they use cryptocurrencies. Although there was an even distribution of males and females that completed the survey, only eight women said that they had used cryptocurrencies before, compared to 17 men. The survey results indicated that from all the respondents that had used cryptocurrencies before, two-thirds were men and one third were women. 76% or 79 people said that they had not used cryptocurrencies yet. Table 6 summarizes the usage statistics by gender:

Table 6: Summary of cryptocurrency usage by gender

	Frequency	Contribution
Use cryptocurrencies	**25**	**24%**
Male	17	16%
Female	8	8%
Have not use cryptocurrencies	**79**	**76%**
Male	34	33%
Female	45	43%
Grand total	**104**	**100%**

Table 7 summarizes the cryptocurrency usage frequency by gender. The data indicates that 43% of female respondents had never used cryptocurrencies before, compared to 32% of male respondents. Most respondents use cryptocurrencies once a month, split almost equally between males and females. The data suggests that males tend to use cryptocurrencies more frequently than females. Twice as many men compared to women use cryptocurrencies at least once a month, three times more men than women use cryptocurrencies at least once a week, and five times more men than women use cryptocurrencies at least once a day.

Table 7: Summary of cryptocurrency usage frequency by gender

	Frequency	Contribution
Less than once per year	**1**	**1%**
Male	1	1%
Once per year	**1**	**1%**
Female	1	1%
Once per month	**11**	**11%**
Male	6	6%
Female	5	5%
Once per week	**8**	**8%**
Male	6	6%
Female	2	2%
Once per day	**6**	**6%**
Male	5	5%
Female	1	1%
More than once per day	**1**	**1%**
Male	1	1%
Never	**76**	**73%**
Male	32	31%
Female	44	42%
Grand total	**104**	**100%**

5.1.3 Respondent age and gender

One respondent preferred not to reveal their gender and their response was removed from the sample data. The highest age bracket was between 25 – 35 years of age and made up 46% of total respondents, as is presented in Figure 11. The second and third highest brackets were the 35 – 44 and 45 – 54 age brackets, making up 25% and 19% respectively. Surprisingly, there was a very low number of respondents aged 18 -24, only contributing 4% of total responses.

There does not seem to be a correlation between age and gender. The 25 -34 age bracket is slightly skewed towards men, making up 56%, while women make up 44%. For the second largest age bracket of 35 – 44, females dominate the contribution with 65%, while males only make up 35%. Finally, the third largest age bracket of 45 - 55 is slightly skewed towards men, with 55% contribution, while women make up the other 45%.

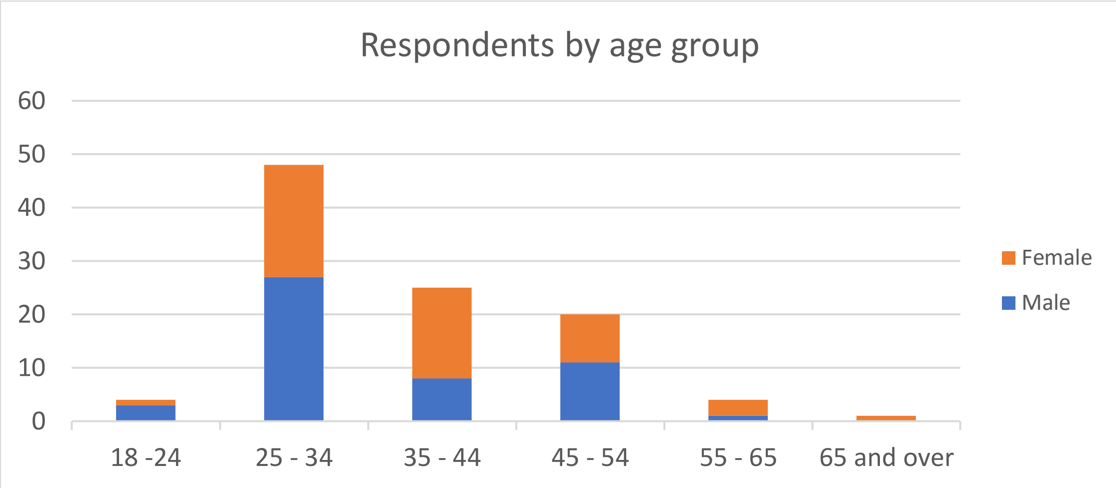

Figure 11: Respondent age and gender frequency plot

5.1.4 Educational levels

The educational level is high for respondents: 80% of them had at least a tertiary education. Only 1% of respondents did not complete high school. This survey was posted on multiple tertiary institution platforms, which could explain the respondents' high levels of education.

5.1.5 Income levels

6 respondents indicated that they prefer not to say what their gross annual income is. 26 respondents or 25% of the sample fall within the "R100 000 – R299 999" income bracket, followed by 16% of respondents in the "above R1 100 000" bracket. The gross annual income was requested in South African rand (R) and thus no currency conversion was required.

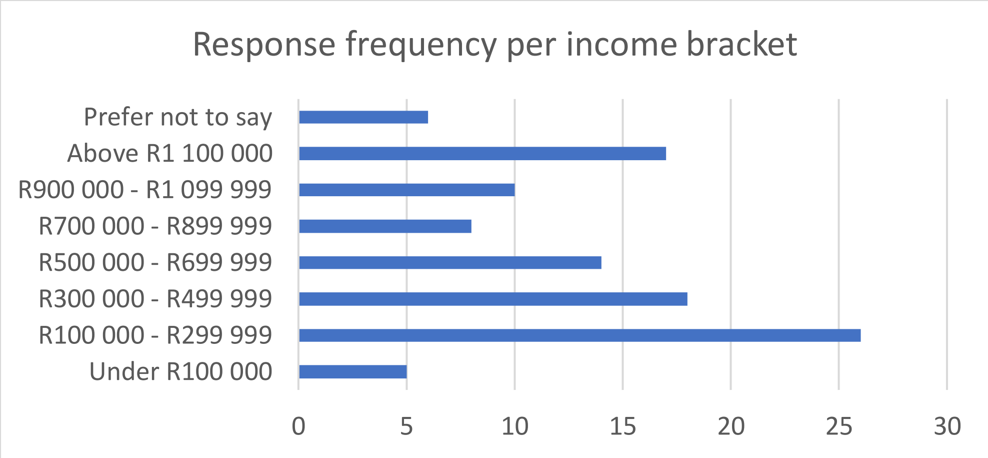

Figure 12: Response frequency plot per gross income bracket

5.2 Validity and reliability

It was decided to conduct a series of multiple linear regressions using the SPSS version 27 software. The sample size is relatively small and for multiple linear regression to be valid, at least 20 samples are needed per dependent variable (Wegner, 2018). The conceptual model has 3 dependent variables and thus a minimum of 60 samples are needed. The sample data consists of 104 responses. The study meets the minimum requirement of running a multiple linear regression analysis.

5.2.1 Reliability (Homogeneity)

Measuring the reliability of the data refers to checking for internal consistency, to ensure the data is free from biases. The reliability is measured by the Cronbach's Alpha coefficient. A Cronbach's Alpha value of 1 means the data is extremely reliable results and reproducible under the same study and collection conditions. The Cronbach's Alpha should be higher than 0.7 to ensure reliability (Montgomery, D. C., Runger, 2011).

Table 8 shows that all constructs have a Cronbach's Alpha higher than 0.7 and range from 0.892 to 0.987, indicating internal consistency of the measurement instrument. It is however important to note that the reliability measurement is not always valid. It only means that the results are reproducible under the same conditions, but it does vot mean that the results are necessarily correct. For this reason, we also needed to test data validity as is discussed in the following section.

Table 8: Summary of reliability statistics

Constructs	Cronbach's Alpha
Performance Expectancy (PE)	0.968
Effort Expectancy (EE)	0.955
Social Influence (SI)	0.952
Facilitating Conditions (FC)	0.910
Hedonic Motivation (HM)	0.987
Price Value (PV)	0.956
Habit (HT)	0.936
Behavioural Intention (BI)	0.892

5.2.2 Convergent validity

Data validity refers to the accuracy of the concept being measured. Heale & Twycross (2015) suggests that there are three types of validity measures namely construct validity, content validity, and criterion validity. Criterion validity refers to the extent to which a measurement instrument is relatable to other instruments that measure the same constructs. Criterion validity is measured in three ways namely convergent validity, divergent validity, and predictive validity (Heale & Twycross, 2015). Convergent validity "shows that an instrument is highly correlated with instruments measuring similar variables." (Heale & Twycross, 2015). Appendix D shows the analysis for the convergent validity of the data while table 9 provides a summary of the convergent validity analysis.

Wegner (2018) suggests that the Pearson's correlation coefficient is measured on a scale of -1 to 1, where -1 implies a strong negative correlation and 1 implies a strong positive correlation. A Pearson's correlation coefficient between -0.3 and 0.3 implies a weak negative and positive correlation respectively and a value of 0 implies no correlation between ratio scaled variables. Table 9 indicates that all survey items have a strong positive correlation with one another. All Pearson's correlation coefficients vary between 0.679 and 0.981.

Table 9: Summary of survey item validity

Performance Expectancy (PE)	**PE1**	**PE3**	**PE4**
PE1	1	.933**	.884**
PE3	.933**	1	.917**

PE4	.884**	.917**	1	
Effort Expectancy (EE)	**EE1**	**EE2**	**EE3**	**EE4**
EE1	1	.800**	.828**	.850**
EE2	.800**	1	.894**	.824**
EE3	.828**	.894**	1	.848**
EE4	.850**	.824**	.848**	1
Social Influence (SI)	**SI1**	**SI2**	**SI3**	
SI1	1	.850**	.858**	
SI2	.850**	1	.900**	
SI3	.858**	.900**	1	
Facilitating Conditions (FC)	**FC1**	**FC2**	**FC3**	**FC4**
FC1	1	.777**	.692**	.704**
FC2	.777**	1	.728**	.731**
FC3	.692**	.728**	1	.679**
FC4	.704**	.731**	.679**	1
Hedonic Motivation (HM)	**HM1**	**HM2**	**HM3**	
HM1	1	.958**	.945**	
HM2	.958**	1	.981**	
HM3	.945**	.981**	1	
Price Value (PV)	**PV1**	**PV2**	**PV3**	
PV1	1	.889**	.873**	
PV2	.889**	1	.879**	
PV3	.873**	.879**	1	
Habit (HT)	**HT1**	**HT2**	**HT3**	
HT1	1	.860**	.829**	
HT2	.860**	1	.836**	
HT3	.829**	.836**	1	
Behavioural Intention (BI)	**BI1**	**BI2**	**BI3**	
BI1	1	.786**	.650**	
BI2	.786**	1	.765**	
BI3	.650**	.765**	1	

** Correlation is significant at the 0.01 level

5.2.3 Multiple regression assumption test

This section will focus on validating the four assumptions made for the regression analysis to ensure validity of the data analysis. Fitting a regression model requires assumptions to be made. Four assumptions must be tested to ensure the linear regression is valid. Linearity, normality, collinearity, and homoscedasticity must al validated to ensure the validity of the data and variables.

Collinearity refers to the correlation between independent variables. Independent variables must not be correlated with one another because it makes predicting the effect each independent variable has on the dependent variable unclear. Collinearity can be assessed in SPSS through the tolerance and Variance inflation factor (VIF). The VIF must be below 10 and the tolerance above 0.1 to ensure no collinearity (Field, 2013). Table 10 shows a summary VIF and tolerance statistics for the three regression tests. Multicollinearity is not a concern when testing PE because a simple linear regression analysis with only one independent variable was modelled. For the BI and U regression analysis, tolerance values are all above 0.1 and VIF values all below 10, indicating no multicollinearity between independent variables. It can thus be concluded that the assumption of multicollinearity is met.

A histogram of the predicted standardized residuals was analysed to test for multivariate normality. Multivariate normality refers to the errors between the predicted and observed values. The histograms follow a normal distribution. It can be concluded that the assumption of multivariate normality holds true. Normality of the constructs is further tested with the Skewness and Kurtosis test. The closer both the skewness and Kurtosis values are to zero, the more likely the constructs are to be normally distributed. Values of smaller than -1.5 and greater than 1.5 suggest that constructs are less likely to meet the assumption of normality (Field, 2013). Table 11 shows a summary of the skewness and kurtosis statistics for each construct. All values are small and suggest normality except the kurtosis for SI and HM. Th data for these constructs should be inspected and outliers removed to ensure constructs meet the assumption of normality.

The assumption of linearity was testing using the normal P-P Plot of standard residuals, as indicated in figure 9. The relationship between the dependent variables and the associated independent variables seems to be linear. Lastly, the homoscedasticity is tested using a scatter plot of the standardized residual values as indicated in figure 10.

The shape of the scatterplot seems to be square will all values for both the predicted and residual values falling within the limits of -3 and 3, indicating that the assumption of homoscedasticity is met.

Table 10: Multicollinearity summary for regression analysis

Performance Expectation (PE)			Behavioral Intention (BI)			Use (U)		
Multicollinearity								
	Tolerance	VIF		Tolerance	VIF		Tolerance	VIF
EE	N/A	N/A	PE	0.285	3.503	FC	0.605	1.654
			EE	0.196	5.098	HT	0.605	1.654
			SI	0.232	4.319			
			HM	0.187	5.341			
			FC	0.259	3.855			
			PV	0.209	4.776			
			HT	0.311	3.213			

Normality

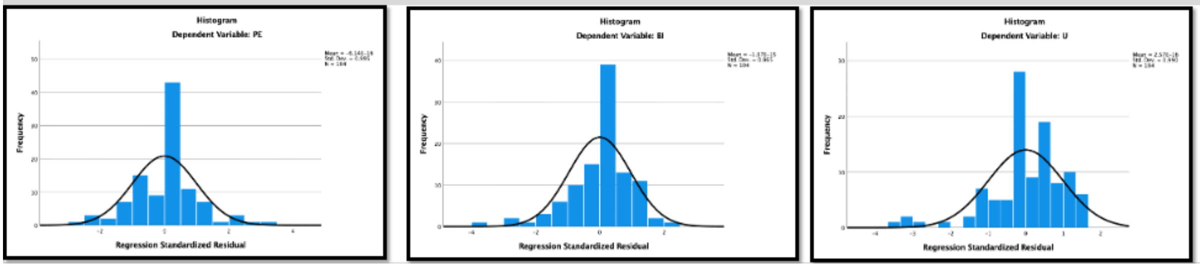

Figure 13: Summary of normal distribution of standardized residuals

Table 11: Skewness and Kurtosis Statistics

Construct	Skewness	Kurtosis
PE	-0.496	-1.356
EE	-0.239	-1.444
SI	-0.008	-1.552
FC	0.346	-1.285
HM	-0.146	-1.644
PV	-0.081	-1.492
HT	-1.075	0.401
BI	-0.187	-1.082

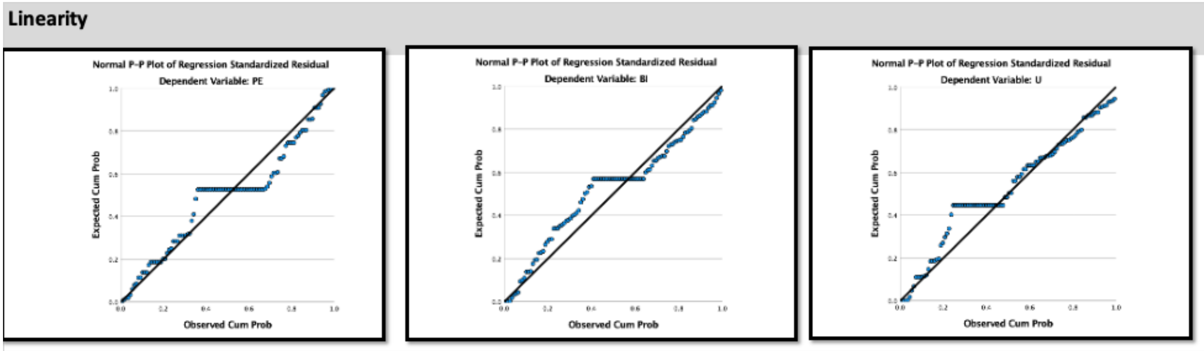

Figure 54: Summary of P-P Plot

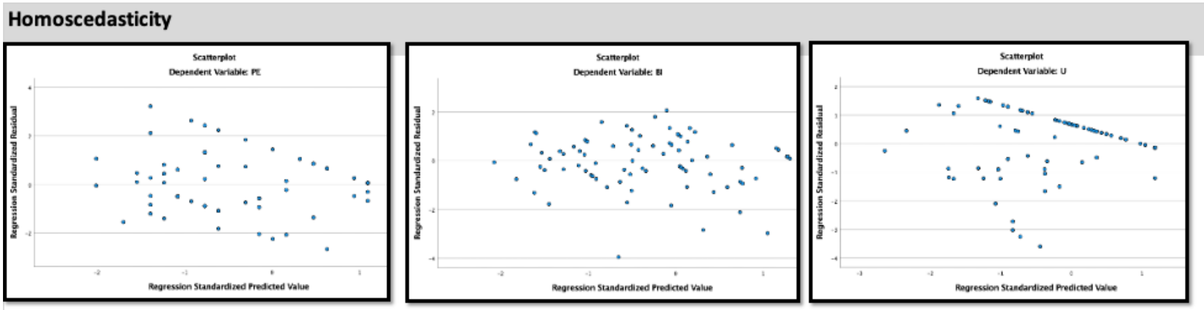

Figure 65: Summary of scatterplot statistics

5.3 Results per hypothesis

Each variable was tested through multiple questions in the survey. A variable was created by taking the average of the results from the questions associated with each variable e.g., EE = (EE1 + EE2 +EE3 +EE4) / 4. Furthermore, the conceptual model included three dependent variables and because multiple linear regression can only have one dependent variable, the conceptual model was broken down into three parts and a regression analysis was done on each part. The three dependent variables are PE, predicted by EE, BI, predicted by PE, EE, SI, FC, HM, HT and PV, and U predicted by BI, FC, and HB

Table 11 provides a summary of the descriptive statistics for each variable tested in the survey where 1 refers to "strongly agree", 5 refers to "strongly disagree" and 6 refers to "not applicable". In the case of cryptocurrency use (U), the frequency of use was measured on a scale of 0 to 6, where 0 refers to "never" use cryptocurrencies and 6 refers to "more than once per day". The descriptive statistics indicates that there is very low usage frequency of cryptocurrencies with a mean of 1.00, indicating usage frequency of roughly once a year. The main reason for the low mean is because 73% of respondents indicated that they never use cryptocurrencies.

Table 12: Descriptive statistics for variables tested in survey

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PE	104	1.33	6.00	4.6859	1.45840
EE	104	1.000	6.000	4.24038	1.611896
SI	104	1.33	6.00	4.0737	1.59419
FC	104	1.000	6.000	3.65865	1.625815
HM	104	1.00	6.00	4.1635	1.76689
PV	104	.75	4.50	3.1130	1.22072
BI	104	1.00	6.00	4.0513	1.54387
U	104	0	6	1.00	1.746
Valid N (listwise)	104				

5.3.1 Sub model 1: Performance Expectancy (PE)

EE is expected to have a positive and significant influence on PE. Figure 16 provides a summary of sub model 1 of the conceptual model. Sub model 1 of the conceptual model tests hypothesis H3.

Figure 76: EE on PE in sub model 1 of the conceptual model

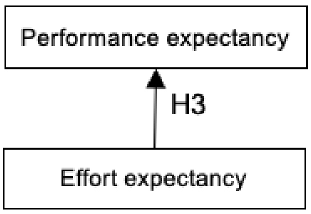

Table 13 summaries the model statistics. Because sub model 1 of the conceptual model is a simple linear regression, the Pearson correlation coefficient (r) is also the multiple correlation coefficient (R) (Chiba 2015). R measures the quality at which EE can predict PE. The R value is on a scale of 0 to 1, with a higher value indicating that the dependent variable (PE) is more closely collocated to the independent variable (EE) and thus providing higher quality predictability of PE. Table 13 indicated an R value of 0.789, indicating a good level of prediction.

The R squared (R^2) value or the coefficient of determination represents “the proportion of variance in the dependent variable that can be explained by the independent variable” and is based on the sample only (Chiba 2015). The Adjusted R^2 value on the other hand provides a smaller R^2 value as it attempts to account for the bias in the sample as one would expect to see in the population. Because of the small sample size, and possibly a significant amount of bias due to the data collection method, the adjusted R^2 is used. Table 13 provides an adjusted R^2 value of 0.618, suggesting that 61.8% of variance in PE can be explained by the model.

Table 13: Model summary statistics for sub model 2

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.789[a]	.622	.618	.90123	.622	167.724	1	102	.000

a. Predictors: (Constant), EE

b. Dependent Variable: PE

The ANOVA tests whether the proposed model is a good fit for the data (Chiba 2015). An important aspect of the ANOVA table is the Significance (p-value). Assuming a 95% confidence interval, a Sig. value below 0.05 indicates a good fit for the data while a value higher than 0.05 indicates the model is a bad fit for the data. Table 14 shows a sig. value 0.000 the model is a good fit for the data and is statistically significant.

Table 14: ANOVA results for sub model 1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	136.227	1	136.227	167.724	.000[b]
	Residual	82.845	102	.812		
	Total	219.073	103			

a. Dependent Variable: PE

b. Predictors: (Constant), EE

Table 15 provides a summary of the coefficients results of the regression model with PE as the dependent variable. From this table, the regression equation can be derived as follows:

$$PE = 1.661 + 0.713(EE)$$

Table 15 further indicates a sig. value of 0.000 for EE, suggesting that EE is a significant predictor of PE at the 95% confidence interval. For this reason, the hypothesis H3 is failed to be rejected.

Table 15: Coefficients results for sub model 1

Coefficients a						
	Unstandardized Coefficients		Standardized Coefficients			
	B	Std. Error	Beta	t	Sig.	Hypothesis Decision
(Constant)	1.661	0.25		6.648	0.000	
EE	0.713	0.055	0.789	12.951	0.000	H3 Accepted

a Dependent Variable: PE

5.3.2 Sub model 2: Behavioural Intention (BI)

In sub 2 of the conceptual model, seven independent variables are assessed as predictors for BI. The variables along with sub model 2 of the conceptual model can be seen in figure 17. Sub model 2 tests H1 (PE), H2 (EE), H4 (SI), H5 (HM), H7 (FC), H8 (PV), and H9 (HT).

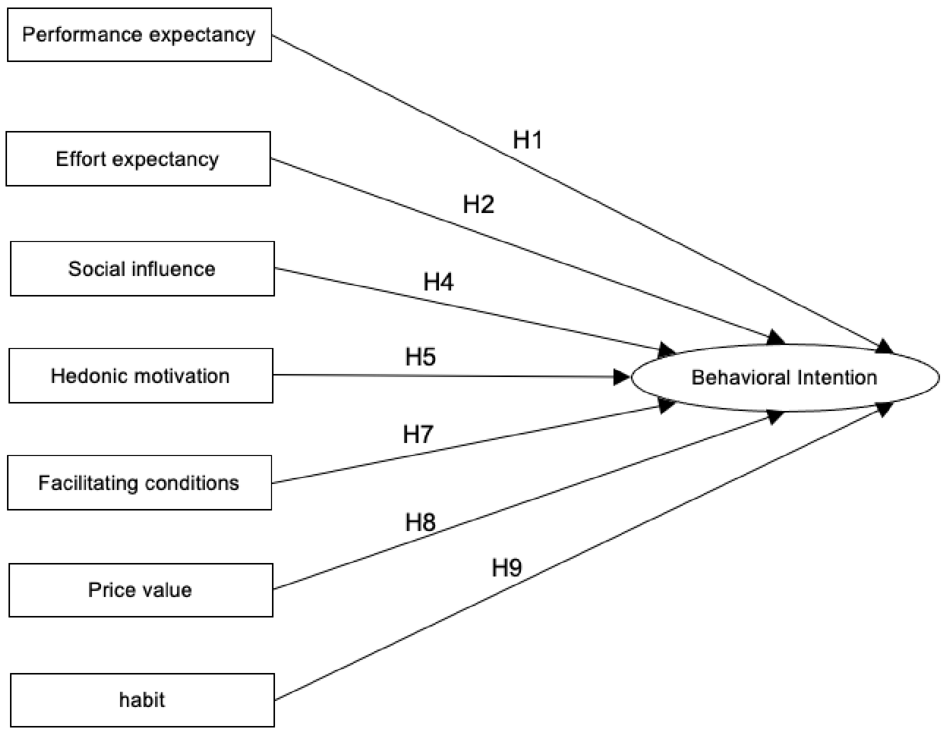

Figure 17: Sub model 2 of the conceptual model

Table 16 provides a summary of the model statistics. An R value of 0.943 for sub model 2 indicates that the model and its associated independent variables is a good predictor of BI and therefor no other predictor variables need to be considered for this model. The adjusted R^2 value for sub model 2 is 0.8822, suggesting that 88.2% of the variance in BI can be explained by the model.

Table 16: Summary statistics for sub model 2

Model Summary[b]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.943[a]	.890	.882	.53111	.890	110.620	7	96	.000

a. Predictors: (Constant), HT, FC, PE, PV, SI, EE, HM

b. Dependent Variable: BI

Table 17 provides a summary of the ANOVA statistics. A sig. value below 0.005 suggests that the model is a good fit for the data. A sig. Sub model 2 presents a sig. value of 0.000, suggesting that the model is statistically significant and a good fit for the data.

Table 16: ANOVA statistics for sub model 2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	218.425	7	31.204	110.620	.000[b]
	Residual	27.080	96	.282		
	Total	245.504	103			

a. Dependent Variable: BI

b. Predictors: (Constant), HT, FC, PE, PV, SI, EE, HM

Table 18 provides a summary of the coefficients results for sub model 2 with BI as the dependent variable. From Table 19, the regression equation can be derived as follows:

$$BI = -0.769 + 0.274(PE) - 0.059(EE) + 0.232)(SI) + 0.041(HM) + 0.298(FC) + 0.07(PV) + 0.274(HT)$$

Also from Table 18, it is evident that EE, HM, and PV do not have statistical significance at the 95% confidence interval. For this reason, hypothesis H2 (EE), H5 (HM), and H8 (PV) are rejected. PE, FC, and HT seem to be the strongest predictors of BI while SI is also a strong predictor of BI with a significance of 0.001 and are therefore failed to be rejected.

Table 18: Summary of coefficients results for sub model 2

Coefficients a

	Unstandardized Coefficients		Standardized Coefficients			
	B	Std. Error	Beta	t	Sig.	Hypothesis Decision
(Constant)	-0.769	0.236		-3.252	0.002	
PE	0.274	0.067	0.259	4.081	0.000	H1 Accepted
EE	-0.059	0.073	-0.062	-0.811	0.419	H2 Rejected
SI	0.232	0.068	0.239	3.396	0.001	H4 Accepted
HM	0.041	0.068	0.047	0.601	0.549	H5 Rejected
FC	0.298	0.063	0.314	4.722	0.000	H7 Accepted
PV	0.07	0.094	0.055	0.748	0.457	H8 Rejected
HT	0.274	0.075	0.222	3.649	0.000	H9 Accepted

a Dependent Variable: BI

5.3.4 Sub model 3: Cryptocurrency Use (U)

Sub model 3 considers the three predictor variables BI, FC, and HT of cryptocurrency use. The predictor variables are hypothesized to have a positive influence of cryptocurrency use, suggesting that cryptocurrency use should increase. Sub model 3 of the conceptual model is presented in Figure 18.

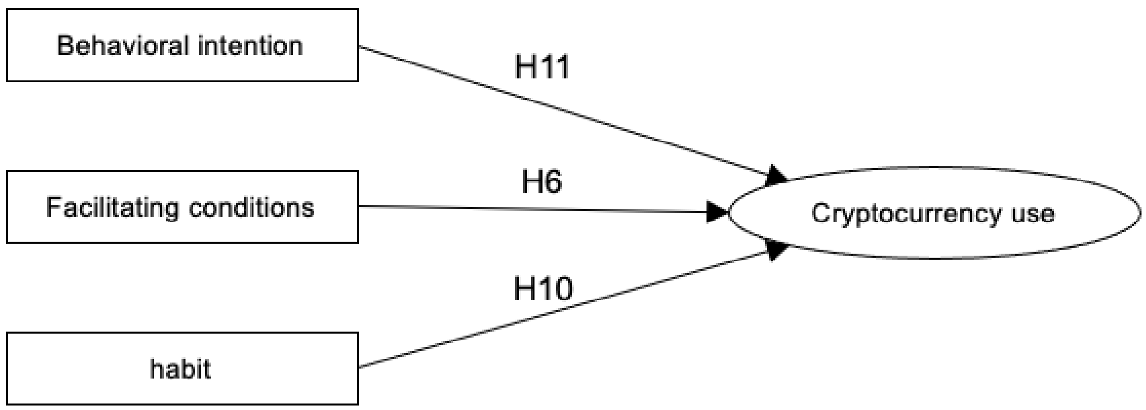

Figure 88: Sub model 3 of the conceptual model

The R value as presented in Table 19 is 0.671, suggests that the three variables are an average predictor of cryptocurrency use. If R < 0.5, the model would have been considered a poor predictor of U and other predictors of U would have to have been investigated and the model updated. However, the R value for sub model 3 is greater than 0.5, suggesting that the model can predict U so some degree. The adjusted R^2 value for sub model 3 is 0.433, suggesting that only 43.3% of the variability in U is predicted by the three predictor variables.

Table 19: Model summary statistics for sub model 3

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.671[a]	.450	.433	1.315	.450	27.235	3	100	.000

a. Predictors: (Constant), BI, HT, FC

b. Dependent Variable: U

The ANOVA table statistics is summarized in Table 20. The ANOVA table indicates a significance of 0.000, which is lower than 0.005, suggesting that sub model 3 is statistically significant and a good fit for the data.

Table 17: Summary of ANOVA statistics for sub model 3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	141.191	3	47.064	27.235	.000[b]
	Residual	172.809	100	1.728		
	Total	314.000	103			

a. Dependent Variable: U

b. Predictors: (Constant), BI, HT, FC

Table 21 summarises the coefficients statistics for sub model 3. The regression equation can be derived from the coefficients statistics as follows:

$$U = 5.294 + 0.093(FC) - 0.652(HT) - 0.345(BI)$$

Furthermore, FC and BI do not have statistical significance at the 95% confidence interval as the sig. value for both FC and BI are greater than 0.05. The hypothesis for H6 (FC) and H11 (BI) are thus rejected. HT has a sig. value of 0.000 suggesting statistical significance in predicting U, therefore H10 is failed to be rejected.

Table 21: Summary of coefficient statistics for sub model 3

Coefficients a

	Unstandardized Coefficients		Standardized Coefficients			Hypothesis
	B	Std. Error	Beta	t	Sig.	Decision
(Constant)	5.294	0.549		9.645	0	
FC	0.093	0.146	0.087	0.637	0.525	H6 Rejected
HT	-0.652	0.174	-0.466	-3.739	0.000	H10 Accepted
BI	-0.345	0.199	-0.305	-1.73	0.087	H11 Rejected

a Dependent Variable: U

5.4 Results summary

In summary, the conceptual model was able to explain 88.2% of the variance in BI and 43.3% of the variance in U. All three regression models were statistically significant and a good fit for the data as the ANOVA statistics showed a sig value (p-value) less than 0.05. EE was found to explain 61.8% of the variance in PE, however EE was determined not to have a significant effect on BI and was therefore excluded from the model. HM and PV were also found not to have a significant effect on predicting BI and was therefore also excluded from the model. The regression analysis also found that BI and FC did not have a significant effect in predicting cryptocurrency use (U) and was therefore also excluded from the model. Figure 19 summarises the conceptual model and its results. The variables marked in red were found not to have a significant impact on their respective dependent variables. Table 22 lists the outcome of all hypotheses as suggested in chapter 3.

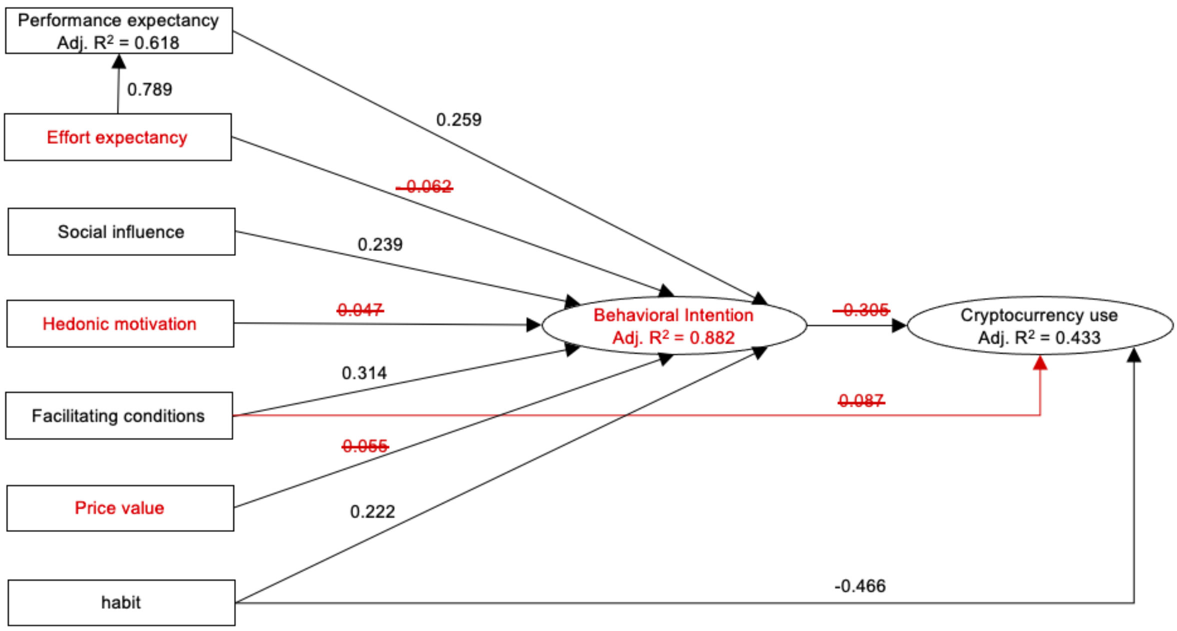

Figure 19: Final model including non-significant predictor variables

Table 22: Outcomes of all hypothesises

Hypothesis no.	**Description**	**Outcome**
H1	<u>Performance expectancy</u> will positively influence a consumer's behavioural intention to use cryptocurrencies in South Africa	H1 Fail to be rejected
H2	<u>Effort expectancy</u> has a positive and significant	H2 Rejected

	influence on behavioural intention in South Africa	
H3	Effort expectancy has a positive and significant influence on performance expectancy of cryptocurrencies in South Africa	H3 Fail to be rejected
H4	Social influence will have a positive and significant influence on a consumer's behavioural intention to use cryptocurrencies in South Africa	H4 fail to be rejected
H5	Hedonic motivation has a positive and significant impact on the consumer's behavioural intention to use cryptocurrencies in South Africa	H5 Rejected
H6	Facilitating conditions has a positive and significant impact on the consumer's use behavior of cryptocurrencies in South Africa	H6 Rejected
H7	Facilitating conditions has a positive and significant impact on the consumer's behavioural intention to use cryptocurrencies in South Africa	H7 fail to be rejected
H8	Price value has a positive and significant influence on the behavioural intention to adopt cryptocurrencies in South Africa	H8 Rejected
H9	Habit has a positive influence on the behavioural intention to adopt cryptocurrencies in South Africa	H9 fail to be rejected
H10	Habit has a positive influence on the use of cryptocurrencies in South Africa	H9 fail to be rejected
H11	Behavioural intention has a positive and significant influence on the use of cryptocurrency in South Africa	H11 Rejected

5.4 Conclusion

A survey was conducted and attracted 146 respondents, of which 104 responses were valid and used in the analysis. The chapter starts by presenting the descriptive statistics and finds a balanced gender response. The sample suggests that more males tend to use cryptocurrencies than females. The sample is biased towards tertiary educated responses and nearly half the respondents were within the age bracket of 25 -34. Reliability and validity tests were conducted on the sample and found both satisfactory for the purpose of linear regression analysis. All variables were found to be reliable with a Cronbach's

Alpha above 0.7. A linear regression analysis was run for each of the three variables PE, BI, and U as the dependent variables. For PE as the dependent variable, EE was found to be a significant predictor. For BI as the dependent variable, PE, SI, FC, and HT were found to be significant predictors. Finally, for U as the dependent variable, only habit was found to be a significant predictor. The final model was able to predict 88.2% of the variance in BI and 43.3% of the variance in U. This chapter focused only on presenting the results of the analysis. The next chapter will focus on discussing the results and linking the outcomes of the results back to the literature and the research problem.

6. Discussion of results

This chapter discusses the findings of each significant and non-significant construct, comparing it to previous research, and providing possible reasons where results of this study conflicted with previous research. Possible reasons are also discussed to explain the differences. This study found performance expectancy (PE), Social influence (SI), Facilitating conditions (FC), and Habit (HT) to be significant predictors of BI and explain 88.2% of the variance in BI. These results are in-line with previous research. HT was found to be the only significant predictor of U, while FC and BI were found to be non-significant. The results relating to U were unexpected and conflict with previous research but are analysed in detail in this chapter. Figure 20 illustrates the final model, showing only the significant predictors of BI and U.

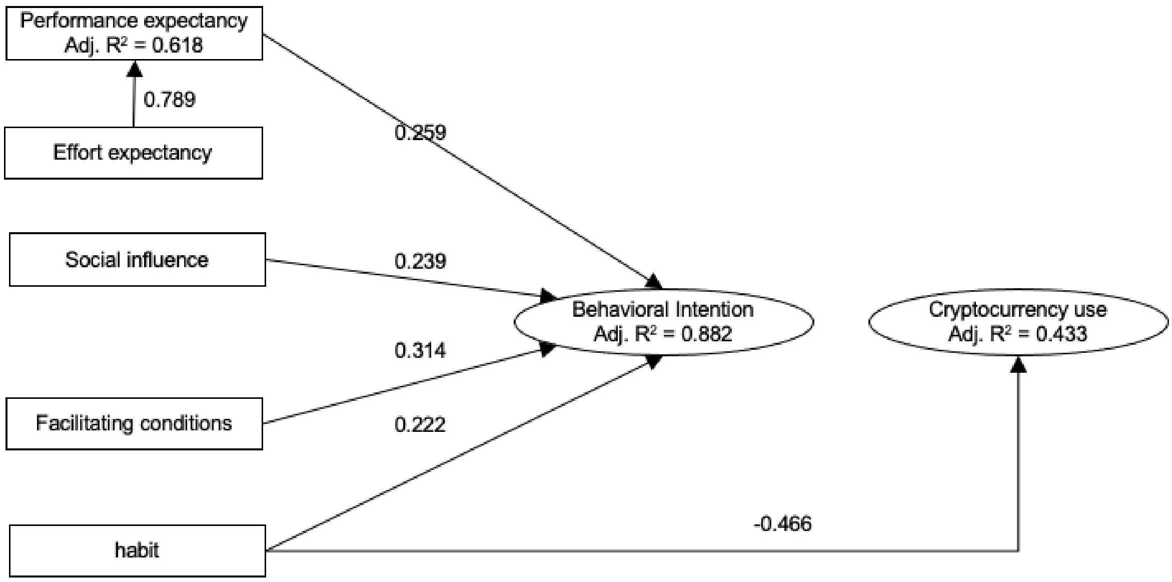

Figure 9: Final model showing only significant predictors

6.1 Discussion of the sample

Samples were collected from 146 respondents, but only 104 responses were valid as the other 42 respondents indicated that they had interacted with cryptocurrencies before January 2020. The target population were those with some knowledge of cryptocurrencies, first interacted with cryptocurrencies after January 2020 or who have not yet interacted with cryptocurrencies directly. Finally, the population criteria required the respondent to have internet access as cryptocurrencies are linked to the internet and the survey was distributed electronically and required an internet connection to complete.

This study found an almost even split for gender demographics, with 49% of respondents identifying as male and 51% identifying as female. This is slightly contrary to previous cryptocurrency adoption studies done in South Africa (Mahomed, 2017; Walton & Johnston, 2018). A study done by Walton & Johnston (2018) was dominated by male respondents, making up 95.4% of the responses. Another study by Mahomed (2017) also had a high response rate from males, contributing 86% of responses. A more recent study, done by Mazambani & Mutambara (2019), had a more balanced gender demographic, with males making up 49.1% of responses and females making up 50.9% of responses. It stands to reason that males adopted cryptocurrencies earlier than females, possibly due to the male-dominated field of technology and risk appetite. This opinion is supported by Mahomed (2017) and suggests that previous research indicates that "men were more likely to adopt and use information technology initially". This study and another more recent study done by Mazambani & Mutambara, (2019) suggests that more females are showing an interest in cryptocurrencies as it becomes more mainstream.

Table 18: Sample descriptive statistics

Variable	**% Of sample**
Gender	
Male	49%
Female	51%
Age groups	
25 - 44	71%
Cryptocurrency usage	
Before 1 January 2020	28%
After 1 January 2020	18%
Never	54%
Usage frequency	
At least once per month	26%
Education level	
Collage Tertiary Education or higher	79%
Income Level	
Less than R100 000 per annum	5%

Most survey respondents were between the ages of 25 and 44, making up 71% of the total responses as is presented in Table 23. Walton & Johnston (2018) observed a similar age demographic in their study, with ages 25 – 44 making up 72% of their study. A similar study by Mahomed (2017) also observed the highest response rate from respondents between the ages of 25 and 44, making up nearly 87% of all responses. Finally, Mazambani & Mutambara (2019) observed that 69% of their respondents were aged between 21 and 40. All four of the studies mentioned above were conducted in South Africa, except for that of Mahomed (2017). Although his study was open to all geographic locations, 88.6% of his respondents were from South Africa, making his results relatable to this study. The study also found that most respondents tend to adopt cryptocurrencies for the purposes of investment. There was a low response rate from younger age groups, between 18 – 24. It could be argued that younger individuals do not have access to excess finances for investment purposes, hence the low adoption and interest by the younger age groups. It is also noted that age demographics could possibly be ascribed to the sampling technique used, i.e. a snowball technique, in which the electronic survey was posted to a business school social media group, where most group members were within the ages of 25 - 44.

Looking at cryptocurrency use results for this study, a total of 46% of respondents said that they had used cryptocurrencies. Table 23 shows the breakdown of cryptocurrency use and indicates that 28% of respondents used cryptocurrencies before 1 January 2020, while only 18% of respondents used cryptocurrencies after 1 January 2020 for the first time. Comparing this to previous studies, Walton & Johnston (2018) found that 44.7% of their respondents use cryptocurrencies, while a study done by Mahomed (2017) found that only 38.6% of respondents used cryptocurrencies. This study had similar cryptocurrency use statistics compared to previous studies. The expectation was to see an increased use by respondents, as suggested by the literature (Arcane Research, 2020; Statista, 2021b, 2021a) and the fact that South Africa is moving into the third phase (early majority) of the technology adoption lifecycle, as proposed by the Diffusion of Innovation Theory (Mora, 2019). It is noted that the reliability of the usage data is questionable due to the sampling technique used, and to the small sample size.

The study found that respondents of the survey were well educated. 79% of respondents had at least a tertiary degree from a collage or higher (Table 23). The study also found respondents formed part of the higher income bracket in South Africa, with only 5% of respondents receiving a gross income of less than R100 000 per annum. These statistics are important to the generalizability of the study to the study population. In South Africa more than 55% of the population lives under the upper-bound poverty line, meaning they receive less than R992 per month (StatsSA, 2017). This means that this study, at best, is only generalizable to higher-income individuals in South Africa and is not generalizable to the entire South African population.

6.2 Discussion of variables

This section focusses on studying the results of each dependent variable behavioural intention (BI) and cryptocurrency use (U) as well as their related independent variables. For BI, the independent variables are PE, EE, SI, HM, FC, PV, and HT and studying the results for BI will assist in answering research question 1. For U, the dependent variables are BI, FC, and HT. Studying the results of U helps answer research question 2.

6.2.1 Dependent variables for BI

PE, SI, FC, and HT were found to significantly predict BI, explaining as much as 88.20% of the variance in BI. In the original study of the UTAUT2 model, Thong et al. (2012) found that their model was able to explain 44% of the variance in BI. Their study focused on the adoption of mobile internet technology. Contrary to the original results of the UTAUT2 study, this study found that EE, HM, and PV did not significantly affect BI. Figure 21 provides a summary of the final model showing all significant predictors of BI.

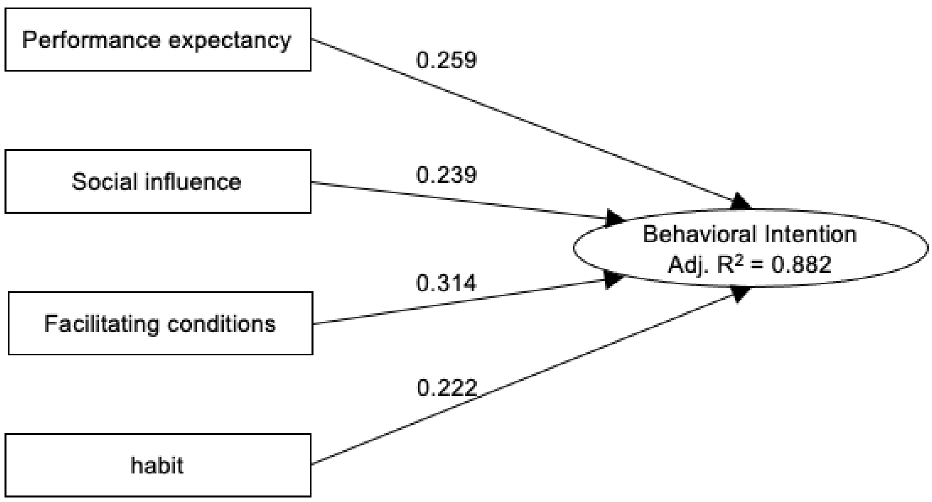

Figure 21: Final model with significant predictors of BI only

- **Performance expectancy**

The study found PE to be a significant predictor of BI ($\beta = 0.256$, p-value < 0.001) while EE was found to be non-significant. PE was also found to be the second strongest predictor of BI, behind FC. The original UTAUT2 study tested both the direct model as well as the indirect model where age, gender and experience were used as moderators for the direct variables (Thong et al., 2012). This study was not able to consider the effects of the moderators implying that only the direct results from the original UTAUT2 study were used for comparative purposes. The direct study also found PE to be a significant predictor of BI ($\beta = 0.21$, p-value <0.001). Al-Amri et al. (2019) conducted a literature review of cryptocurrency adoption from 2014 – 2017: from 25 studies, they concluded that PE is a significant predictor of BI. Studies done by (Mahomed, 2017; Walton & Johnston, 2018) in a South African context also found PE and perceived usefulness to be significant predictors of BI. Perceived usefulness (PU) was first introduced in the TAM model and performance expectancy was derived from PU in the UTAUT model and later also used in the UTAUT2 model, making them comparable (Davis, 1989; Venkatesh et al., 2003). There is strong evidence to suggest that studies done before 2020 found PE to be a significant predictor of BI. This study validates the previous studies that PE is a significant predictor of BI and starts to answer research question 3; that PE is a significant predictor of BI for early adopters as well as the early majority of cryptocurrencies.

- **Effort expectancy**

EE was tested as a predictor of PE as well as BI. EE was found to be a significant predictor of PE ($\beta = 0.789$, p-value <0.001) and was found to predict 61.8% of the variance in PE. However, EE was also found to be non-significant in predicting BI. In their literature review of cryptocurrency adoption, Al-Amri et al. (2019) found multiple studies concluding that EE is a significant predictor of BI. Studies done in South Africa on cryptocurrency adoption presented mixed results. Walton & Johnston (2018) found that perceived ease of use (PEOU) from the TAM model has a significant effect on a user's attitude, which in turn has a significant effect on intention to use cryptocurrencies. Mahomed (2017) on the other hand found that EE is non-significant in predicting BI to use cryptocurrencies.

The original UTAUT model suggests that age, gender and experience have a moderating effect on EE, so that younger women, with early stages of experience, will have a stronger effect. This study did not consider the moderating effect of age, gender and experience and it is noted that from the sample of 53 female respondents, 21 indicated "no knowledge" of cryptocurrencies, suggesting that the male respondents had more of an impact on the study. The moderating effect of EE for males is lower than for females, which could possibly explain why the study found EE to be non-significant.

Another reason why EE was found to be non-significant is because of the high performance that cryptocurrencies have been observed recently. In The last year alone, the cryptocurrency market capitalization has grown by 545%. It could be argued that with such attractive growth on capital, effort plays less of a role when one is considering adoption. It might be worth investigating what effect actual performance has on EE as a predictor of use. Because of the varying results from previous studies done before January 2020, Research Question 3 cannot be answered conclusively. It is unclear whether EE is a predictor of BI in early adopters as well as early majority users.

- **Social Influence**

Social influence was found to have a significant ($\beta = 0.239$, p-value <0.01) and positive effect on BI. In the original UTAUT study on which the UTAUT2 model was based, Venkatesh et al. (2003) found social influence to be a significant predictor of BI. SI has consistently been shown to be a significant predictor of BI in mobile banking and mobile payments; however, the findings of this study conflict with relation to other cryptocurrency studies. In studies by Arias-Oliva et al. (2019) and Ji-Xi et al. (2021), both teams found SI to be a non-significant predictor of BI. In the South African context, Mahomed (2017) also found SI to be non-significant.

Ji-Xi et al. (2021) pointed out that a possible reason why SI was not found to be a significant predictor of BI was possibly the lack of knowledge of or familiarity with cryptocurrencies. When Mahomed (2017) did their study in South Africa in 2017, the technology and the concept was still novel: there was possibly also a lack of knowledge and familiarity and knowledge around the concept of cryptocurrencies. Cryptocurrencies have since gained popularity in South Africa and the adoption rate has increased significantly over the last two years (Arcane Research, 2020; Statista, 2021b). Mora (2019) suggests that innovators and early adopters tend to adopt new technologies for inherent reasons, and not for social reasons. He further argues that the early majority and late majority users tend to be socially influenced to adopt a new technology. This could explain why previous studies of cryptocurrency adoption found SI to be non-significant historically, but as adoption increases, so, too, does the social influence, and this explains why this study found SI to be a significant predictor of BI.

In conclusion, to partially answer Research Question 3, SI was a non-significant predictor for early adopters, but is a significant predictor of BI for the early majority users.

- **Hedonic motivation**

Hedonic motivation was found to be a non-significant predictor of BI in this model. This result conflicts with a study done by Mahomed (2017) that found HM to be the strongest predictor of BI. He further suggested that HM was found to be indirectly proportional to practicality, meaning that enjoyment decreases the more something is designed to be practical rather than attractive. Roos (2015) studied the adoption of cryptocurrencies in SME's and found HM to be non-significant. The literature review on cryptocurrency adoption done by Al-Amri et al. (2019) did not specifically mention that HM was a significant predictor of BI, suggesting that the results varied between studies and the findings were not consistent enough to definitively state HM's predictive ability on BI. For this reason, it is inconclusive whether HM as a predictor of BI differs between early adopters and early majority users. This statement is made considering the inconsistent findings of HM on BI for early majority users.

- **Facilitating conditions**

FC was hypothesized to significantly affect both BI and U. FC was found to be the strongest predictor of BI (β = 0314, p-value <0.001). Mahomed (2017) justified not studying the effect of FC on BI because of the novelty of cryptocurrencies at the time. However, he predicted that as time goes one, FC would have a more significant effect on both BI and U. This prediction is confirmed by this study in that FC is the most significant predictor of BI. This result was expected to some degree. There are many content creators who create videos to simplify and explain the complexities of cryptocurrencies. Cryptocurrency exchanges are easy to access and come with video tutorials to assist new users in navigating the cryptocurrency landscape. Exchanges such as Luno in South Africa have made it easy to buy and sell cryptocurrencies on their platform. These are all FCs that break down barriers of adoption for consumers.

Smartphone access in South Africa is also increasing and 64% of the South African population have a smartphone (Hootsuite, 2021). It is well noted however that this study only focused on internet users. Results from the income levels suggests that respondents can afford internet, smartphones, and to allocate a portion of their funds to cryptocurrencies. This creates the further expectation that FC play a significant role in predicting BI.

Roos (2015) also found facilitating conditions to be a significant predictor of BI. Therefore, to partially answer research question three, FC is a significant predictor of BI for both early adopters and early majority users.

- **Price value**

PV was found to be a non-significant predictor of BI in this study. Thong et al. (2012) Added PV to the UTAUT2 model to expand the scope of the model to consumers. The literature is very scarce on PV as a predictor for BI in the cryptocurrency environment. Roos (2015) was one of the few studies that included PV as a predictor variable in their model. The study found PV to have a significant effect on BI. Mahomed (2017) also planned on testing PV as a predictor of BI, however their study found PV data to be unreliable and was consequently not tested.

Only 5% of the sample group received less than R100 000 per annum. This suggests that respondents are less price sensitive. Individuals with higher incomes also tend to get uncapped or unlimited internet and already own a smartphone, making the cost of using cryptocurrencies almost zero, as the user already has all the infrastructure in place and does not need to purchase any additional equipment to enable the use of cryptocurrencies. Although cryptocurrencies have been known to drastically reduce transaction fees, it is possible that the real value for adopters lies in the potential growth of the coin value, which is more closely related with performance expectancy. This could explain why PV was found to be a non-significant predictor of BI. It can be concluded that PV was a significant predictor of BI for early adopter, but not for the early majority users.

- **Habit**

Surprisingly, habit was found to be a significant predictor of BI ($\beta = 0.222$, p-value <0.001). This is surprising because this study only focused on users that adopted cryptocurrencies after 1 January 2020, so the respondents could have used cryptocurrencies for 18 months at most. Table 5 also indicates that only 27% of respondents have used cryptocurrencies before. Thong et al. (2012) view HT as a “perceptual construct that reflects the results of prior experiences”. They found that after repeated interaction with a technology, and assuming the consumer had a positive experience with the technology, a habit is formed which drives not only the consumer's use of the technology, but also their intention to use the technology. Referring to the low use rate by respondents again, 25% of the 27% of respondents that use cryptocurrency use it at least once a month. Put in another way, 93% of respondents that indicated they use cryptocurrencies, use it at least once a month. 14% of the 27% or 52% of respondents that indicated cryptocurrency ~~use~~ usage, use cryptocurrencies at least once per week. This could explain why habit was found to be a significant predictor of BI.

The researcher was unable to find many studies that included habit as a construct in cryptocurrency adoption. One study that investigated the effect of HT on BI in cryptocurrency adoption found habit to be a significant predictor of BI (Roos, 2015). Based on this one study that was done in 2015, the conclusion is that HT is a significant predictor of BI for both early adopters and early majority users. It is noted however that the conclusion drawn for HT on BI between early adopters and early majority users is only based on one previous study for early majority users, suggesting that this conclusion should be further to find more studies that included HT as a predictor of BI to ensure a more robust conclusion can be drawn.

6.2.2 Dependent variables for use

This study investigated the effect of predictor variables BI, FC, and HT on cryptocurrency use (U). The study found only HT to be a significant predictor of U, explaining 43.3% of the variance in U. Figure 22 provides a summary of the final model with U as the dependent variable. The original UTAUT2 model was able to predict 35% of U using BI, FC, and HT as predictors, with BI being the strongest predictor, followed by HT (Thong et al., 2012). Mahomed (2017) found BI and FC to be significant predictors for U, explaining 28.8% of the variance in U.

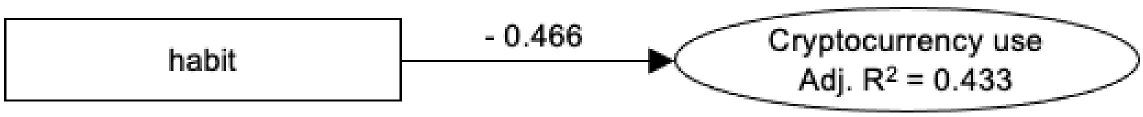

Figure 22: Final regression model with Use as the dependent variable

- **Facilitating conditions**

In this study, FC was found to have a non-significant affect in predicting U. This contradicts the original UTAUT and UTAUT2 model studies that found FC to be a significant predictor of U in both studies ($\beta = 0.17$, p-value < 0.01 and $\beta = 0.15$, p-value < 0.05 respectively). Not many studies have studied the effect of FC on U in the adoption of cryptocurrency, making comparisons difficult. Mahomed (2017) however found FC to be a significant predictor of U ($\beta = 0.341$, p-value < 0.001) and found FC to be the strongest predictor of U, ahead of BI.

The fact that FC is a significant predictor of BI, but not U, suggests that FC drives an intention to adopt cryptocurrencies, but does not play a significant role in converting the intention into action. This insight has practical advantages: businesses know that having the right support, awareness and training material in place will not necessarily translate to the attraction of new customers, although it could attract interest from new customers. Business will still have to work ensure a strong sales pitch along with other contributing factors to get prospective customers over the line.

Thong et al. (2012) suggests that age, gender, and experience have a moderating effect on FC, so that the effect will be stronger for older women with low levels of experience of a new technology. The sample is split equally by gender, however, when only considering respondents that indicated cryptocurrency use, the split is 68% to 32% in favour of males. This could explain why FC is non-significant in predicting U. Future studies should incorporate moderating effects to gain more insights into the effect of FC on U. In conclusion, based on this study and the study done by Mahomed (2017), FC has a significant effect on early adopters, but not on early majority users.

- **Habit**

Surprisingly, HT was found to have a negative effect on cryptocurrency use ($\beta = -0.466$, p-value <0.001). In the original UTAUT2 study that focused on mobile money adoption, HT was found to be a positive and significant predictor of U ($\beta = 0.24$, p-value <0.001) Thong et al. (2012).

To explain why HT could possibly have a negative correlation with U, one must understand the recent failure of companies that offered cryptocurrency-related services. In 2020 alone, two companies were declared bankrupt after the owners of the company disappeared with the cryptocurrency (Comins, 2020; Viljoen, 2020). Investors lost R227 million and R9 billion respectively from the two companies. In 2021 another company, called Africript went under after the cryptocurrencies disappeared along with the company owners (Henderson & Prinsloo, 2021). Investors lost cryptocurrency to the value of R54 billion, a number that has yet to be confirmed. These are just the largest companies that went bankrupt over the last two years: many smaller companies ended up with similar outcomes and many investors lost lots of money. As the focus of this survey was on people that adopted cryptocurrencies in the last two years, it is possible that some respondents had invested money in these companies and lost their money and triggering them to withdraw from cryptocurrency, possibly explaining why HT has a negative effect on U.

It is suggested that the negative correlation between HT and U is investigated in more detail by possibly including trust, perceived risk, and other constructs that could influence HT and its effect on cryptocurrency use in South Africa. No other studies testing the effect of HT on U were found and thus it is not possible to draw conclusions of HT between early adopters and early majority users.

- **Behavioural intention**

BI was found to have a non-significant impact on U. This outcome was not expected, as the relationship between BI and U has been widely tested and BI has been found to have a significant, positive effect on U (Thong et al., 2012; Venkatesh et al., 2003). The limited studies that tested the effect of BI on U in a cryptocurrency environment have further validated the relationship between BI and U (Mahomed, 2017).

The results of this study suggest that PE, SI, FC and HT explain 88.2% of the variance in BI, and that these constructs create the intention to use cryptocurrencies, but these constructs do not necessarily translate to actual use of cryptocurrencies. This outcome conflicts with the study done by Mahomed (2017) that found BI to be a significant predictor of U. It is worth noting that Mahomed (2017) found BI to be the weaker predictor of U. FC was found to be the strongest predictor of U.

Wu & Du (2014) critically examined the BI and U constructs to better understand their relationship to each other. The study found (1) that BI has a higher correlation with its dependent variables than U, which is supported by this study, and (2) BI is not a good substitute for U. This means that BI does not necessarily translate to actual use, which is also suggested by the findings of this report. Wu & Du (2014) further suggest that there are three types of Us, namely actual use, reported use, and assessed use. Their study found assessed use to have the highest correlation with BI, and actual use to have the lowest correlation. This study favoured self-reported use, which could explain why BI was found non-significant in predicting U. For future research it is suggested that researchers' measure assessed usage as opposed to reported usage.

Finally, based on this study and the study done by Mahomed (2017), it would be logical to suggest that BI is a significant predictor of U for early majority and not for early majority users, however context matters. As mentioned previously, there has been a series of companies that have gone under and investors have lost large sums of money, diminished trust, and affecting the way consumers use cryptocurrencies. This result is only applicable in a South African context, and possibly only over the short term. A similar study in the future could find conflicting results is consumers forget about previous tragic events and companies become more reliable.

6.3 Conclusion

The sample is evenly distributed between males and females, with most respondents being between the ages of 25 – 44. The sample is well educated with most respondents having a tertiary degree from at least a college. The income statistics correlated with the education level, with 95% of the sample earning more than R100 000 per annum. Most valid respondents (73%) indicated that they have not used cryptocurrencies yet, with males making up two-thirds of the use statistics, which is similar to previous studies done on cryptocurrency adoption.

This study had three objectives: firstly, to determine constructs that influence a user's behavioural intention to use cryptocurrencies; secondly, to determine constructs that influence the actual use of cryptocurrencies, and thirdly, to compare all measured constructs to previous research to determine whether the constructs are the same or different when comparing early adopters to early majority users. The study found PE, SI, FC, and HT to be significant predictors of BI, with FC being the strongest predictor of BI. It comes as no surprise that FC is the strongest predictor of BI. Because of the novelty of cryptocurrencies, and the complexities associated with them, consumers need material to help them understand the concept, and infrastructure to simplify the process of interacting with cryptocurrencies, such as exchanges that have made it very easy for consumers to buy and sell cryptocurrencies. Facilitating conditions play a stronger role for the less technologically inclined consumers, as is the case with early majority users when compared to early adopters of new technology.

Interestingly, only habit was found to significantly predict actual use, contradicting previous literature that suggests BI and FC are significant predictors of actual use. Habit was further found to have a negative effect on cryptocurrency use, suggesting that the stronger the habit, the less it relates to use. This could be explained from the series of companies that went bankrupt and disappeared with investors' money during the last two years. It is possible that people used cryptocurrencies, which formed the habit, but decided not to use cryptocurrencies anymore after losing their investment.

From this research it was concluded that for predictors of PE, FC, and HT are predictors of BI for both early adopters and early majority users. SI was found to be a significant predictor of BI for early majority users, but the literature suggests it is not one for early adopters. PV on the other hand is a significant predictor of BI for early adopters, but not for early majority users. Finally, none of the constructs related to actual use were found to be significant predictors for both early adopters and early majority users. The literature suggests BI and FC are significant predictors of U for early adopters, but not for early majority users. HT on the other hand was found to be a significant predictor of U for early majority users, but the literature suggests it is not one for early adopters.

7. Conclusion

This study sought to identify the drivers of cryptocurrency adoption for early majority users of the technology by investigating constructs that drive customer behavioural intention to use cryptocurrencies, as well as constructs that drive the actual usage of cryptocurrencies. The study further sought to compare drivers of cryptocurrency adoption for early majority users with those of early adopters of cryptocurrencies. This section begins by outlining the principal findings of the study; this is followed by a discussion of the theoretical contribution and practical implications for management and for the relevant stakeholders. Finally, this section critically reviews the limitations of the study and suggests future research opportunities.

7.1 Principal conclusions

This study sought to investigate (1) the factors that drive behavioural intention to adopt cryptocurrencies, (2) the factors driving actual usage, and (3) how these factors compare between early adopters and early majority users, as defined by the diffusion and innovation theory (Mora, 2019). A critical review of the literature review identified the constructs relevant to cryptocurrency adoption as well as a model used to analyse the constructs. The UTAUT2 model was judged to be the best fit for its consumer-focused approach (Thong et al., 2012). An electronically distributed survey was used to collect data on current and potential cryptocurrency users. Multiple linear regression was used to analyse the data. The analysis found multiple constructs to significantly affect behavioural intention and usage. The findings of the analysis are presented below in no particular order:

1. Respondents were evenly balanced in terms of gender. Most respondents were between the ages of 25 – 44, held at least a bachelor's degree from a college, and earned more than R100 000 per month.
2. Only 27% of respondents indicated actual usage. Most respondents that indicated actual usage, used cryptocurrencies at least once per month. Two-thirds of respondents that indicated actual usage were males.
3. The final model was able to explain 88.2% of the variance in behavioural intention and 43.3% of the variance in actual usage. Moderating effects were not considered in this study.
4. Performance expectancy, social influence, facilitating conditions and habit were found to significantly predict behavioural intention. Facilitating conditions was

found to be the strongest predictor of behavioural intention. This outcome is not surprising due to the complexities and novelty of cryptocurrency.

5. Effort expectancy, hedonic motivation, and price value were found to be non-significant in predicting behavioural intention.
6. Surprisingly, habit was found to be the only significant predictor of actual usage. Habit was further found to have a negative effect on actual usage, which seems counter-intuitive. This observation could be explained by the fact that numerous cryptocurrency-linked companies disappeared with investors' money during 2020 and 2021, which is the same time-frame of the target population of early majority users. Consumers used cryptocurrencies, which created the behaviour, but lost their investment, resulting in their withdrawal from cryptocurrency.
7. Behavioural intention, which has widely been found to significantly effect usage was found to be non-significant in this study (Mahomed, 2017; Thong et al., 2012; Venkatesh et al., 2003). Wu & Du (2014) found behavioural intention to be a poor substitute for actual usage. This study validated their observation, finding behavioural intent in consumers to adopt cryptocurrencies, but little translation to actual usage of cryptocurrencies.
8. Only 43.3% of the variance in usage was explained by habit, suggesting that there are other factors that are missing from the final model, that could better explain the variance in actual usage. This study suggests including constructs such as trust, which could play a significant roll due to unreliable companies that con investors out of their money, as well as perceived risk, which could play a role due to the volatility observed in cryptocurrency prices.
9. Performance expectancy, facilitating conditions, and habit were found to be significant predictors of behavioural intention for both early adopters and early majority users.
10. Social influence was found to be significant predictor of BI for early majority users, but not for early adopters. This result is not surprising. The literature suggests that early adopters tend to adopt a new technology based on belief principles rather than social influence, while social influence tends to play a larger role in decision-making for early majority and late majority users (Mora, 2019).
11. Effort expectancy and hedonic motivation yielded varying results for early adopters, and could thus not reliably be compared to the outcome of this study. It is therefore inconclusive whether these two constructs have a significant influence on behavioural intention for both early adopters and early majority users, and this

should be explored further.

12. Facilitating conditions and behavioural intention were found to be significant predictors of actual usage for early adopters, but not for early majority users.

7.2 Theoretical contribution

Technology adoption has been widely studied, especially related to topics of mobile banking and mobile money (Alalwan et al., 2017; J. Thong et al., 2012; Venkatesh et al., 2003). Research into the adoption of cryptocurrency has been limited, with many studies using variations of TAM and TPB models (Mazambani & Mutambara, 2019; Walton & Johnston, 2018), or purely focusing on drivers of behavioural intention (Gunawan & Novendra, 2017; Roos, 2015; Ji-Xi et al., 2021; Walton & Johnston, 2018). Al-Amri et al. (2019) conducted a literature study of cryptocurrency adoption between 2014 and 2017 and concluded that more studies needed to be done on adoption models, using amongst others, UTAUT models. They also suggested that more consumer and merchant focused studies be done.

This research addressed the suggestions made by Al-Amri et al. (2019) by using the UTAUT2 model which is consumer focused, to find constructs that influence the behavioural intention and actual usage of cryptocurrencies. Because of the low number of studies that measure actual usage, it is difficult to compare findings in different contexts, and to draw robust conclusions. This study adds to the body of knowledge of cryptocurrency adoption from a consumer perspective.

The study goes one step further to specifically study the drivers of cryptocurrency adoption for early majority users. This is the first phase of mass adoption of cryptocurrency. The second phase of mass adoption is considered late majority users as defined by the DIT(Mora, 2019). This study also compares the results of this study, which is early majority focused, to previous studies which are early adopter focused, to determine whether the drivers of cryptocurrency adoption are the same or different of early adopters and early majority users. To the researcher's knowledge, there has been no study focused on comparing cryptocurrency adoption drivers to the different technology adoption lifecycle phases.

7.3 Managerial Implications

The total cryptocurrency market capitalization is more $2.5 trillion and increasing daily (CoinMarketCap, 2021b). Banks are rushing trying to adapt to the impact cryptocurrencies might have on them, investment houses are looking for ways to incorporate cryptocurrencies into their service offering, and start-ups are focusing their attention and resources on cryptocurrencies. With the high growth cryptocurrencies have seen since inception, there is protentional for companies to capitalize as well.

An important aspect for companies is their customer segmentation. It impacts the company strategy, marketing plan, and resource allocation. This study has identified the market segment as both males and females between the ages of 25 and 44, who is well educated and earns more than R100 000 per annum. The literature highlights the shift from a male dominated interest in cryptocurrency to an increased female interest as cryptocurrencies become more mainstream.

Facilitating conditions was found to be the strongest predictor of behavioural intention. Cryptocurrencies are still a novelty technology based on complex technological principles. The results suggest that consumers want facilitating conditions before considering cryptocurrency adoption. Companies need to make sure they are transparent in their processes, and they need to focus simplify the adoption process for the consumer. It is however important to note that behavioural intention does not necessarily translate to actual usage. Habit showed a negative effect on actual use, suggesting that people that used cryptocurrencies have since withdrawn from cryptocurrency activities. It is possible that consumers do not trust cryptocurrencies due to the bad publicity gained from fraudulent companies that disappeared with consumer investments. Companies need to focus on rebuilding trust between consumers and cryptocurrencies which will attract more customers.

7.4 Research limitations

Firstly, the researcher received many queries from respondents requesting clarity on some of the questions. This feedback suggests that the questions might have been unclear and not adequately converted to fit the cryptocurrency context. The sampling approach used consisted mostly of snowball approach. This means that everyone in the population did not have an equal opportunity or probability of completing the survey. The survey was distributed on the tertiary education platform as well as on multiple logistics company platforms, which garnered many responses. The implication of the snowball sampling approach is that the results of this study are not generalizable to the entire population of South Africa. The sample is only generalisable to individuals earning more than R100 000 per annum, and who are between the ages of 18 and 71, which was the age of the oldest respondent.

It is also important to note that outliers were not tested in this analysis, and thus no outliners (if any were present) were removed. This could possibly affect and reliability of results. This study only studied constructs from the UTAUT2 model and did not include any additional constructs such as trust or perceived risk. Although 88.2% of the variability in behavioural intention was explained by the tested constructs, only 43.4% of usage variance was explained, suggesting that there are other factors that could contribute to the variance in actual usage. The additional constructs suggested constructs are discussed in chapter 7.5. It should also be noted that no moderating effects, including age, gender and experience from the original UTAUT2 model were tested.

Although every effort was made to identify respondents who had some knowledge of cryptocurrencies, 28% of respondents still indicated that they have no knowledge of cryptocurrencies, bringing into question the reliability of their responses.

Finally, Wu & Du (2014) suggested that assessed usage has a higher correlation compared to reported usage. This study collected self-reported usage data. Wu & Du (2014) suggests that people tend to misinterpret actual usage for intention to use. Therefore, self-report usage statistics from this sample could be slightly unreliable.

7.5 Suggestions for future research

Although cryptocurrency adoption has moved into the early majority phase, the underlying software and process is still novel and complex to understand, especially for non-tech-savvy consumers. Cryptocurrency is a broad term that encompasses many types of coins, each fulfilling a different function. Bitcoin, as an example, has established itself as a “store of value” coin, while Ethereum uses its blockchain technology as a platform for other coins, such as Ripple, to transact on. Ripple and Cardano, on the other hand, are focused on Decentralised Finance (DeFi) innovation such as smart contracts. Redoing this study (with or without additional constructs) but focusing on a subcategory of cryptocurrency, as defined by Giudici et al. (2020), would be useful. It is possible that different categories of cryptocurrencies attract different types of people, along with different drivers of behavioural intention and actual usage.

Wu & Du (2014) found that behavioural intention has a higher correlation with its predictors than usage does. The further suggest that behavioural intention is a poor substitute for usage. This study confirms the theory as behavioural intention was a non-significant predictor of cryptocurrency usage. Usage can be broken down into three categories, namely assessed, reported and actual usage (Wu & Du, 2014). This study collected self-reported usage data from respondents, but Wu & Du (2014) found reported usage to have a weak correlation with behavioural intention. They suggest collecting assessed usage as well as actual usage for the best possible correlation. For future research in cryptocurrency adoption, it is suggested that the focus is on collecting and examining actual and assessed usage to better understand the relationship between usage and its predictor variables.

Trust plays a significant role in cryptocurrency adoption, due to novelty of the technology (Mahomed, 2017). Cryptocurrency pricing is also very volatile, despite its large market share, highlighting constructs such as risk. For future research in cryptocurrency adoption, it is proposed that additional constructs are explored, such as trust and perceived risk, that might be specifically related to cryptocurrencies, and can better explain the drivers of cryptocurrency adoption.

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Appendix A: Mastercard cost of cash study

Appendix B: Survey disclaimer

Good day, my name is Nelius Greeff. I am a student at Gordon Institute of Business Science (GIBS) and doing research as partial fulfilment of a Master of Business Administration (MBA).

I am researching variables that influence the adoption of cryptocurrencies. My research aims to understand whether the variables that influence cryptocurrency adoption today are the same as the variables that influenced cryptocurrency adoption historically.

To that end, you are asked to complete a survey about your perception of cryptocurrencies. This will help us better understand what drives cryptocurrency adoption today and should not take more than 10 minutes to complete. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous, and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, do not hesitate to contact my supervisor or me. Our details are provided below.

Researcher name: Nelius Greeff
Email: 29249814@mygibs.co.za
Phone: 079 504 3991

Supervisor name: Craig Penfold
Email: craig.penfold@nhs.net
Phone: +44 7765 660685

Appendix C: Survey Questions

Part 1: Understanding cryptocurrency engagement

1. Have you ever used cryptocurrencies?
    a. Yes
    b. No

2. When did you first start using cryptocurrencies?
    a. Before 1 January 2020
    b. After 1 January 2020
    c. Never

    *If before 1 January 2020 the survey will end

3. How often do you use cryptocurrencies?
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

4. How would you describe your knowledge of cryptocurrencies?
    a. Expert understanding
    b. Deep understanding
    c. Basic understanding
    d. No understanding

5. How comfortable are you with mobile banking? E.g. E-wallet, Snapscan, Zapper, internet banking
    a. Very comfortable
    b. Comfortable
    c. Neutral
    d. Uncomfortable
    e. Very uncomfortable

Part 2: Gathering Demographic information

1. Age
    a. 17 or younger*
    b. 18 – 24
    c. 25 – 34
    d. 35 – 44
    e. 45 – 54
    f. 55 – 64
    g. 65 and older

*Survey will end should 17 or younger be selected

2. Gender
    a. Male
    b. Female

c. Prefer not to say

3. Annual gross income
    a. R100 000 or below
    b. R100 000 – R300 000
    c. R300 000 – R500 000
    d. R500 000 – R700 000
    e. R700 000 – R900 000
    f. R900 000 – R1 100 000
    g. R1 100 000 and above

4. Level of education
    a. High school not completed
    b. High school graduate
    c. Bachelor's Degree
    d. Honours degree
    e. Postgraduate degree (Masters or PhD)
    f. Other: [Text box]

Part 3: Gathering UTAUT2 data

This last section aims to understand your reasons for accepting or adopting cryptocurrencies. Cryptocurrencies in this survey is used as a collective for digital coins such as Bitcoin, including Altcoins, and stable coins. It also includes any services associated with digital coins including exchanges and cryptocurrency wallets.

1. I find cryptocurrencies useful in my daily life
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

2. Using cryptocurrencies helps me accomplish things more quickly
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

3. Using cryptocurrencies increases my productivity
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

4. Learning how to use cryptocurrencies is easy for me
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree

    e. Strongly disagree
    f. Not applicable

5. My interaction with cryptocurrencies is clear and understandable
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

6. I find cryptocurrencies easy to use
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

7. It is easy for me to become skillful at using cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

8. People who are important to me think that I should use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

9. People who influence my behavior think I should use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

10. People whose opinions that I value prefer that I use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

11. I have the resources necessary to use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral

d. Disagree
e. Strongly disagree
f. Not applicable

12. I have the knowledge necessary to use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

13. Cryptocurrencies is compatible with other technologies I use
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

14. I can get help from others when I have difficulties using cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

15. Using cryptocurrencies is fun
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

16. Using cryptocurrencies is enjoyable
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

17. Using cryptocurrencies is very entertaining
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

18. Cryptocurrencies are good value for money
    a. Strongly agree
    b. Agree

c. Neutral
d. Disagree
e. Strongly disagree
f. Not applicable

19. Cryptocurrencies are reasonably priced
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

20. At the current price, cryptocurrencies provide a good value
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

21. The use of cryptocurrencies has become a habit for me
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

22. I am addicted to using cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

23. I must use cryptocurrencies
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable

24. I intend to use cryptocurrencies in the future
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable
    g.

25. I will try to use cryptocurrencies in my daily life

a. Strongly agree
b. Agree
c. Neutral
d. Disagree
e. Strongly disagree
f. Not applicable

26. I plan to continue using cryptocurrencies frequently
    a. Strongly agree
    b. Agree
    c. Neutral
    d. Disagree
    e. Strongly disagree
    f. Not applicable
    g.
27. Please choose your usage frequency of cryptocurrencies for **low-cost and fast money transfer**
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

28. Please choose your usage frequency of cryptocurrencies to **make private transactions**
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

29. Please choose your usage frequency of cryptocurrencies as an **alternative store of value**
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

30. Please choose your usage frequency of cryptocurrencies as an **investment opportunity**
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

31. Please choose your usage frequency of cryptocurrencies to **borrow or lend currency on a peer-to-peer basis e.g., smart contracts**
    a. Less than once a year
    b. Once per year
    c. Once per month
    d. Once per week
    e. Once per day
    f. More than once per day
    g. Never

Appendix D: Correlation Analysis results from SPSS

Correlations		PE1	PE3	PE4	EE1	EE2	EE3	EE4	SI1	SI2	SI3	FC1	FC2	FC3	FC4	HM1	HM2	HM3	PV1	PV2	PV3	HT1	HT2	HT3	BI1	BI2	BI3
PE1	Pearson Correlation	1	.933**	.884**	.677**	.826**	.750**	.696**	.679**	.616**	.646**	.464**	.602**	.640**	.479**	.790**	.786**	.784**	.745**	.654**	.682**	.735**	.672**	.654**	.662**	.709**	.752**
PE3	Pearson Correlation	.933**	1	.917**	.675**	.805**	.744**	.679**	.670**	.640**	.650**	.479**	.589**	.626**	.474**	.754**	.756**	.750**	.729**	.647**	.684**	.765**	.723**	.665**	.667**	.730**	.801**
PE4	Pearson Correlation	.884**	.917**	1	.628**	.762**	.709**	.650**	.637**	.609**	.707**	.485**	.569**	.645**	.448**	.729**	.708**	.716**	.701**	.577**	.643**	.685**	.685**	.593**	.637**	.737**	.791**
EE1	Pearson Correlation	.677**	.675**	.628**	1	.800**	.828**	.850**	.717**	.653**	.664**	.578**	.750**	.654**	.663**	.659**	.693**	.676**	.699**	.638**	.675**	.655**	.548**	.635**	.747**	.699**	.613**
EE2	Pearson Correlation	.826**	.805**	.762**	.800**	1	.894**	.824**	.716**	.679**	.678**	.555**	.734**	.684**	.577**	.851**	.840**	.848**	.739**	.703**	.786**	.812**	.719**	.732**	.689**	.731**	.791**
EE3	Pearson Correlation	.750**	.744**	.709**	.828**	.894**	1	.848**	.710**	.639**	.678**	.553**	.701**	.643**	.619**	.832**	.823**	.810**	.751**	.679**	.753**	.772**	.664**	.656**	.674**	.681**	.736**
EE4	Pearson Correlation	.696**	.679**	.650**	.850**	.824**	.848**	1	.699**	.626**	.649**	.641**	.800**	.752**	.678**	.726**	.724**	.725**	.720**	.674**	.714**	.691**	.579**	.620**	.691**	.689**	.661**
SI1	Pearson Correlation	.679**	.670**	.637**	.717**	.716**	.710**	.699**	1	.850**	.858**	.588**	.717**	.780**	.645**	.709**	.732**	.706**	.812**	.783**	.781**	.599**	.506**	.600**	.840**	.718**	.619**
SI2	Pearson Correlation	.616**	.640**	.609**	.653**	.679**	.639**	.626**	.850**	1	.900**	.645**	.706**	.739**	.651**	.684**	.719**	.687**	.761**	.729**	.758**	.661**	.572**	.625**	.818**	.692**	.692**
SI3	Pearson Correlation	.646**	.650**	.707**	.664**	.678**	.678**	.649**	.858**	.900**	1	.624**	.712**	.737**	.607**	.690**	.710**	.692**	.777**	.704**	.753**	.635**	.546**	.598**	.817**	.716**	.726**
FC1	Pearson Correlation	.464**	.479**	.485**	.578**	.555**	.553**	.641**	.588**	.645**	.624**	1	.777**	.692**	.704**	.638**	.614**	.619**	.581**	.535**	.580**	.555**	.501**	.525**	.767**	.650**	.585**
FC2	Pearson Correlation	.602**	.589**	.569**	.750**	.734**	.701**	.800**	.717**	.706**	.712**	.777**	1	.728**	.731**	.716**	.701**	.708**	.699**	.668**	.715**	.641**	.527**	.575**	.809**	.694**	.670**
FC3	Pearson Correlation	.640**	.626**	.645**	.654**	.684**	.643**	.752**	.780**	.739**	.737**	.692**	.728**	1	.679**	.717**	.732**	.727**	.732**	.673**	.704**	.590**	.502**	.558**	.766**	.674**	.644**
FC4	Pearson Correlation	.479**	.474**	.448**	.663**	.577**	.619**	.678**	.645**	.651**	.607**	.704**	.731**	.679**	1	.586**	.586**	.590**	.651**	.614**	.657**	.485**	.383**	.471**	.715**	.568**	.529**
HM1	Pearson Correlation	.790**	.754**	.729**	.659**	.851**	.832**	.726**	.709**	.684**	.690**	.638**	.716**	.717**	.586**	1	.958**	.945**	.770**	.748**	.789**	.783**	.720**	.681**	.704**	.748**	.816**
HM2	Pearson Correlation	.786**	.756**	.708**	.693**	.840**	.823**	.724**	.732**	.719**	.710**	.614**	.701**	.732**	.586**	.958**	1	.981**	.794**	.781**	.779**	.804**	.726**	.739**	.729**	.735**	.788**
HM3	Pearson Correlation	.784**	.750**	.716**	.676**	.848**	.810**	.725**	.706**	.687**	.692**	.619**	.708**	.727**	.590**	.945**	.981**	1	.779**	.765**	.787**	.785**	.709**	.722**	.708**	.719**	.791**
PV1	Pearson Correlation	.745**	.729**	.701**	.699**	.739**	.751**	.720**	.812**	.761**	.777**	.581**	.699**	.732**	.651**	.770**	.794**	.779**	1	.889**	.873**	.655**	.585**	.625**	.822**	.739**	.677**
PV2	Pearson Correlation	.654**	.647**	.577**	.638**	.703**	.679**	.674**	.783**	.729**	.704**	.535**	.668**	.673**	.614**	.748**	.781**	.765**	.889**	1	.879**	.682**	.575**	.608**	.754**	.703**	.610**
PV3	Pearson Correlation	.682**	.684**	.643**	.675**	.786**	.753**	.714**	.781**	.758**	.753**	.580**	.715**	.704**	.657**	.789**	.779**	.787**	.873**	.879**	1	.714**	.641**	.589**	.763**	.683**	.702**
HT1	Pearson Correlation	.735**	.765**	.685**	.655**	.812**	.772**	.691**	.599**	.661**	.635**	.555**	.641**	.590**	.485**	.783**	.804**	.785**	.655**	.682**	.714**	1	.860**	.829**	.609**	.677**	.824**
HT2	Pearson Correlation	.672**	.723**	.685**	.548**	.719**	.664**	.579**	.506**	.572**	.546**	.501**	.527**	.502**	.383**	.720**	.726**	.709**	.585**	.575**	.641**	.860**	1	.836**	.555**	.657**	.784**
HT3	Pearson Correlation	.654**	.665**	.593**	.635**	.732**	.656**	.620**	.600**	.625**	.598**	.525**	.575**	.558**	.471**	.681**	.739**	.722**	.625**	.608**	.589**	.829**	.836**	1	.613**	.693**	.763**
BI1	Pearson Correlation	.662**	.667**	.637**	.747**	.689**	.674**	.691**	.840**	.818**	.817**	.767**	.809**	.766**	.715**	.704**	.729**	.708**	.822**	.754**	.763**	.609**	.555**	.613**	1	.786**	.650**
BI2	Pearson Correlation	.709**	.730**	.737**	.699**	.731**	.681**	.689**	.718**	.692**	.716**	.650**	.694**	.674**	.568**	.748**	.735**	.719**	.739**	.703**	.683**	.677**	.657**	.693**	.786**	1	.765**
BI3	Pearson Correlation	.752**	.801**	.791**	.613**	.791**	.736**	.661**	.619**	.692**	.726**	.585**	.670**	.644**	.529**	.816**	.788**	.791**	.677**	.610**	.702**	.824**	.784**	.763**	.650**	.765**	1

** Correlation is significant at the 0.01 level (1-tailed).

Appendix E: Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Nelius Greeff,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards