UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Gordon Institute of Business Science
University of Pretoria

# Understanding consumer adoption of cryptocurrencies

**Nadim Mahomed**

**24119441**

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.

6 November 2017

## Abstract

Cryptocurrency, most notably Bitcoin, has continued to attract attention and consequently substantial investment from businesses, consumers, and the media. Understanding what drives consumer adoption of the technology, however, is not understood. This study uses the UTAUT2 technology adoption theory in order to fill this research gap. A conceptual model is built through a review of the technical aspects of cryptocurrency, an analysis of the technology as currency, and finally a review of technology adoption theory to date. UTAUT2 is found to be the most appropriate adoption theory directly dealing with consumer context. The model conceptualised is tested using multiple linear regression analyses on primary survey data. The findings indicate that facilitating conditions have the highest explanatory effect on actual usage ahead of behavioural intention to use cryptocurrency. Behavioural intention was predicted most strongly by hedonic motivation, followed by perceived trust, and social influence. Interestingly, effort expectancy and performance expectancy were found to be non-significant, contrary to much of the studies in related fields. The study also aimed to identify the primary use-case finding that investment was the primary consumer use. Due to characteristics of the sample collected, the study's findings are limited to the South African context.


Keywords: Cryptocurrency, Technology Adoption, UTAUT2, Bitcoin, Virtual Currency

## 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.

Nadim Mahomed

6 November 2017

# Contents

## Table of Figures

## Table of Tables

# Chapter 1: Introduction to Research Problem

In an increasingly digital and globalised world, the development of digital payment systems is core to our economic evolution. Internet usage continues to increase around the world with an estimated 44% of the world using the internet in 2016 (Passport, 2016b). In South Africa, 53.5% had internet access in 2016 with a smartphone penetration rate of 61.3% (Passport, 2017). In step with this is digital payments. For instance, in the UK, a leader in e-commerce adoption, 17% of all consumer payments were through a digital channel in 2015 (Passport, 2016b). In South Africa, internet retailing grew 16% year on year in 2016 (Passport, 2017). Driven by smartphone usage, mobile applications and marketplaces, small transaction amounts are also becoming typical. These developments have resulted in a growing interest in enabling micropayments – transactions typically of 1 US Dollar (USD) or less (Hinds, 2004). The problem is that credit card processing fees are a large proportion of the transaction cost. However, it is not just monetary costs in digital payments that are prohibitive. From a psychological cost perspective, the arbitrariness to which financial controls and monetary regimes seem to be enacted and affect consumers has resulted in a trust deficit amongst consumers (Edelman, 2016; Penfold, 2015). Either as part of the natural evolution of money or as a reaction to the string of economic crises and stalled world growth and banal incumbent systems, cryptocurrencies present one possible solution to the problem multitude. Cryptocurrency, as initially conceived, represents a way to transfer money from person to person (or peer-to-peer) without going through a financial intermediary using cryptography (Raymaekers, 2015).

Perhaps by design or fortune, it was in the middle of The Great Recession in January 2009, that the first of these cryptocurrencies, Bitcoin, began operations (Hileman & Rauchs, 2017). Bitcoin remains the largest cryptocurrency by value despite forking into Bitcoin Cash and the introduction of a multitude of novel alt-coins such as the programmable Ethereum. Cryptocurrency as decentralised, digital, programmable money, therefore, lends itself to an increasingly digital world, the advent of the Fourth Industrial Revolution, and as a possible solution to the shortcomings of the current centralised world economic order (Raymaekers, 2015). The underlying technology has somewhat surpassed the cryptocurrency application in mainstream interest. Called the blockchain - the immutable distributed digital ledger – by decentralising trust, inspires the promise of an entirely new paradigm of services not just in the financial sector (Mougayar & Buterin, 2016; Tapscott & Tapscott, 2016). The first of these enabled technologies is cryptocurrency. Cryptocurrencies, by deprecating central authority in favour of a distributed peer-to-peer (p2p) monetary system, places consumers at the heart of this potential revolution. However, not much is understood in the behaviour and intentions around this crucial stakeholder in adopting cryptocurrency (Badev & Chen, 2014; Schuh & Shy, 2016). The research proposed here, therefore, seeks to add to this neglected perspective by understanding the reasons consumers adopt cryptocurrencies.

Globally, cryptocurrencies have seen increasing media, consumer, government, and most notably, financial industry interest since Bitcoin – the first of these – was released in 2009 (Carr, Marsh, Dunn, & Grigorescu, 2015; Raymaekers, 2015). Figure 1 shows the popularity of the search term “cryptocurrency” since 2008 using Google Trends data (normalised for a 100 which equals maximum popularity). As can be seen, the news term was most popular in September 2017. Interestingly, South Africa has shown the most interest in cryptocurrency globally as measured by search volume in the last six months (Figure 2) - calculated from 26 October 2017 (Google, 2017). In the last 12 months, Nigeria is ranked number one globally (Google, 2017). This is perhaps due in part to the currency volatility experienced in these countries during the period.

Figure 1: Popularity of news search term “cryptocurrency” on Google search (Google, 2017).

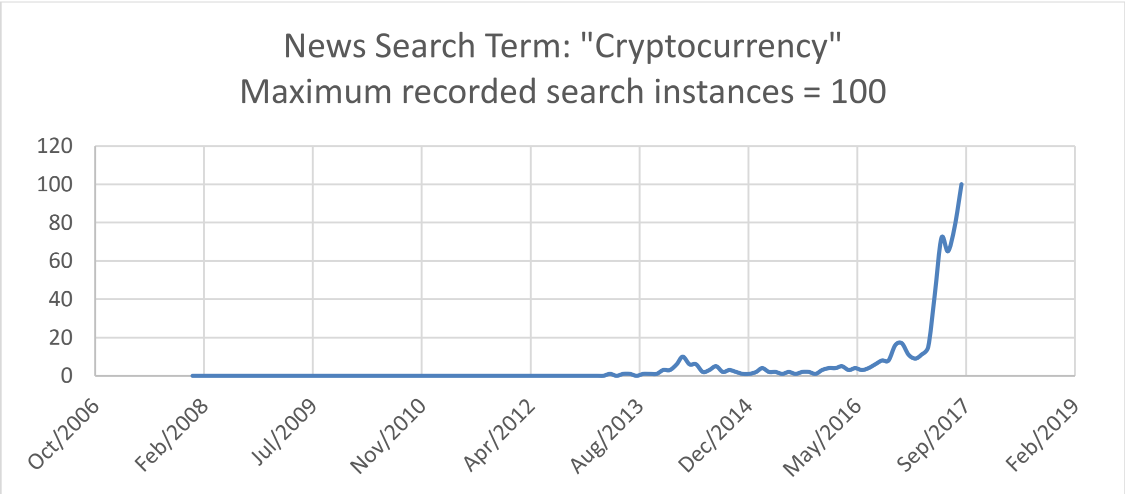
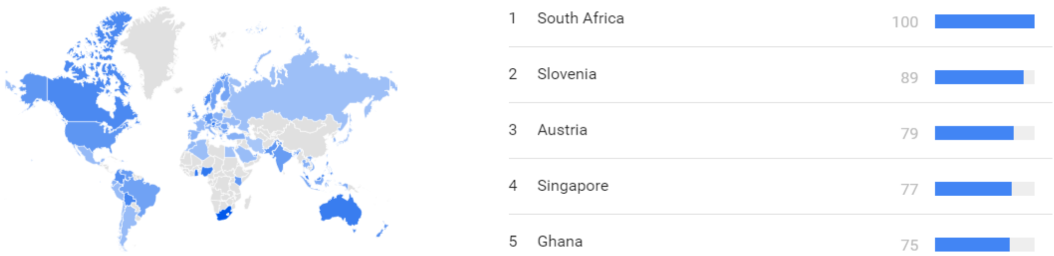



Figure 2: Top regions by volume for search term “cryptocurrency” (Google, 2017).




The technology has therefore captured the imagination of developers, consumers and financiers. In a short space of time Bitcoin has forked into, and inspired a multitude of other alternative cryptocurrencies or alt-coins. Total market capitalisation, reported in a Global Cryptocurrency Benchmarking Study, has grown more than three times since February 2016 alone to reach 25bn USD by March 2017 (Hileman & Rauchs, 2017). More surprisingly is that since the issue of the report, market capitalisation at the time of writing was 97bn USD (CoinMarketCap, 2017a). Much of the interest has been driven by the excessive growth in the value of cryptocurrency coins especially Bitcoin (BTC) and Ethereum. BTC growth is shown in Figure 3. In the last 12 months alone, Bitcoin has increased from 600 USD/BTC to just over 6000 USD/BTC at the time of writing (October 2017). This is shown graphically in Figure 4.

Figure 3: Bitcoin closing price plotted per day since inception (CoinDesk, 2017).


Figure 4: Bitcoin closing price plotted per day for the last 12 months (CoinDesk, 2017).


Cryptocurrency supporters herald the technology as revolutionary to not only consumer trade but as a driver of socio-economic reorganisation – an evolutionary force on par with the adoption of the internet. Its detractors refer to it as a fad similar to the dot-com bubble of the 1990's and have dismissed it as an "irrational exuberance" amplified by the internet age and a small group of beneficiaries, going so far as to label it a Ponzi scheme (Bjerg, 2016). Academic interest has followed, albeit in a delayed fashion. Despite this and by its very decentralised and disintermediated nature – elaborated on below – the definition of the currency has not yet been formalised. Ahead of this academic taxonomy, cryptocurrency interest and debate has continued amongst early tech-savvy adopters, technology entrepreneurs, financial institutions and most recently governments (Carr, Marsh, Dunn, & Grigorescu, 2015; Gantori et al., 2017; Schuh & Shy, 2016). However, it is potentially through the development of innovative products and services enabled by the idiosyncrasies of cryptocurrencies rather than the similarities with traditional systems that will spur adoption (Carr et al., 2015). Online retailers across the globe, including South Africa are already accepting Bitcoin as payment alongside traditional payment methods (Passport, 2016a). This evolution will ultimately result in the fuzzy boundaries between cryptocurrency as money, a financial instrument, or generic transactional technology to be more defined. It is imperative, therefore, for consumer-related businesses to be able to navigate the current landscape and more importantly have the foundational understanding of how consumer adoption is shaped and evolves. This imperative is potentially stronger in emerging economies where the adoption path may leapfrog more advanced economies following the adoption of cell phones, mobile banking, and mobile money (I. Brown, Cajee, Davies, & Stroebel, 2003; Carr et al., 2015). Carr et al. (2015) posit that accelerated development of the cryptocurrency market is likely to take place in developing markets where the need for a new currency regime is less evident to consumers. This advantage of emerging economies over developed ones is seen as being due to the lack of strong incumbent players and offerings (Baur, Bühler, Bick, & Bonorden, 2015; Carr et al., 2015). In fact, in a US study, those with access to debit cards were less likely to adopt cryptocurrency (Schuh & Shy, 2016), indicating the link between lack of alternatives and adoption.

While cryptocurrency was originally conceived as money, many have argued that it behaves more like a financial instrument (Bohr & Bashir, 2014; Christian et al., 2014; Grinberg, 2012; Yermack, 2013). The reasons for its adoption are therefore not well understood. The underlying technology lends itself to both, and therefore both views may be true in different contexts (Hileman & Rauchs, 2017). Further, financial institutions who stand to lose the most, have shown interest more in its underlying technology than its transactional and investment potential (Mougayar & Buterin, 2016). Government regulators have been mostly silent and have only recently started to make their positions known – ranging from outright banning of cryptocurrencies to integration with national currency and monetary policy (Bech & Garratt, 2017). For instance, Japan recently passed a law recognising Bitcoin as legal tender (Kharpal, 2017), and Sweden is investigating a central bank issued eKrona (Bech & Garratt, 2017). However, the intricacy and interactivity of global financial markets mean that this may not be the deus ex machina that supporters hope for. The currency price oscillates wildly on the back of news relating to hacking, theft, and most importantly government regulatory activity (Badev & Chen, 2014; Christian et al., 2014; Yermack, 2013). Nevertheless, it seems that whether fad or revolution, the currency will be around for the foreseeable future, with consumers at the very centre by design. Consequently, it is important that academic study be applied to the cryptocurrency domain precisely to elaborate on the drivers of its adoption.

Prior academic research on adoption of cryptocurrency is scarce (Baur, Bühler, Bick, & Bonorden, 2015). Baur et al. (2015) found four streams of research: technical, economic, regulatory, and social sciences, the latter being the least developed. As an example, a search using EBSCOhost revealed two English language journal articles using the search term “cryptocurrency AND adoption”. Using the search terms “cryptocurrency AND acceptance” yielded four academic articles, none of which were related directly to consumer adoption. Quantitative research is naturally scarce since transaction data on a per-user basis is almost impossible to come by publicly as a result of the anonymity aspect baked into the technology (Hileman & Rauchs, 2017). Unpublished theses provide more insight, but the rigour is questionable since this body of work is not extensively peer-reviewed. Schuh and Shy (2016) looked at US consumer adoption of cryptocurrency. Spenkelink (2014) in his thesis on the adoption process used qualitative research to synthesise salient factors from Innovation Diffusion Theory to arrive at a systems dynamics model. Roos (2015) in his thesis focused on cryptocurrency adoption by SMEs. Baur et al. (2015) in a conference paper using interview data looked at the perceived benefits of users, and the drivers behind the adoption of consumers and merchants. Penfold (2015) analysed mass adoption antecedents as a prerequisite for price stability as part of his efforts to create a model for cryptocurrency competition. Notably, Penfold (2015) identified the need to study adoption using the technology adoption model (TAM). Interestingly, no quantitative academic research could be found on the topic of consumer adoption directly, using Google Scholar (search date 2017 October). Accordingly, the need for the research presented here is evident.

Firstly, research outcomes will help to understand why consumers adopt cryptocurrencies. This is important for the viability of the currency (contingent on network effects) as well as for price stability – which is discussed later. Secondly, the research contributes to Information Systems (IS) research in the field of technology adoption. Research outcomes may allow generalisations to similar technology adoption in the future, i.e. where entirely novel and wide-ranging technologies originate organically from a decentralised user community. Lastly, the usefulness of the research proposed will inform the strategies of multiple stakeholders around the cryptocurrency ecosystem. This includes incumbent business interests of primarily the financial sector, financial technology ('fin-tech') companies offering cryptocurrency services, merchants looking to leverage of the trend in consumer adoption and policy and legislative arms of governments. The research will contribute to these stakeholders by identifying why consumers are adopting cryptocurrency (the use cases), what is it that leads to an intention to adopt, and lastly how this intention translates into actual usage.

This thesis begins with a literature review into the nature of cryptocurrencies, how it is (or isn't) money, and then a study of the technology adoption theory. First, the nature of cryptocurrencies is discussed, with a definition of cryptocurrency from the literature provided and a technical overview of its operation. Next, the nature of money is reviewed, to understand its centricity to the consumer, its social aspects, and finally to answer the question of "Is cryptocurrency money?". Finally, the preeminent technology adoption models are reviewed. This last aspect is critical to the development of the research methodology and of all factors will most influence the research questions targeted here. Technology adoption in step with the growth of technology, its ubiquity and transformative ability, has shown increasing interest in recent years (Chuttur, 2009; Venkatesh, Thong, & Xu, 2016). There are therefore several models from which to choose both complicating the choice as well as offering more tailoring options for compatibility with the problem domain. Using the selected adoption theory, a model is conceptualised that is then tested quantitatively for strength of effect and predictive power. The findings are used to provide insight to some of the key stakeholders already identified and as a first signboard for future quantitative research into cryptocurrencies.

A summary of the main research questions is provided next.

## 1.1 Research Questions

RQ1. What is the purpose of consumer adoption of cryptocurrency – transaction or investment?

RQ2. What factors influence individual consumer's behavioural intention to use cryptocurrencies?

RQ3. What factors influence individual consumer's usage of cryptocurrency?

## 1.2 Conclusion

The emergence of cryptocurrencies – notably Bitcoin has been outlined. Its relevance to businesses and consumers both as a transactional medium and as an investment asset has also been described. The dramatic value increases in various cryptocurrencies have been demonstrated to increase the interest of consumers most notably in South Africa in the last three months. Despite this mass attention, the research universe into cryptocurrencies and the reasons for adoption remain sparsely populated – a fact more apparent for quantitative research. The research presented here attempts to bring quantitative rigour to the understanding of cryptocurrencies and the reasons consumers adopt them. The remaining sections start with a review of the literature in the field of cryptocurrency and adoption theory before a research model is proposed. The methodology for statistically testing the hypothesised interactions for adoption of cryptocurrency is described. Thereafter, results are presented and discussed before concluding with the study's principal findings and their implications for businesses and management. Also, limitations and suggestions for future research are included in this last chapter.

# Chapter 2: Literature Review

The literature review to follow, broadly outlines the concept of cryptocurrencies and provides in sufficient detail the workings of the cryptocurrency system. A review of the history of money and its economic and philosophical definitions follow in order to inform the study's understanding of how consumers perceive the technology. Finally, to operationalise the study of consumer behaviour, an overview of technology adoption theory is provided. As far as the volume of research on cryptocurrencies itself goes, research papers start to be published around 2011 with peer-reviewed journals publishing works from 2013 (Baur, Bühler, Bick, & Bonorden, 2015). Academic development around the technology is therefore in its infancy – a more acute problem for adoption theory relating specifically to cryptocurrency.

## 2.1 An Explanation of Cryptocurrency

Cryptocurrency refers to virtual, decentralised, partially anonymous, and irreversible transaction system using cryptographically signed digital tokens with public traceability. Cryptocurrency, therefore, represents both a technology and a technology-enabled service. The "currency" in most cases is not backed by any government or commodity such as gold (Bjerg, 2016; Christian et al., 2014; Grinberg, 2012). The concept was introduced by a programmer using the pseudonym Satoshi Nakamoto in his or her seminal paper, *Bitcoin: A Peer-to-Peer Electronic Cash System* (Nakamoto, 2008). Nakamoto, who has yet to be identified, further adds that the currency is 'trust-less' in that counterparties do not require intermediation to ensure integrity. Bitcoin and alternatives are openly traded on multiple exchanges around the world where fiat currency is exchanged for cryptocurrency. The price of Bitcoin reached an all-time high closing at 6343 USD on October 31, 2017, on the CoinDesk Bitcoin Price Index (BPI) having closed at 997.69 at the start of the year (CoinDesk, 2017). An almost unprecedented increase in value, warranting further scrutiny.

Hileman and Rauchs (2017) defined four subsectors in the cryptocurrency industry: exchanges, wallets, payments, and mining. Users convert fiat currency into cryptocurrency using exchanges. The cryptocurrency is then stored on a user wallet that may be online or offline – the latter could be stored on a Universal-Serial-Bus (USB) storage drive. The wallet stores the keys to the user's cryptocurrency funds and facilitates payments and account balance calculations. Mining is part of the technical system that supports the cryptocurrency system and is discussed below. Hileman and Rauchs (2017) defined four use cases: Speculative digital asset/investment, medium of exchange, payment rail (for cross-border transactions), and non-monetary use cases.

Non-monetary use cases are beyond this study's scope. It is important to note that a consensus on taxonomy has not emerged with each author providing a slightly different view of the principal components of cryptocurrencies. Schuh and Shy (2016) pointed to the fact that economists themselves have not reached consensus and with virtual, digital and cryptocurrency being used interchangeably despite distinct differences, exacerbating confusion amongst consumers. A recent study by the University of Cambridge provides some insight into the scale of the cryptocurrency ecosystem with an estimated 2.9 to 5.8 million unique active users operating cryptocurrency wallets (Hileman & Rauchs, 2017).

In the following sections, a technical overview of the cryptocurrency system is provided. This includes a general overview of the technology's primary workings, a description of how ownership is recorded on the transaction chain, and the incentive system that provides the infrastructure that enables the entire system. A look into cryptocurrencies beyond Bitcoin is presented. Finally, a summary of the advantages and disadvantages of cryptocurrency compared to traditional instruments is presented.

### 2.1.1 The Technical Operation of Cryptocurrencies

At the time of writing there were more than a 100 alt-coins active, with three making up 74% of market capitalisation (CoinMarketCap, 2017b). While there are many innovative spins on the basic technology in these alt-coins, a look at the Bitcoin technology is instructive. What follows is based largely on the seminal work by Nakamoto (2008) supplemented by Badev and Chen's (2014) technical background paper and other sources as referenced. The summary to follow indicates that cryptocurrencies exhibit a complex architecture, the workings of which will be beyond most consumers (Badev & Chen, 2014).

Nakamoto (2008), in developing Bitcoin sought to solve two problems in e-commerce: (1) high trust related transaction costs and (2) the double-spend problem (Nakamoto, 2008). In the first problem, third parties are required to ensure integrity in electronic payment systems and provide mediation in dispute situations (Bjerg, 2016; Nakamoto, 2008). This led to the added requirement of irreversibility of payments. These costs, related to mediation, insurance, fraud, amongst others further result in a floor on the minimum viable transaction value. The second problem originates from the transition from physical to digital money. Physical money can only be spent once since each note is unique by way of its serial number. A digital asset, however, presents a double-spend problem since, by virtue of being digital, it can be copied and exist in multiple locations. This further increases costs by increasing the complexity of online systems, to ensure that funds are accounted for in the correct chronological order and that digital money cannot be spent more than once. To solve these problems, Nakamoto (2008) devised a mechanism involving a network of connected computers that ensure: (1) there is a single chronologically ordered public record of transactions and (2) a transaction chain records ownership pseudo-anonymously (Carr et al., 2015). Bitcoin's explicit aim was, therefore, the disintermediation of trust providers by negating the need for trust in transactions – it is therefore referred to as a 'trust-less' peer-to-peer transaction mechanism (Tapscott & Tapscott, 2016). Bitcoin at its core is simply a digital file that lists accounts and balances – a digital ledger (CuriousInventor, 2013). Every computer that participates in the Bitcoin network stores and updates a copy of the ledger. Since there are multiple copies, the system uses algorithms to determine which copy is the right one, based on consensus. The system uses public-private key cryptography, a commonly used technology in payments and communications, for instance, mobile instant messenger applications (Carr et al., 2015). The public key is akin to an account number on the ledger and a private key a password to access that account. These keys are typically stored in a user's wallet.

An explanation of the key components follows. It must be noted that the explanation below is a simplification intended to garner a conceptual understanding in the reader. The explanation is distilled from multiple sources (Badev & Chen, 2014; CuriousInventor, 2013; Grinberg, 2012; Nakamoto, 2008; Velde, 2013; Vit, 2013).

#### *2.1.1.1 Transaction Process*

To send money, a user broadcasts a digital signature that is a function of their private key and the message (Badev & Chen, 2014). The latter includes the amount to be transferred and the recipient's public key. This is done using cryptography, and since the signature is a function of the message and public key, each signature is unique and cannot be altered. Nodes – computers that participate in the network – use the signature and verify that the public key belongs to the signature. The public key is viewable by anyone on the shared blockchain – discussed below. The private key and therefore the user identity is never revealed since verification is conducted on the signature mathematically, and not directly on the private key using a hashing algorithm (Badev & Chen, 2014). More complex transactions are also possible. For instance, in an escrow situation, more than one private key may be needed to access funds. This requires programming the transaction itself. As an example Ethereum, a cryptocurrency platform which also has a currency (ETC), allows users to script more complex transactions amongst other non-currency related applications (Mougayar & Buterin, 2016). All transactions are recorded in a transaction chain.

### 2.1.2 The Transaction Chain

In actuality, there are no accounts and therefore no account balances. The ledger only records the ownership chain of Bitcoins in a transaction chain. Each transaction essentially creates a link to every other transaction since the first Bitcoin was created. Therefore, before a transaction is effected, nodes check the ownership of Bitcoins by looking at the entire transaction chain and calculating that the user has enough unspent input Bitcoins to make the transaction. These inputs are included in the transaction message and are known as reference inputs. The transaction chain is also the reason the network is not entirely anonymous since an analysis of the entire chain of transactions could reveal identity. Nevertheless, governments especially have slated cryptocurrency for enabling illicit transactions which have been highlighted in high profile public incidents such as the Silk Road money laundering scheme (Carr, Marsh, Dunn, & Grigorescu, 2015).

Since there is no central intermediary, and accounts are not linked to any particular owner, there is no recourse to challenge a transaction once effected. Transactions are permanent and irreversible. This also applies if the recipient address is incorrect or if the private key is lost. That is, without the private key, funds allocated to the public key on the public ledger are permanently inaccessible. Millions of dollars of Bitcoins are purported to have been lost in this way (Li, 2017). In addition, some services store private keys on their servers for the convenience of users which open up the potential for theft through hacking such as experienced by the Mt. Gox bankruptcy (Badev & Chen, 2014; Carr, Marsh, Dunn, & Grigorescu, 2015; Christian et al., 2014). Having discussed how ownership is accounted for, a mechanism for determining transaction order is required.

### 2.1.3 Transaction Ordering and the Consensus Mechanism

Due to network delays and fraudulent timestamps, it is possible to double-spend a coin – known as a double-spend attack (Carr et al., 2015; CuriousInventor, 2013). This could be done for instance by completing a transaction – transaction A – and after receiving delivery of the product or service, referencing the same input coins in another transaction - transaction B. Due to propagation delays, some nodes (i.e. computers operating on the network) will see transaction A first, while others will see B. Nakamoto, therefore proposed a consensus mechanism to ensure all ledgers and ordering of transactions were the same across nodes, i.e. a single record agreeing on whether transaction A or B was first.

New transactions are collected into a block on the chain every ten minutes by all active computers (called nodes) on the Bitcoin network (more appropriately the blockchain network). All transactions in a block share the same timestamp. Since some blocks may have different transactions due to network propagation differences (e.g. A or B), the network uses a probabilistic consensus method to determine which block is the "right" one. This mechanism involves nodes solving a mathematical puzzle – the first node to solve the puzzle broadcasts the block to be added to the chain. The longest chain then gets taken forward as *the* chain for future transactions. Transactions in blocks that were not selected - referred to as orphaned blocks – then get added to the next block. Solving the problem is known as "proof of work". Other consensus mechanisms have been developed, e.g. "proof-of-stake" (Mougayar & Buterin, 2016).

The blockchain is a chain because each math puzzle is a function of previous blocks. The puzzle is solved by making random guesses at the solution. A single node may take several years to solve a block by randomly guessing at the answer. However, the entire network will take on average ten minutes. In order to double-spend, an attacker node would have to add two blocks in sequence, referencing the previously spent inputs back to the attacker. Since the math puzzle to be solved is dependent on the previous blocks, a block cannot be pre-computed. Therefore, an attacker node would have to solve the math puzzle faster than the entire network for their block to be added and for their fraudulent blockchain – the longest chain – to be taken up by the rest of the network. To have a 50% chance of solving two blocks in sequence, the attacker would need more than 50% of the entire network's computing power (CuriousInventor, 2013). To corrupt blocks and therefore transactions further back in the chain would require even more computing power. The suggestion, therefore, is to wait 10 minutes to confirm a transaction or up to an hour (six blocks) for larger transactions (CuriousInventor, 2013). Nodes that add blocks to the chain are incentivised to participate in the system through a rewards scheme discussed next.

### 2.1.4 Mining and the Incentive System

New coins are created and awarded to the winning node each time a block is solved. This is an incentive system to participate in the network. The award value which started off as 50 nodes halves every four years until the year 2140 when the last Bitcoin will be mined (Badev & Chen, 2014; Grinberg, 2012). Incentives may then turn to transaction costs. Some alt-coins already include transaction costs. The coin award represents a deterministic growth of the money supply contrary to the current practice of governments to grow the money supply unilaterally (Badev & Chen, 2014). However (Yermack, 2013) notes that the growth rate seems to not hinge on any economic optimum. This mining mechanism is also an incentive to miners to behave honestly since it is more lucrative to use massive computing power to earn Bitcoins through mining than to attack the network (Nakamoto, 2008).

Initially, mining was performed by hobbyists. However, specialist mining hardware (computers) have been developed making the mining process a professional endeavour (Hileman & Rauchs, 2017; Spenkelink, 2014). As hardware improvements are made, the difficulty of the math puzzle is increased to ensure a probabilistic solution time of ten minutes. While lower transaction times are possible (e.g. LiteCoin uses 2.5 minutes), the time target ensures a low probability of two nodes solving a block at the same time (Nakamoto, 2008). The costs related to mining are therefore the capital cost of mining hardware and the operating costs of electricity. Essentially miners are exchanging electricity for coins.

### 2.1.5 Alt-Coins

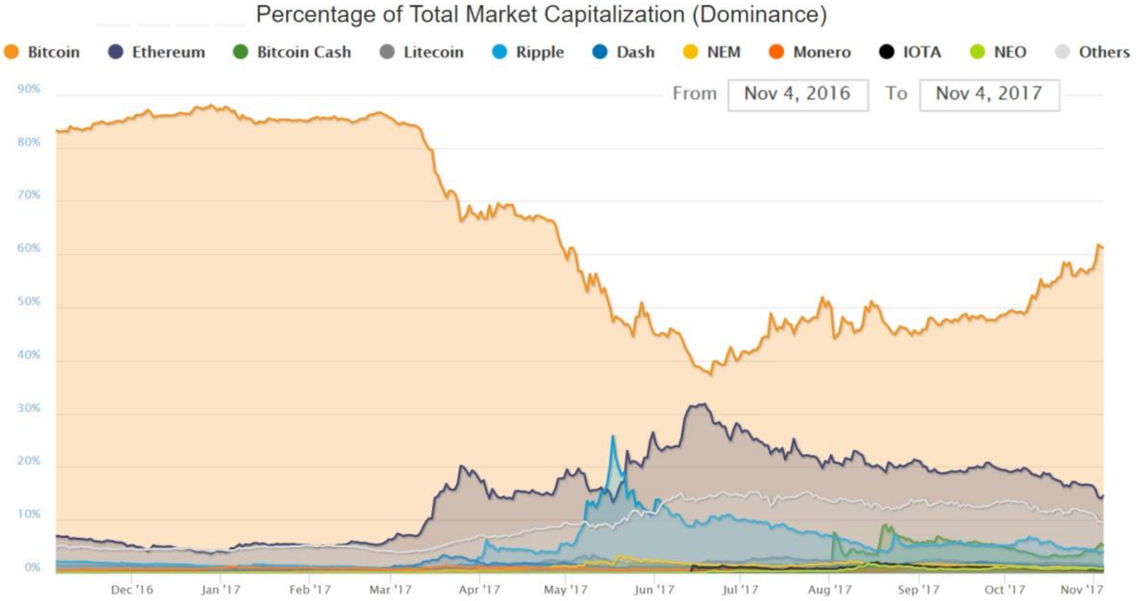
Bitcoin has spurned a variety of copy-cats as well as novel cryptocurrencies that act more as platforms than mere currencies, such as Ethereum. Table 1 shows the market capitalisation of Bitcoin and other alt-coins indicating a substantial but diminishing share for Bitcoin. Bitcoin, while ceding market share to others, remains dominant with a 58% share (CoinMarketCap, 2017b). Figure 5 shows how the market has evolved in the last 12 months – with the Ethereum 'alt-coin' the primary competition for Bitcoin.

Table 1: Top five cryptocurrencies by market capitalisation (CoinMarketCap, 2017a).

| # | Logo | Name | Code | Market Cap | %Change | Price | %Change |
|---|---|---|---|---|---|---|---|
| 1 | | Bitcoin | BTC | $ 97,487,611,018.00 | 821% | $ 5,855.78 | 782% |
| 2 | | Ethereum | ETH | $ 28,595,818,259.00 | 2793% | $ 299.96 | 2490% |
| 3 | | Ripple | XRP | $ 7,930,291,620.00 | 2418% | $ 0.21 | 2266% |
| 4 | | Bitcoin Cash | BCH | $ 5,748,689,098.00 | N/A* | $ 343.94 | N/A* |
| 5 | | Litecoin | LTC | $ 3,031,354,841.00 | 1463% | $ 56.62 | 1305% |
| *12-month price changes calculated on October 27, 2017* | | | | | | | |

* BCH less than 12 months old.

Figure 5: Evolution of market share of various cryptocurrency coins (edited) (CoinMarketCap, 2017a).




What is common amongst these, and therefore what makes them cryptocurrencies, is their distributed nature, use of cryptography to ensure integrity, and the use of the underlying blockchain technology to order transactions. Variations include the consensus mechanism used, the cryptographic algorithms used, the math problem that must be solved, value and nature of awards, privacy mechanisms, and block solution time amongst others. The open-source nature of the programs that are Bitcoin lends itself to competition along the lines of Hayek's theory of competitive currencies (Ametrano, 2016). Since the barriers to entry are low, competing currencies can and have emerged. This implies that Bitcoin's existence is by its nature dependent on its ability to competitively service its customers (Bjerg, 2016).

Ethereum, the second most popular alt-coin by market capitalization, is also a blockchain and cryptocurrency development platform (Tapscott & Tapscott, 2016). It enables developers to create their own currencies and applications that run on the blockchain. It is, therefore, more of a blockchain technology than a currency platform. This leads to programmable digital money and smart contracts where immutable contractual requirements could be built into a transaction. Autonomous applications could further operate by ensuring terms of transactions are met by consulting databases in which events are stored – referred to as oracles (Mougayar & Buterin, 2016; Tapscott & Tapscott, 2016). Blockchain technology and its applications have therefore garnered more mainstream acceptance than cryptocurrencies. The blockchain is often referred to as an immutable distributed ledger. Interest in blockchain technology, conceived by (Nakamoto, 2008) as part of Bitcoin, has therefore taken on a life of its own but is still linked to its progenitor Bitcoin and the adoption of cryptocurrencies (Hileman & Rauchs, 2017). The fundamental novelty of the entire technology and its use, therefore, goes beyond digital money.

#### 2.1.6 A Summary of the Advantages and Disadvantages of Cryptocurrency

A summary of the major benefits claimed by cryptocurrency and distilled from the preceding explanatory sections appears here. Benefits are as follows:

1. Cryptocurrency core algorithms are usually open-source and rely on the consensus of the crowd which means it is highly resistant to counterfeiting or subverting the network for a single entity's objectives.
2. Low-cost transactions are possible by reducing reliance on complex systems of reconciliation provided by third-party trust providers.
3. The ability to prevent double spending through the distributed nature of the network and the probabilistic method used to add new transactions to the chain.
4. The commonly employed limit of coins in the network (e.g. BTC limited at 21 million coins) results in the inability of central control to artificially create money thereby causing inflation. This could, of course, be a negative for central authorities who use the monetary system as a national tool for influencing the money supply.
5. The transaction speed and permanence of transaction records without any intermediary. Speed is almost real-time – taking ten minutes to process a block in the Bitcoin system and smaller time spans for other cryptocurrencies. This speed is relative to clearing times for traditional payment systems.
6. The decentral nature of the network results in resilience with no single point of failure and the inability of single entities to subvert the technology.
7. The protection of privacy through the quasi-anonymity provided by private-public key cryptography. A pertinent benefit as identity theft becomes more prevalent due to the availability of information in internet-connected databases leading to hacking and large-scale data breaches.
8. The public availability of transaction data results in increased transparency without sacrificing personal privacy.
9. Scalability of the system which is inbuilt in term so incentivising new miners as well as automatically adjusting block clearance times.

Some of the disadvantages or weaknesses (which are somewhat a matter of perspective and ideology) are:

1. The ability to use the pseudo-anonymity for illicit purposes and to bypass national regulations.
2. The illiquidity of the market – even during the price booms of the past year – where costs incurred included those related to large bid/ask spreads and fees for wallets, exchanges, and other services eating into the advantage of low-cost transactions (Carr, Marsh, Dunn, & Grigorescu, 2015).
3. The dependence on a disparate group of developers who maintain the code and their ability to reach decisions on technical decisions on the future of the technology. Such as was recently experienced in the Bitcoin fork due to the scaling debate – a topic beyond the scope of this research (Rao & Sutton, 2014).
4. The extreme price volatility resulting in exchange-rate risks between cryptocurrencies and fiat currencies creates an additional costs of holding coins.
5. The fact that there is no recourse if a user has lost their private key. Estimates on irrecoverable Bitcoins are already at 25% of all coins in issue (Li, 2017).
6. The irreversibility of payments makes recourse for incorrect transactions a problem since it requires a reimbursement through agreement between the counter-parties.

Having discussed the mechanisms through which cryptocurrencies operate and the resultant benefits and disadvantages, the discussion turns to the nature of cryptocurrency as money followed by how it is used in actuality.

## 2.2 Money

Since the creator of Bitcoin sought to introduce a new form of digital money, it is important that both the economic and philosophical constructs of money is understood. The question to be asked – if not obvious – is, is Bitcoin money? Carr et al. (2015) pointed to the characteristics of cryptocurrency spanning multiple categories including currency, financial asset, and technology protocol. Further, economists refer to money as a social contract (Salemi, 2012). The social dimension of the money concept is, therefore, necessary to understanding consumer adoption. The sections to follow start with a look at the economic theory before discussing one philosophical view in relation to Bitcoin. However, first, a brief history of the evolution of money is instructive in the understanding of cryptocurrency as money.

### 2.2.1 A Brief History of Money

Money in its current form is fiat money in which its value is regulated and guaranteed by governments, or more correctly by the central banks of those governments. This applies to most nation states today (Salemi, 2012). Fiat money by definition derives its value by the decree of the central authority – government – and the (often implicit) trust its citizens place in it. Its development was a function of necessity and has developed in tandem with socio-economic changes in human history. The evolution of social organisation started with hunter-gatherers, through pastoral and agrarian societies and then to industrialised and post-industrialized nations (Boundless, 2016). The latter two categories represent most of the world today. This evolution exhibits increased productivity due to increased specialisation or the division of labour. Adam Smith opined in his seminal text, The Wealth of Nations that “The greatest improvement in the productive powers of labour … seem to have been the effects of the division of labour” (Smith, 1976, p. 8). However, in order for specialisation, a means of exchanging one’s specialised productivity outputs for other needs and wants is fundamental, i.e. the need for trade. Money seeks to create a more efficient means of trade significantly lowering transaction costs at each stage (Miles, Scott, & Breedon, 2012).

Salemi (2012) provided a brief history. Trade proceeds from barter in the earliest social structures to the use of fiat money today. The move from barter to money solved the problem of the double coincidence of wants, i.e. the problem of finding someone with the required good needing a good that one happens to have in one’s possession and of the goods being of equivalent value. The earliest form of money was based on some agreed upon scarce commodity, often chosen by some governing authority. However, these commodities were not necessarily valued in other societies, and so coined money developed due to the prevalence of metals being held as valuable, the intrinsic value of metals in use, durability, and its transportability. However here too, transaction costs in the form of validating metal content and weighing were prohibitive. Paper money backed by a commodity was the next stage in the evolution. Paper money originated in the practice of storing one’s precious commodities in secure places (such as a temple) and receiving a receipt for the deposit. The realisation that receipts could be traded rather than withdrawing a deposit results in the concept of paper money. As an aside, depositories realised that they could issue loans on the deposits of their customers beyond the actual value of the deposits held, since not all depositors would withdraw their holdings simultaneously. This is the origin of the fractional reserve banking system present today where banks may lend a multiple of their deposit holdings (Miles, Scott, & Breedon, 2012). In 1844, the Bank of England established a direct link between the gold it held and the amount of money in circulation. This became known as The Gold Standard.

The Gold Standard, came to an end in 1973 when the president of the United States (US), Richard Nixon, decreed that dollars be no longer be redeemable for gold, the result being fiat money. Globally, this was however not an isolated decision and was due to multiple pressures including financing the two World Wars and of gold supply failing to match economic growth (Yermack, 2013). Fiat money or money that is valuable due to the decree of the government is, therefore, the current status quo. Potentially the next stage of this evolution is not only digital but cryptographic.

The history just presented endeavoured to show that money and its value are determined by the mutual agreement of those who use it, involving trust, and is therefore inherently a social construct. Further, it is evident that at least initially, the practicality of reducing transaction costs to allow easier trade, and thus greater specialisation and economic output has led to its evolution. While transaction costs are still a driving factor, more recently its evolution has been due to governments seeking centralised control over their economies in an increasingly globalised world. This leads to the question of what exactly is money and how do cryptocurrencies relate to this concept. This will allow us to understand how consumers perceive Bitcoin and move us closer to an answer to the question, is Bitcoin money?

### 2.2.2 The Economic Definition of Money

Economically, money is defined as a medium of exchange, store of value and unit of account (Miles et al., 2012). Yermack (2013) argued that Bitcoin is not money against this definition by systematically looking at each of its three components.

As a medium of exchange, Yermack (2013) argued that the bulk of activity is between speculative investors, with a minuscule proportion involved in trade. Supporting this assertion, he cites a 2014 CoinBase figure of 20% of activity apportioned to transactions with the rest being speculative. However, Yermack himself noted that this is up from 5% a year earlier. A more recent study by Hileman and Rauchs (2017) using report data from a CoinBase/Ark report, again estimated that 46% of its users use Bitcoin for transactions. Badev and Chen (2014) found that almost half of all BTC have been used for transactions. In addition, econometrics results from studies in the US indicate that consumers at least view cryptocurrency as a means of payment (Schuh & Shy, 2016). From the time of each of these figures, an increasing trend is apparent. Further analyses on usage, is provided in a dedicated section later.

Secondly, usability is cited as being a barrier to adoption (Carr, Marsh, Dunn, & Grigorescu, 2015; Spenkelink, 2014). However, it is arguable that usability and understanding of the underlying technology are moderated by technology maturity. A review of the adoption of the internet is instructive. Initially, internet usage was amongst technically astute academics and researchers who employed the technology for narrow purposes. As the technology matured, understanding the underlying technology became less important. Today, the complexities of the underlying protocols and mechanisms through which applications and web browsers deliver content are all but obfuscated to end-user eyes.

Lastly, Yermack (2013) cited price volatility as a barrier, since consumers and merchants are disincentivised to hold cryptocurrency – instead of exchanging it for fiat currency almost immediately. As stated above, more merchants are accepting Bitcoin as payment, but this is quickly converted into fiat currency. Merchants interviewed, indicated that the primary reason for accepting Bitcoin was to seem innovative, i.e. as a marketing tool (Baur, Bühler, Bick, & Bonorden, 2015). Yermack's view was validated by Baur et al. (2015) who found in their qualitative study that volatility was seen as the main threat by merchants and consumers. Penfold (2015) found similarly that mass adoption was conditional on price stability. However, Yermack's assertion may be premature, given the recency of its development, and is, in fact, trending downwards in volatility, forecast to reach fiat currency levels by 2019 (Simnett, 2017; WillWoo, 2016). Nevertheless, Carr et al. (2015) report estimates ranging from five to seven times higher volatility than regular foreign exchange trading. As a unit of account, the volatility of the currency is raised as a disqualifier with significant disparity between prices and a departure from an efficient market paradigm, i.e. a single price. As a store of value, again Yermack (2013) cited its extreme volatility as a non-starter comparing Gold and other developed economy currencies. Yermack (2013) therefore surmised that Bitcoin is in fact not a currency but rather a speculative investment akin to gold. Perhaps unsurprisingly, it is this volatility that has attracted wide interest in cryptocurrency as a speculative investment (Schuh & Shy, 2016). In fact, the US Internal Revenue Service has categorised cryptocurrencies as property for this reason (Badev & Chen, 2014).

### 2.2.3 A Philosophical Perspective on Money

Contrary to Yermack's (2013) dismissal of Bitcoin and therefore cryptocurrency as money, Bjerg (2016) took a more philosophical approach to the concept of money in analysing the question: "Is Bitcoin money?". This question inspired by the economic failings of our current system is at its heart a questioning of long-held fundamental beliefs and definitions of money. In fact, much of our monetary theory, such as Keynesian economics is undermined by cryptocurrencies as by their very definition prevent interference by a central authority. Bjerg (2016) in reformulating the concept of money looked through the ontological orders of Slavoj Žižek – real, symbolic, and imaginary. In the deconstruction – for which a summary follows – Bjerg used three general economic theories on the concept of money.

Firstly, using the commodity theory of money, e.g. The Gold Standard, Bjerg argued that Bitcoin is "a more honest form of gold money" (Bjerg, 2016, p. 60). Gold lacks (relative) intrinsic value with its value being derived by its connection to money – it is therefore symbolically linked to money. On the other hand, Bitcoin accepts the arbitrariness of the value of gold by negating the need for commodity backing and directly leveraging the value of money as originating from the social contract – i.e. it has value because we accept it does. Bjerg titled this analysis the Gold Standard without gold since the growth of the Bitcoin stock is algorithmically pre-determined and scarce, and similar to a finite, scarce commodity where effort must be expended to increase the stock (Badev & Chen, 2014).

Secondly, he used the chartal theory of money, where the state creates money by demanding payment in its created money (Arestis & Sawyer, 2006). The value of money is, therefore, a desire by the state – referred to as the big Other in the symbolic order. By legally anointing that debts to the state, such as taxes, are paid in this created money, a cascade of demand is initiated, where private actors demand this money to comply with the law. The state, therefore, creates both supply and demand. The mechanism of this creation of value is then inculcated in all private actors in the economy so that the desire of the big Other is now the desire of the public. With Bitcoin, however, its value is due to the social community that agrees it is valuable. Even without a central authority to drive supply and demand, Bitcoin is being used for trade with more and more corporations and retailers accepting it for payment (Hileman & Rauchs, 2017).

Lastly, in the credit theory, money is defined in its relation to credit. Commercial banks create "credit money" through the fractional reserve banking system. This credit money is then spent as if it was fiat money. Value is linked to the credit-worthiness of the debtor for which banks are "the sublime creditors" (Bjerg, 2016, p. 65). Bjerg further argued that this credit money is, today, almost exclusively virtual with ledgers recording the relationship between debtors and creditors. Using this fact, Bjerg drew attention to the fundamentally different way Bitcoin creates new money. That is, the new money is free from debt and deterministically created. Banks, therefore, cannot lend Bitcoin without having deposits and cannot create Bitcoins artificially by crediting a borrower's account.

Using the three arguments above, Bjerg argued that current forms of money, under existing theories, all exhibit a form of exploitation and risk, which once integrated into the economic fabric is accepted as natural. These same risks, in diametric opposition to Yermack's normative economic argument, leading Bjerg to conclude that Bitcoin is "in some sense a fake form of money" (Bjerg, 2016, p. 68). Or, at least, "Bitcoin is no more fake than more conventional forms of money" (Bjerg, 2016, p. 68). Bjerg's logic, therefore, points to social-cognitive aspects of the value of money rather than the current economic theories which he deemed inadequate to deal with the novelty of cryptocurrencies. These social aspects are key to understanding the adoption of cryptocurrency by consumers without being constrained by potentially outmoded constructs. However, it is notable that perceptions are the operative constructs in much of the adoption literature, and it is there where at least currently, Bjerg's argument may fail. Bjerg (2016) summarises:

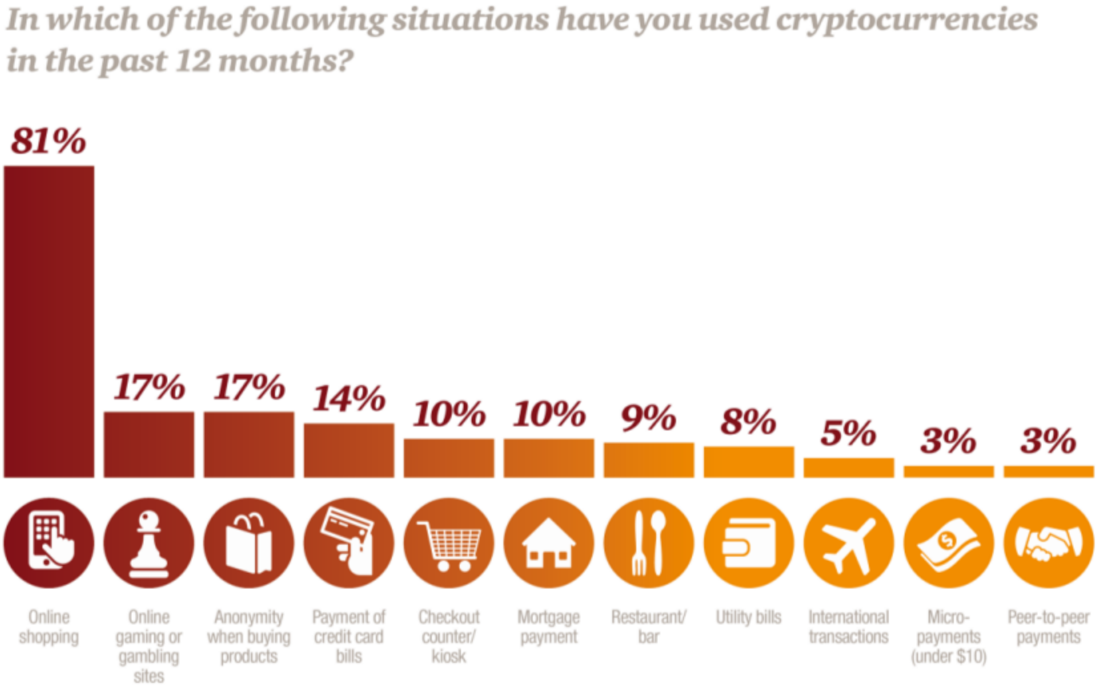
> "Our analysis of Bitcoin may thus be summarised by a paraphrase of Winston Churchill's famous remark about democracy: 'Bitcoin is the worst form of money, except for all the others" (p. 69).

## 2.3 Cryptocurrency Usage

This section summarises some of the available research and reports on cryptocurrency usage. As noted above, the pseudo-anonymous nature of cryptocurrencies makes studying direct usage difficult. Despite this difficulty, through the use of surveys, analysis of the public blockchain, and access to proprietary databases, a picture of the cryptocurrency user begins to emerge.

PricewaterhouseCoopers' (PWC) Financial Services Institute conducted a survey of US consumers in 2015 (Carr et al., 2015). In PWC's 2015 consumer survey only 6% of consumers were very or extremely aware of cryptocurrencies with only 3% actually having used cryptocurrency in the preceding year (Carr et al., 2015). The findings indicated that due to volatility, the largest number of users are speculator investors. Of the use cases, 81% used cryptocurrency for online shopping, followed by 17% for online gaming and to remain anonymous when buying online. The full result for use cases is presented in Figure 6. The study noted that the full potential of cryptocurrency would be reached once volatility reduces and transactions become the primary use case. In fact, 86% of those who had used cryptocurrencies in the preceding year indicated they expect their use to increase going forward. Penfold (2015) validates this positive outlook in his study using interview data. Spenkelink (2014) further found mass adoption would follow price stability. Amongst concerns in PWC's survey were, in order of importance: fraud, price stability, and acceptance by vendors.

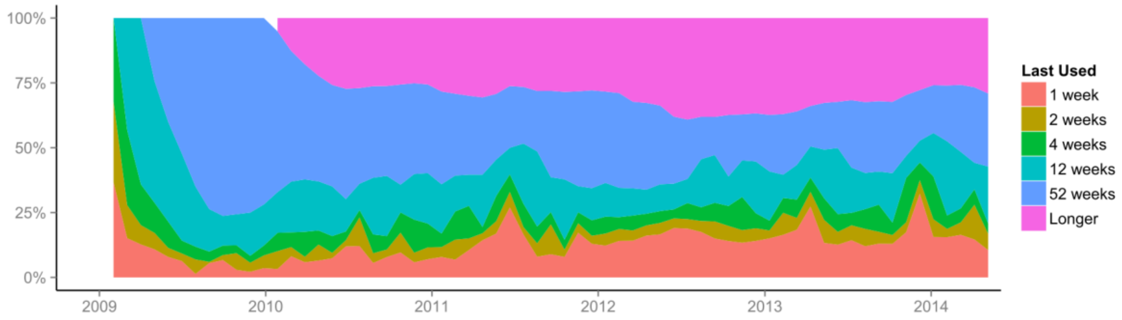
Figure 6: Results from a 2015 consumer cryptocurrency survey (Carr, Marsh, Dunn, & Grigorescu, 2015).




Schuh and Shy (2016) lay claim to the first national academic study on consumer adoption in the US. They used data from the Federal Reserve Bank of Boston collected through the annual Surveys on Consumer Payment Choice (SCPC) which specifically asked about Bitcoin as well as other cryptocurrencies. Using SCPC data, they found that only 47% of US consumers had heard of a cryptocurrency of which 90% were only slightly or not at all familiar with cryptocurrency. Awareness and use of cryptocurrency were correlated with high income or highly educated males. Interestingly, less educated younger males were more likely to own Bitcoin due to expectations of value appreciation. A small minority – at most 1.5% – have ever owned a cryptocurrency. Almost all adopters had used a cryptocurrency for payment and indicated this use case as the primary reason for adoption. Payments as the primary reason for adoption increased from a third in 2014 to two-thirds in 2015.

Christian et al. (2014) looked at the intentions behind cryptocurrency usage of individuals by analysing an exchange's data and publicly available blockchain data. The dataset is limited to the period between January 2011 and October 2013. This is during the initial stages of mass media interest in the currency. The researchers by looking at the relationship between volume traded and volume on the Bitcoin system found that new users treat Bitcoin as an investment. This indicated that new users were keeping their Bitcoin. Badev and Chen (2014) used a different methodology to analyse usage. They looked at velocity; calculated as how often Bitcoin addresses change. Addresses were categorised as an investment for those addresses that were dormant for at least a year. They found that 'investment accounts' were 75% of all addresses although there was a trend towards lower proportions. They further found that approximately 50% of transactions were under 100 USD. Christian et al. (2014) also looked at how price changes reacted to events and found that users were positively biased with no significant effect for negative news. This may indicate a trend-chasing bias. Based on these two studies, investment may be the primary use case currently.

Figure 7: Value-weighted number of Bitcoin addresses categorised by last use (Badev & Chen, 2014).




## 2.4 Technology Adoption

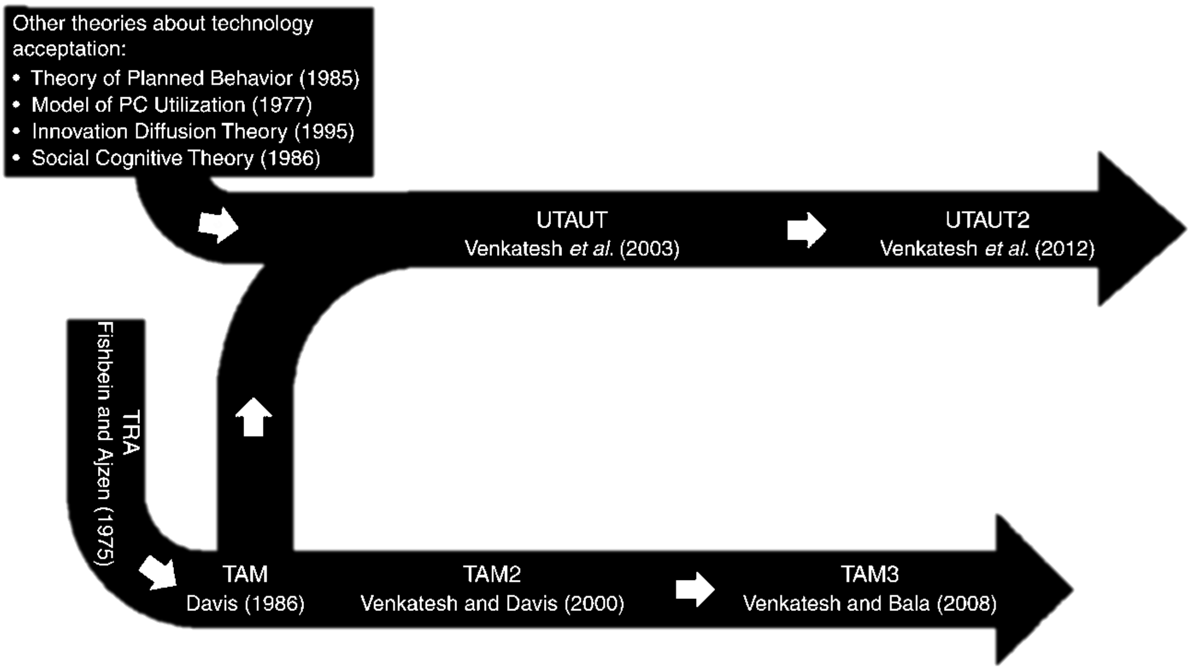
There are various models that study the adoption of new technologies and innovations. These models, in general, have found widespread use but are not without their critics. Furthermore, each model is configured for specific use cases by virtue of their design choices from preceding social, psychological, and cognitive theories (Straub, 2009). To choose an appropriate model for studying cryptocurrency adoption, the various models are reviewed in relation to their ability to capture the novelty of the currency innovation and the consumer context.

Rogers (1995) defined innovation as "an idea, practice or object that is perceived as new by an individual or other unit of adoption"(p. 11). Straub (2009) further highlights both that it is the perception of novelty rather than the reality of it that is important. Also, innovation does not necessarily mean improvement. These are important points, since cryptocurrency may be adopted for a variety of means, and not solely based on a rational evaluation of utility. Straub (2009) further distinguishes between adoption and diffusion, referring to the former as a micro-perspective examining an individual's choices on, and the extent to which, an innovation is accepted and integrated. Diffusion, on the other hand, is a macro-perspective studying the spread and evolution of an innovation across time and where the unit of study is a population. Nevertheless, he noted, that these concepts are fundamentally interdependent and indistinct. On the other hand, Straub

(2009) surmised that most theories share three categories of characteristics: individual, innovation, and contextual characteristics. Straub (2009) further asserted that all models are based on Social Cognitive Theory by Bandura (1997), whether implicitly or explicitly. Specifically, two of the concepts of social learning and self-efficacy are highlighted. The former refers to learning through the experiences of others – vicarious learning. This is an important concept for the proposed research for two reasons. Firstly, money, as discussed above, is a social contract. Secondly, cryptocurrency being an internet technology would lend itself to the influence of online social networks. The second concept, self-efficacy, refers to the belief of an individual in their ability to complete a specific task in a given situation. The specificity of the task distinguishes self-efficacy from broader concepts of self-esteem and self-confidence. These two concepts are at the heart of much of the attributes influencing adoption.

Adoption is measured in terms of behavioural change with the predictors understood through either contextual, cognitive or affective factors, while no single theory incorporates all of these (Straub, 2009). Each theory, therefore, provides a limited perspective. In this study, the context is a consumer one, and both affective and cognitive factors require study. The discussion considers therefore which model covers these aspects most appropriately. The discussion begins with an overview of the evolution of the various theories.

Figure 8: The evolving theory of technology acceptance taken from (Rondan-Cataluña, Arenas-Gaitán, & Ramírez-Correa, 2015)



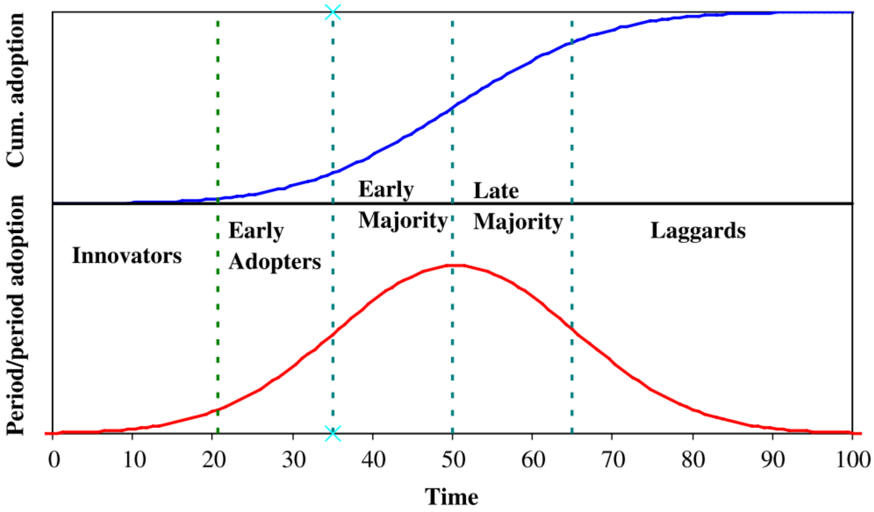
Rondan-Cataluña et al. (2015) conducted a comparative study of the different adoption models and provided an origin history as well. The first model on technology acceptance could be considered the Theory of Reasoned Action (TRA) (Fishbein, M. & Ajzen, 1975). Fishbein and Ajzen (1975) asserted that "the best predictor of a person's behaviour is his intention to perform the behaviour…" (p. 381). Fishbein and Ajzen (1975, p. 382) however, cautioned that intent is "viewed as the immediate antecedents" to behaviour and that intervening events may change intent up to the point of usage. Usage as a construct is also ill-defined and may imply actual usage (through direct measurement), reported usage (such as through surveys or interviews), assessed usage (reported on an ordinal scale) (Wu & Du, 2012).

Thus TRA introduced the concept of behavioural intention as a determinant of actual behaviour (Rondan-Cataluña et al., 2015), a concept repeated in most adoption models to follow. Preceding this, and not strictly an adoption model, the first of the adoption/diffusion models to see widespread use was the Innovation Diffusion Theory (IDT) by Everett Rogers in 1962. Later, The Technology Acceptance Model (TAM), was proposed by Davis (1985) based on behavioural change and informed by TRA and the Theory of Planned Behaviour (TPB). TRA and TPB have not found widespread usage in recent academic work based on a cursory search of academic databases. Various expansions and alternative adoption models have also developed since. These include the TAM2, TAM3, and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM and UTAUT are borne explicitly out of a need to understand Information Systems (IS) adoption (Straub, 2009; Venkatesh & Davis, 2000). IDT provides a broader framework and includes a macro perspective on diffusion. The literature review is therefore limited to IDT, TAM, and UTAUT due to their recency and frequency of use in academic literature.

### 2.4.1 Innovation Diffusion Theory (IDT)

The description that follows is based on the analysis by Straub (2009) and Meade and Islam (2006) of IDT by Rogers (1995) as presented in his book *Diffusion of Innovation* together with various other sources as referenced. Innovation was defined by Rogers (1995) as "an idea, practice, or object perceived as new" (p. 11). A commonly used IDT model in business and academia is the adopter distribution and cumulative adoption curve (also used as a surrogate for market share) (Meade & Islam, 2006). The curve is a normal frequency distribution divided into five sections using standard deviations from the mean (Rogers, 1995). This results in Rogers' (1995) five categories of adopters: innovators, early adopters, early majority, late majority, and laggards. The frequency of adoption naturally correlates with a cumulative adoption curve that tracks the frequency of adoption. The curve is shown in Figure 9.

Figure 9: Adoption frequency and cumulative adoption curves as taken from (Meade & Islam, 2006).




In Rogers' (1995) work, adoption processes directly affect diffusion. The diffusion effect was defined by Rogers (1995) as "the cumulatively increasing degree of influence upon an individual to adopt or reject an innovation, resulting from the activation of peer networks about the innovation in the social system" (p. 234). This relates to cryptocurrency adoption, as the study is only useful in so far as it leads to insight into mass adoption. The adoption decision has five stages: awareness of innovation affected by personal traits, and socioeconomic factors; (2) persuasion where an individual gains sufficient knowledge to make a judgement; (3) decision to adopt or reject; (4) implementation, i.e. usage and finally (5) confirmation, where a second decision on continuation of adoption is taken. As stated above, the adoption process of individuals as sub-units leads to diffusion which is a special form of communication. The primary components are, therefore (1) the actual innovation (2) communications channels, (3) social system and (4) time. First, innovation attributes are reviewed. Rather than looking at the general framework proposed by Rogers, Moore and Benbasat (1991) adapted the five attributes for use in IS adoption research. The constructs were determined through a rigorous testing and validation process, which used factor analysis amongst other statistical tools to determine the most valid and reliable constructs. The attributes of the innovation that were found to be positively correlated with adoption are presented as follows:

i. Voluntariness: The degree to which usage is perceived to be voluntary.

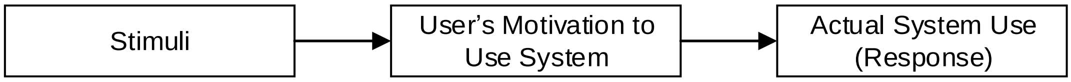
ii. Relative Advantage: The perception of the innovation being better than previous similar ideas.
iii. Compatibility: The degree to which one perceives the innovation as being aligned with existing values and past experiences of the individual.
iv. Image: The degree to which the use of the innovation enhances one's status in the organisation or social group.
v. Result Demonstrability: The degree of tangibility of the results which includes how observable the results are and how they are communicated.
vi. Ease of Use: The perception of the difficulty to comprehend the innovation. Ease of use is the opposite of the perception of complexity originally proposed by Rogers (1995).
vii. Visibility: How visible the innovation is. This leads to a social threshold where the pervasiveness of the innovation leads to more individuals considering adoption.
viii. Trialability: The opportunity to experiment with the innovation.

While Rogers' (1995) IDT is general, Moore's conceptions were developed specifically to organisational contexts. The effect of this on usage in consumer contexts is therefore unknown. The applicability may still be valid, given that Moore's context was for initial adoption in a voluntary context. Spenkelink (2014) used IDT attributes proposed by Moore and Benbasat (1991) in his qualitative analysis to create a model explaining the factors influencing cryptocurrency adoption. Spenkelink (2014) further conducted expert interviews through which he validated his model. However, no quantitative analysis applying the instrument developed by Moore and Benbasat (1991) on end-users adoption was conducted. The remaining three components of IDT are communication channels, social system, and time. Communication channels refer to the means through which information on the particular innovation spreads (Straub, 2009). This includes the effect of mass media. The social system refers to context, culture, and environment. Time was conceived in a diffusion curve that has become a popular tool to explain the evolution of adoption - Figure 9.

### 2.4.2 Technology Acceptance Model (TAM)

TAM was based on the Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB) which sought to understand intention as a mediator between an individual's attitudes and primarily in the field of social psychology action (Slade, Williams, & Dwivdei, 2013; Venkatesh & Davis, 2000). TAM sought to include both cognitive and affective determinants of behavioural intention and actual usage (Rondan-Cataluña et al., 2015). Therefore TAM, as well as UTAUT, expanded on the technical aspects of the innovation to include social and individual factors (Koenig-Lewis, Marquet, Palmer, & Zhao, 2015). Overall TAM and UTAUT (discussed later) operate on the basic conceptual model in Figure 10. The link between user intent and usage is examined in section 2.7 below.

Figure 10: Conceptual Model of Technology Acceptance adapted from (Davis, 1985)




The basic model proposed by Davis (1985) stated that usage is determined by perceived usefulness (PU) and perceived ease of use (PEOU) with PU the stronger moderator (Davis, 1989; Venkatesh & Bala, 2008). TAM is cited as explaining 40% of the variance in Information Technology (IT) systems usage (Venkatesh & Bala, 2008). This is a good point to highlight Davis' caution applicable to the rest of this discussion that PU and PEOU are subjective measures not necessarily reflective of society and are not a replacement for objective measures (Davis, 1989). Since its initial conception, the model has undergone an expansion to include factors affecting these two constructs and has subsequently resulted in TAM2 (Venkatesh & Davis, 2000), and TAM3 (Venkatesh & Bala, 2008).

Since PU was found to typically have an R-squared of 0.6, research focused on unpacking this concept first. In TAM2, researchers proposed two groups of factors that influence PU – social influence (SI) processes and cognitive instrumental processes. Some of these factors were found to not only influence PU but to interact with each other and directly on intention (Venkatesh & Davis, 2000). The determinants of perceived usefulness were found to be perceived ease of use – the second direct determinant of intention; subjective norm; image; job relevance; output quality; and result demonstrability (Venkatesh & Bala, 2008). Image and result demonstrability were taken from Moore and Benbasat (1991) above. Perceived ease of use is again similar to Moore and Benbasat's (1991) construct. The remaining three concepts are defined as follows (Venkatesh & Bala, 2008):

- Subjective Norm: The perception of an individual that those important to him/her think he/she should use the system.
- Job Relevance: The perception of applicability of the innovation to the individual's job.
- Output Quality: The degree to which the individual perceives the innovation assists in their job performance.

The four constructs of perceived ease of use, job relevance, output quality, and result demonstrability are part of the cognitive instrumental processes. Arguably, the former two concepts are specific to an organisational context. The remaining constructs are part of the social influence processes. Notably, subjective norm was theorised to attenuate with experience (Venkatesh & Davis, 2000).

TAM2 was further expanded to include determinants of perceived ease of use to form TAM3 (Rondan-Cataluña et al., 2015). The determinants are a degree of the following beliefs (Venkatesh & Bala, 2008):

- Computer Self-Efficacy: The ability to perform a specific task.
- Perception of External Control: The level of support deployed by the organisation for the use of the innovation.
- Computer Anxiety: Apprehension or fear related to computer usage.
- Computer Playfulness: Spontaneity in computer usage.
- Perceived Enjoyment: Enjoyment of system usage aside from outcomes.
- Objective Usability: Actual, rather than perceived, usability relative to other systems.

TAM3 represented a slight improvement over TAM2 in predicting behavioural intentions (Venkatesh & Bala, 2008). However, the importance of the contribution is in understanding the above-listed attributes which were found to have significant and often interacting effects. Again, much of the TAM work was done in a mandatory organisational context. This limits applicability to this research context, i.e. a voluntary and non-organisational context.

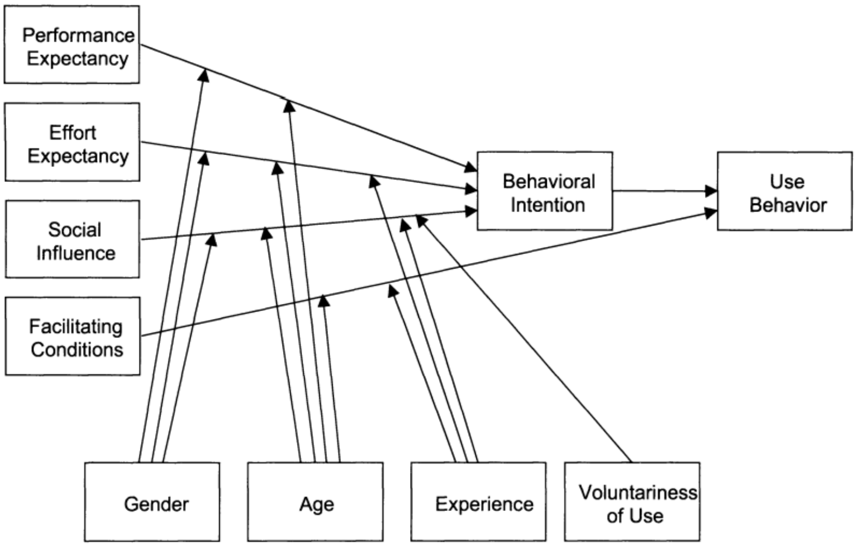
Straub (2009) summarised two academic criticisms levelled. Firstly, perceived ease-of-use and self-efficacy are linked. However, the former is a judgement of the system and the latter of the individual. Secondly, limiting the explanatory variables to two constructs is thought to be a significant weakness, i.e. the model ignored individual differences such as age, gender and prior experience. The researchers attempted to correct this weakness in developing the UTAUT model below. Important to the research proposed here, is that the number of constructs proposed, 16 including interactions, present a challenge for operationalisation, specifically for the nascent and conceptually tricky concept of cryptocurrencies.

### 2.4.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

By examining eight of the most common theoretical frameworks and selecting the most salient constructs, UTAUT was created in 2003 (Venkatesh, Morris, Davis, & Davis, 2003). The objective of developing UTAUT was to create a unified view given the broad and unstructured use and extensions of previous models (Rondan-Cataluña et al., 2015). The paper has since been cited more than 17000 times (according to Google Scholar). In synthesising UTAUT, (Venkatesh et al., 2003) considered eight prolific models including TRA, TAM, TPB, IDT and social cognitive theory. The model arrived at four determinants of usage intention and five moderators (Venkatesh et al., 2016). Moderators were gender, age, experience and voluntariness of use. The four determinants were defined as follows (all in degrees of influence), and is shown in Figure 11 below:

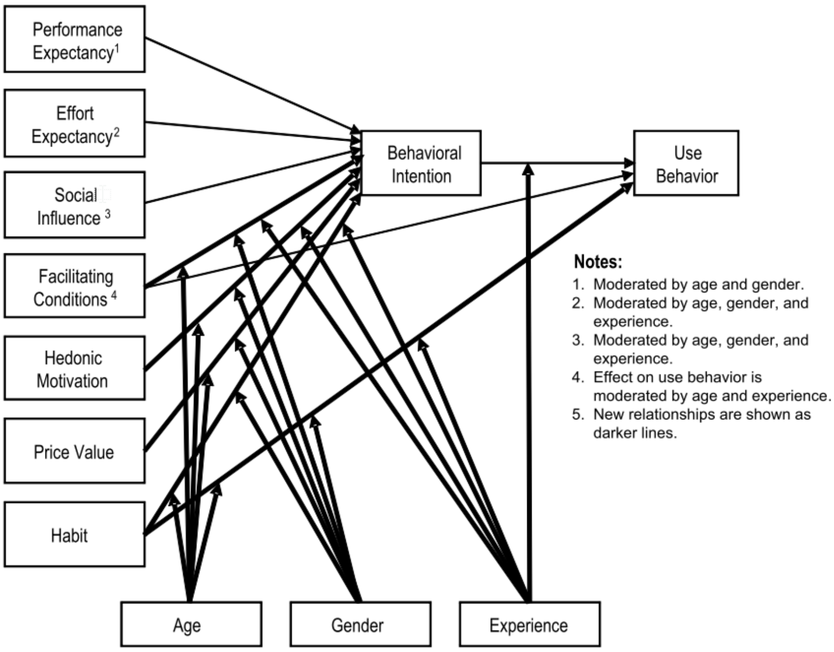
- Performance Expectancy (PE): Belief in the technology's ability to assist in task performance.
- Effort Expectancy (EE): The amount of effort perceived to be necessary to use the technology.
- Social Influence (SI): Social pressure to use a technology.
- Facilitating Conditions (FC): Perception of resource and support available for the usage of the technology.

Figure 11: UTAUT from (Venkatesh, Thong, & Xu, 2012).




UTAUT explained 77% of the variation in behavioural intention and 52% of actual usage in longitudinal field studies (Venkatesh et al., 2016). Similar to TAM and IDT, UTAUT was developed for organisational contexts with primarily utilitarian usage (Rondan-Cataluña et al., 2015). In 2012, UAUT2 was conceived to address the consumer context explicitly (Venkatesh et al., 2012). To include consumer-specific constructs, UTAUT2 added hedonic motivation (or enjoyment); costs or price value (PV) which augment the time/effort resource aspects of the base model; and finally habit as an alternative mediating mechanism to behavioural intention. Additionally, voluntariness was dropped from UTAUT, since the assumption was that consumers behave voluntarily (Slade et al., 2013). A summary of the model appears in Figure 12 with a summary of the novel concepts below.

Figure 12: Research Model: UTAUT2 taken from Viswanath Venkatesh et al. (2012).




The reason for the inclusion of hedonic motivation (HM) was cited as the strong influence in technology adoption and use in prior research. In digging deeper into the cited sources, Childers, Carr, and Carson (2001) looked at both instrumental and hedonic factors affecting e-commerce website use. Their findings indicated that hedonic aspects were at least as important as instrumental aspects, e.g. ease of navigation. However, it is important to note that this was within the context of online shopping and general applicability is questionable. In fact, Childers et al. (2001) note that "relative importance of instrumental characteristics versus immersive/hedonic aspects will likely vary across contexts" (p. 528). The authors further noted that in grocery shopping – a more utilitarian pursuit – hedonic factors were less influential. It is arguable, therefore, that hedonic factors would show a low impact on adoption of cryptocurrencies. However, HM in a consumer content was found to be a more influential determinant than performance expectancy was in an organisational context (Venkatesh et al., 2012). The authors further suggested that in consumer contexts, both hedonic motivation and utilitarian benefits coexist in varying degrees (Venkatesh et al., 2012).

Price value (PV) is defined as "the cognitive trade-off between the perceived benefits of the applications and the monetary costs of using them" (Viswanath Venkatesh et al., 2012, p. 161). While the monetary trade-offs are minimal regarding barriers to entry and transaction costs, price volatility is not. This is more so since it is not the rational trade-off to which price value refers but the perceived cognitive trade-off. It is therefore possible that price value would be a significant factor in cryptocurrency adoption – where volatility is seen as either a cost to consumers or a lack of trust in the cryptocurrency.

Habit (as linked to experience) is the third and final addition to the base UTAUT model. Experience and habit are distinct interacting constructs, where experience is antecedent to habit (Venkatesh et al., 2012). Experience refers to the opportunity (measured in time) to use the technology. Habit, on the other hand, refers to how past experiences with a technology relate to automatic behaviour as distinct from intent (Limayem, Hirt, Limayem, & Hirt, 2003). Habit is operationalised as the perception that the behaviour is automatic. Due to the newness of cryptocurrency technology and consequently adoption, habit is not expected to play a role in determining adoption.

Overall, individual characteristics (demographic and experience) moderated performance expectancy, effort expectancy, and social intention on behavioural intention. Furthermore, behavioural intention which had a more direct influence on usage and was moderated by experience in UTAUT2. Increased experience with a technology was found to decrease behavioural intention as a driver. It is hypothesised that this is due to habit rather than the intention to use becoming the more influential mechanism. In other words, the behaviour is automatic, not requiring intention to precede the behaviour. UATUT2 was able to predict 74% of the variance in behavioural intention when including interaction terms (Venkatesh et al., 2012). With only direct effects, 44% of the variation was explained. Similarly, without moderating effects, 35% of usage was explained, and 52% in the full moderated model. UTAUT2 model, therefore, showed different factors viz. HM and PV, influencing intention and usage compared to the organisational context where performance expectancy was the primary driver. A summary of the validated hypotheses in the original UTAUT2 model was provided by (Slade et al., 2013) as replicated in Table 2.

Table 2: Summary of validated hypotheses in UTAUT2 from (Slade et al., 2013).

| Independent variable | Dependent variable | Moderators | Explanation |
|---|---|---|---|
| Facilitating conditions | Behavioural intention | Age and gender | Effect stronger for older women |
| Facilitating conditions | Technology use | Age and experience | Effect stronger for older individuals with high levels of experience with the technology |
| Performance expectancy | Behavioural intention | Age and gender | Effect stronger for younger men |
| Effort expectancy | Behavioural intention | Age, gender, and experience | Effect stronger for older women with limited experience of the technology |
| Social influence | Behavioural intention | Age, gender, and experience | Effect stronger for older women with limited experience of the technology |
| Habit | Behavioural intention | Age, gender and experience | Effect stronger for older men with high levels of experience with the technology |
| Habit | Technology use | Age, gender and experience | Effect stronger for older men with high levels of experience with the technology |
| Hedonic motivation | Behavioural intention | Age, gender, and experience | Effect stronger for younger men with limited experience of the technology |
| Price value | Behavioural intention | Age and gender | Effect stronger for older women |
| Behavioural intention | Technology use | Experience | Effect stronger for individuals with limited experience of the technology |

In summary, UTAUT2 represents one of the few consumer-focused technology adoption models. However, its weakness is in the newness of the model with little independent verification of its usage in alternative contexts and for alternate technologies.

### 2.4.4 Model Choice

Diffusion of innovation theory as modified by Moore and Benbasat (1991), represents a viable choice. The general IDT model may be useful, however, since the model is not targeted to specific technology adoption but also to diffusion, it would result in difficulty operationalising. In addition, the application in a quantitative study remains limited despite the age of the model (Slade et al., 2013). Furthermore, the complexity and novelty of the topic under research – cryptocurrency – make the concern over operationalising distinct. While potentially providing a much broader view of cryptocurrency adoption, a longitudinal study would not be practical in the research project time constraints.

While TAM has been applied to the consumer context, it was distinctly developed around the organisational context (Slade et al., 2013). This changes the relationships between observed variables and the appropriateness of their inclusion or rejection in the models and extensions thereof. For instance, price value did not feature strongly since in organisational contexts monetary costs are not incurred by the users directly (Venkatesh et al., 2012). This makes TAM obsolete in the consumer context in favour of more contextually appropriate models such as UTAUT2. UTAUT itself suffers from the same organizational constraint. Slade et al. (2013) conducted a study of multiple antecedent variables of mobile payment adoption and found that UTAUT2 was most appropriate despite suggesting extensions. Rondan-Cataluña et al. (2015) found that UTAUT2 had higher explanatory power compared with TRA, TAM, TAM1, TAM2, TAM3, and UTAUT in their study of mobile internet usage.

Due to the consumer focus of UTAUT2 and conversely the organisational setting of other models (Alalwan, Dwivedi, & Rana, 2017; Venkatesh et al., 2012), UTAUT2 is proposed for the research to follow. Specifically the adaptation of the model by Alalwan et al. (2017) to include the trust construct which is found to be important in financial applications. Due to the recency of the model, independent verification is limited (Slade et al., 2013). Usage of the model is also not yet widespread. A search of the Business Source Complete Database revealed 23 English language journal articles (search term “UTAUT2”). In addition, the appropriateness of specific antecedent variables and the absence of others must be investigated. For instance, hedonic motivation may need to be further investigated. As noted above, HM for purely utilitarian pursuits by consumers may not be relevant, and may only lead to increasing instrument length and complexity. Secondly, factors that may have been excluded but are salient for emerging markets such as trust are absent. Lastly, while this study seeks to understand cryptocurrency adoption from a general consumer perspective, moderating demographic variables may be unnecessarily complicating to the analysis.

Despite these misgivings and given the shortcomings of other models on the one hand, and UTAUT2’s applicability to consumer research and its high predictive scores on the other, UTAUT2 represents the best fit model for studying cryptocurrency adoption by consumers. In the following sections, various UTAUT2 factors and extensions are considered where these require more focus given the cryptocurrency context. Before this, the discussion looks at two potentially important constructs – Trust and Gender – due to their pertinence to this study.

## 2.5 Trust

As discussed above, money is a social contract founded on trust. Furthermore, Nakamoto (2008) explicitly designed Bitcoin – and therefore cryptocurrencies – to disintermediate third-party trust providers. Since intermediaries must ensure integrity in the system and mediate between counterparties, additional costs are added to the transaction (Nakamoto, 2008). These costs include technical systems costs, governance, communication, reputation, fraud and insurance costs to ensure that valid intent is executed when transacting over a communications channel such as online. Therefore, in removing these trust providers, the transaction can be technically 'trust-less'. However, the perception of trust is a different construct entirely, especially so when attempting to predict behaviour. Also, trust in emerging markets is relevant for another important dimension – institutions (Penfold, 2015). While institutional trust has declined in developed economies, it is a systemic problem in emerging markets. Therefore, trust, moderated by context-specific factors may directly influence cryptocurrency adoption. More detailed analysis of trust is therefore required.

Gefen, Karahanna, and Straub (2003, p. 55) defined trust as "as belief in the integrity, benevolence, ability, and predictability of the e-vendor" in their study of adoption of online shopping. E. Slade et al. (2013) defined trust simply as the "subjective belief that a party will fulfil their obligations" (p. 14). Zhou (2012) in his literature review of trust antecedents described knowledge-based trust (based on experience), institution-based trust (including normality – the extent to which the interaction is similar to past experiences – and structural assurances – potential legal recourse or regulations), calculative-based trust (a risk-based cost-benefit analysis centring on incentives and counter-incentives to cheat), cognition-based trust (trust based on observations that seek to confirm an initial view rather than first-hand experience), and personality based trust (an individual's personal outlook on other's motivations). Luo, Li, Zhang, and Shim (2010) in their study of emerging technology adoption defined two additional dimensions of trust alongside structural assurance: trust belief or the perception of trustworthiness of specific entities and disposition to trust or the general belief of individuals in the goodness of humanity. The latter construct is similar to Zhou's (2012) personality based trust. Noteworthy is the inclusion by Luo et al. (2010) of perceived risk (along with its antecedents) and in line with later studies (Yan & Pan, 2015; Zhou, 2012).

Trust is distinctly crucial in the field of personal finance and electronic transactions, due to the uncertainty and perceived risk arising from anonymity and the lack of social cues that would otherwise accompany face-to-face transactions (Yan & Pan, 2015; Zhou, 2012). However, it is important to note that while trust is belief about the counterparty, perceived risk is a belief about one's own susceptibility to threats (Luo, Li, Zhang, & Shim, 2010). In the South African context, it was found through expert interviews that trust was a major inhibitor to using digital payments (Passport, 2017). Perceived risk was found to be a significant predictor of m-payment adoption by Koenig-Lewis et al. (2015) validating previous research highlighting the importance of security in financial services. Gefen et al. (2003) found that trust was an influential factor in e-commerce transactions together with perceived ease of use and perceived usefulness. Zhou (2012) found that trust had a significant effect on behavioural intention. Yan and Pan (2015) found that structural assurance, perceived ease of use and perceived usefulness affect trust and trust affected behavioural intention, with structural assurances having the largest effect. This confirmed earlier work by Zhou (2012) who found structural assurances having the largest effect on initial trust in mobile banking. Complexity for consumers arising from multiple providers and the plethora of disconnected technologies in cryptocurrencies' usage may lead to increased perceived risk (Slade et al., 2013). Related to perceived risk and trust is price stability which has been identified as a barrier to mass adoption (Neil Haran, 2017; Penfold, 2015).

It is, therefore, essential to understanding how trust plays a role in the perception of cryptocurrencies. It is further shown that trust plays an important role in user adoption as is shown in the adoption of mobile banking (Alalwan et al., 2017).

## 2.6 Gender Effects

Gender and age differences in technology adoption are at least anecdotally apparent to most individuals. The common assumption is that older users and women appear on one end of the spectrum with young males at the other in terms of technology adoption. This section is primarily a summary of the gender and age effects already discussed above. Regarding the gender construct, the differentiation between biological and psychological assignment is beyond the scope of this research and gender here refers to biological assignment in line with much of the extant literature. The study of gender effects also requires controlling for confounding variables such as education and income since men are currently overrepresented at the higher end of income and education (Venkatesh, Morris, & Ackerman, 2000).

Venkatesh and Morris (2000) studied gender as a moderating effect in TAM for both short-term and long-term effects. The necessity of two time-spans was due to the effect of experience. The study aimed to answer the question of the presence of differences between genders in the decision-making process in adoption, with the answer in the affirmative. PU was more salient for men and PEOU for women. Subjective norm had no effect on men. For women, the effect was significant during initial stages of adoption only. The researchers surmised that men are more instrumentally focused, and women more process and socially motivated.

Venkatesh et al. (2000) looked at how gender moderated initial technology adoption using the TPB in a longitudinal study. The analysis indicated that women were much more strongly influenced by subjective norm (related to social influence in UTAUT) and perceived behavioural control. Furthermore, gender differences were more pronounced for initial adoption rather than the mechanisms relating to sustained usage. Similarly, Goswami and Dutta (2016) in their literature review of UTAUT in various contexts found mixed effects. In the context of usage, however, men displayed a higher readiness to adopt technology. Moreover, within the UTAUT framework, moderating effects as already discussed in the sections above, indicated distinct differences in the specific mechanisms driving behavioural intention and usage. In the mobile banking space, men were more likely to use the technology. These differences, however, were not as pronounced or were absent in the online shopping context.

## 2.7 Adoption Theory in Practice

In this section, the application of adoption models and the developed constructs are examined particularly for cryptocurrency and related technologies. The section starts with a review of the UTAUT2 literature to determine the availability of relevant research – specifically in the cryptocurrency application domain. Due to the recency of the domain, related application domains, as well as the application of alternate adoption theories, are considered. This allows an expansion of the relevant body of work that may inform this study.

Since the UTATU2 model is fairly recent in the IS literature, its application has not been extensive least of all for cryptocurrency of which there were no studies found. A search of Google Scholar (in October 2017) revealed 1490 results for the search term "UTAUT2", compared with 20,700 for "UTAUT", and 2,550,000 for "Technology Acceptance Model". A search of online academic databases turned up even fewer results for UTATU2 in abstract or title. EBSCOhost found 22 English language articles, and Emerald Insight found six. The research, therefore, expands to concepts in related adoption models including TAM and IDT. In lieu of the scarcity of extant literature, the discussion continues with the study of concepts from related adoption theory where necessary. For the studies that focus on cryptocurrency adoption the search terms: "cryptocurrency", "adoption", "virtual currency", as well as the UTAUT search terms already listed. In the limited body of work that did apply UTAUT2, certain topics were recurring – adoption of health technology (Gao, Li, & Luo, 2015; Slade & Williams, 2013; Yuan, Ma, Kanthawala, & Peng, 2015); education technology (Natalie Gerhart, Peak, & Prybutok, 2015; Raman & Don, 2013; Yang, 2013); mobile internet, devices and applications (Abdullah, Dwivedi, & Williams, 2014; Hew, Lee, Ooi, & Wei, 2015; Huang & Kao, 2015; Huang, Kao, Wu, & Tzeng, 2013; Kraljić & Peštek, 2016; Wong, Wei-Han Tan, Loke, & Ooi, 2014); and mobile banking and payments (Alalwan et al., 2017;

Koenig-Lewis, Marquet, Palmer, & Zhao, 2015; Mahfuz, Khanam, & Wang, 2017; Morosan & DeFranco, 2016; Slade et al., 2013) and a range of other disparate topics.

The study of consumer financial technology – mobile banking (Alalwan et al., 2017; Mahfuz et al., 2017), mobile payments (Kim, Mirusmonov, & Lee, 2010; Koenig-Lewis et al., 2015; Morosan & DeFranco, 2016; Slade et al., 2013; Yang, Lu, Gupta, Cao, & Zhang, 2012) and online commerce (Gefen, Karahanna, & Straub, 2003) – is in some ways analogous with the study presented here insofar as the technology under study is within the consumer finance domain. This is due to the high technical, technology and market uncertainty that was prevalent in the initial adoption of mobile banking and online commerce (Luo et al., 2010). The expectation is that there would be analogous relationships when looking at personal finance adoption and the use of cryptocurrency that could both inform research design as well as the expectation of results. Prior research in this field is therefore considered instructive. The search terms: “m-payment”, “financial”, “m-banking”, “mobile banking”, “mobile payment”, “NFC”, were included with those already listed in various combinations. A list of works used in the discussion of adoption theory in practice appears in Table 3 below.

Table 3: List of authors used in discussion in cryptocurrency and related fields.

| Author | Model | Domain | Method | Focus Area |
|---|---|---|---|---|
| (Alalwan, Dwivedi, & Rana, 2017) | UTAUT2 | Mobile Banking | Quant | Trust |
| (Mahfuz, Khanam, & Wang, 2017) | UTAUT2, ITM | Mobile Banking | Quant | Culture and trust |
| (Kraljić & Peštek, 2016) | UTAUT2 | Mobile Internet | Qual | The impact of quality |
| (Morosan & DeFranco, 2016) | UTAUT2 | Mobile Payments | Quant | |
| (Koenig-Lewis, Marquet, Palmer, & Zhao, 2015) | UTAUT2, TAM | Mobile Payments | Quant | |
| (Hew, Lee, Ooi, & Wei, 2015) | UTAUT2 | Mobile Apps | Quant | |
| (Baur, Bühler, Bick, & Bonorden, 2015) | TAM | Cryptocurrency | Qual | |
| (Abdullah, Dwivedi, & Williams, 2014) | UTAUT2 | M-Technologies | Qual | Model expansion |
| (Martins, Oliveira, & Popovič, 2014) | UTAUT | Internet Banking | Quant | |
| (Spenkelink, 2014) | IDT | Cryptocurrency | Qual | |
| (Slade, Williams, & Dwivdei, 2013) | UTAUT2 | Mobile Payments | Qual | Model expansion |

| | | | | |
|---|---|---|---|---|
| (Yang, Lu, Gupta, Cao, & Zhang, 2012) | TAM | Mobile Payments | Quant | PIIT |
| (Kim, Mirusmonov, & Lee, 2010) | TAM | Mobile Payments | Quant | |
| (Luo, Li, Zhang, & Shim, 2010) | TAM | Mobile Banking | Quant | Risk and trust |
| (Shin, 2009) | UTAUT | Mobile Wallet | Quant | |
| (Dickinger, Arami, & Meyer, 2008) | TAM | Push to Talk | Quant | Enjoyment |
| (Lu, Liu, Yu, & Wang, 2008) | TAM | Mobile Internet | Quant | |
| (Gefen, Karahanna, & Straub, 2003) | TAM | Online Shopping | Quant | Trust |
| (I. Brown, Cajee, Davies, & Stroebel, 2003) | IDT | Mobile Banking | Quant | |

Slade et al. (2013) sought to extend UTAUT2 by conducting a literature review of other adoption theories and constructs that were found to be significant. Abdullah et al. (2014) conducted a similar study into mobile internet and m-government adoption showing similar trends in significant findings. The analysis performed by Slade et al. (2013) also included a review of significant predictors in the extant literature on mobile banking and payment adoption. Table 4 below is a summary of their findings as it relates to this study. The number of studies is reported rather than the actual studies as was the case in the original paper. Included in the table below are related constructs in UTAUT2 for this study. This analysis provides a benchmark against which the results of this study may be compared.

Table 4: A summary of the number of significant and non-significant predictors in technology adoption research into m-payment adoption (Slade et al., 2013).

| **Independent Variable** | **Dependent Variable** | **Related (~) Construct in UTAUT2** | **Significant** | **Non Significant** |
|---|---|---|---|---|
| Perceived ease of use | Perceived usefulness | Effort Expectancy | 11 | 0 |
| Perceived Usefulness | Behavioural Intention | Performance Expectancy | 11 | 2 |
| Perceived ease of use | | Effort Expectancy | 9 | 1 |
| Perceived risk | | - | 9 | 4 |
| Compatibility | | Facilitating Conditions | 8 | 1 |
| Attitude | | - | 7 | 0 |
| Trust | | Trust* | 7 | 2 |
| Perceived financial cost | | Price Value | 6 | 2 |

| | | | | |
|---|---|---|---|---|
| Social influence | | Social Influence | 5 | 2 |
| Performance expectancy | | Performance Expectancy | 4 | 0 |
| Relative advantage | | - | 4 | 0 |
| Behavioural Intention | Usage | Behavioural Intention | 4 | 0 |

* Trust is not in the original UTAUT2 model but in extensions related to consumer finance.

### 2.7.1 Predictors of BI

The predictors of behavioural intention (BI) in the original model by Venkatesh et al. (2012) are already summarised in section 2.4.3 above. From Table 4, only PE was found to be significant in all studies. However, Abdullah et al. (2014) found two studies with a non-significant relationship. In all other cases, EE, FC – a similar concept to compatibility (Venkatesh, Morris, Davis, & Davis, 2003), and social influence (SI) were found to be significant in a large number of cases. However, in all cases, at least one insignificant result was found. Trust which was not included in the original UTAUT2 model, but identified in the literature review as a potential significant predictor, was found to be significant in seven out of nine studies.

Alalwan et al. (2017) used a simplified UTAUT2 model in their study of mobile banking adoption in Jordan. The moderating effects of demographic variables were ignored while an additional independent variable, trust (TR), was added. This addition was based on earlier work where Gefen et al. (2003) extended TAM to include trust in their own study of mobile banking adoption. The concept of trust has already been discussed in earlier sections. As noted above, a related concept to trust is perceived risk. Within the perceived risk dimensions – perceived social, performance, financial, time, security, and privacy – only perceived social and performance risk were found to be significant. In studying mobile wallet adoption, Shin (2009) found that trust ($\beta = 0.621$, p-value $< 0.01$) and perceived risk ($\beta = 0.530$, p-value $< 0.05$) were the strongest predictors of intention to adopt mobile wallets. Alalwan et al. (2017) using the UTAUT2 model with trust, was able to explain 65% of the BI variance using PE, EE, HM, and PV. Interestingly, SI was found to be non-significant. PE was significantly predicted by EE and TR. Martins et al. (2014) found that adding perceived risk as an independent variable for BI increased the explanatory power from 56% with just PE, EE, and SI to 60%. In the study by Martins et al. (2014) on internet banking adoption, perceived risk was modelled with its own dependent variables including TR and the other risk constructs previously mentioned. The combined model explained 81% of the variance in BI.

Shin (2009) found that SI moderated the relationship between perceived security (related to TR). SI was found to be a significant predictor in a majority of studies as indicated above. Koenig-Lewis et al. (2015) found that peer influence had a significant positive effect on HM, PE, as well as directly on BI in their study of m-payment adoption. Peer influence – social norms - was postulated to be stronger for a younger audience by Dickinger et al. (2008) although the moderating effects of age were not studied quantitatively. Mahfuz et al. (2017) using a model combining Hofstede's culture dimensions, an initial trust model, and UTAUT2 found no significant effects on BI for Habit, HM, PE, SI, EE. The only significant effects on BI were from PV ($\beta = 0.089$) although this was a weak effect, and initial trust (($\beta = 0.167$). There were significant effects for FC ($\beta = 0.273$) and BI ($\beta = 0.514$) on usage.

Social influence and perceived enjoyment (~HM) are theorised to be linked due to the social aspect of consuming some technologies (Koenig-Lewis, Marquet, Palmer, & Zhao, 2015). Dickinger et al. (2008) found that perceived enjoyment strongly predicted BI in their study on adoption of Push-To-Talk (PTT) mobile services. Notably, social norm strongly predicted ($\beta = 0.937$) perceived enjoyment showing a strong link between the construct of enjoyment or HM and social influence. The extensive media attention afforded to cryptocurrency may, in fact, result in an overexpression of the social influence factor in cryptocurrency adoption at this stage in line with these findings. Koenig-Lewis et al. (2015) applied the UTAUT2 model in order to study the effects of perceived enjoyment (~HM) finding that there was no direct significant link between HM and BI, contrary to prior research. However, a strong link through perceived usefulness (~PE) was found. The authors further found that HM and SI moderated the effects of perceived risk lower on BI. PEOU (~EE) had no significant effect on BI, with the authors positing the moderating effect of experience. The question of whether HM is relevant for what could be considered a purely instrumental pursuit, i.e. cryptocurrency adoption. Morosan and DeFranco (2016) studied adoption of Near-Field-Communication (NFC) mobile payments. The use of NFC mobile payments may be analogous to the utilitarian objectives of cryptocurrency users at least from a transactional perspective. HM was found to be a predictor of BI in this study. HM was second in its predictive power to PE and ahead of FC, and SI. Interestingly, EE was found to be non-significant.

Lastly, in the South African context, Wentzel, Diatha, and Yadavalli (2013) used a grounded theory approach to identify extensions to the TAM model to study technology-enabled financial services. The South African context is salient due to the use of snowball sampling and this study's author being based in this country. The five additional constructs were trust, social, hedonistic, task, and self-efficacy, each an independent variable of BI. These constructs are strikingly similar to the UTAUT2 constructs and the trust extension by Alalwan et al. (2017). The relationships are social which relates to SI, Hedonistic to HM, Task to PE and FC, and Self-Efficacy to EE. In the study by I. Brown et al. (2003) of mobile banking adoption in South Africa may be applicable to this research. In their study based on IDT and TPB, relative advantage, compatibility (~FC), perceived complexity (~EE), trialability, experience, banking services needed, perceived risk, self-efficacy, and FC were hypothesised to affect adoption. Of these, only relative advantage, trialability, banking services needed and perceived risk had significant effects. Interestingly facilitating conditions and compatibility were found to be non-significant.

### 2.7.2 BI and Usage

Having discussed the predictors of BI, the discussion turns to the effect of BI and other predictors on usage. In Slade et al. (2013) review of UTAUT2, BI on usage was found to be significant in all four studies in mobile payment and mobile banking literature. Abdullah et al. (2014) found six studies with significant effects and one without. Alalwan et al. (2017) was able to predict 59% of the variance in BI using the original UTAUT2 model unchanged, and 65% of the variance with TR as an added predictor. Hew et al. (2015) were able to explain 68.67% of the variance in mobile app BI using UTAUT2. Mahfuz et al. (2017) using a model combining cultural dimensions, an initial trust model, and UTAUT2 explained 80.90% of the variance in BI and 39.4% in usage of mobile banking. Koenig-Lewis et al. (2015) explained 62% of the variance in BI in their study of mobile payment adoption. The study used UTAUT2 constructs selectively, and added (prior) knowledge, and perceived risk with multiple interacting effects. Shin (2009) used UTAUT to study adoption of mobile wallets. They achieved R-squared values of 0.72 for BI and 0.81 for usage. BI was the strongest predictor ahead of FC with 31% of the variance explained. These studies, therefore, confirm significant effects of BI on usage, except for few dissenting results. The relationship consequently warrants further inquiry.

Much of the technology acceptance theories are based on Fishbein and Ajzen's (1975) assertion that intention is the best predictor of behaviour. Slade et al. (2013) found that the relationship between BI and usage was significant in all four studies on m-payment adoption reviewed. In addition, much of the conceptual work in TAM, and UTAUT have found significant relationships between the constructs as discussed in the literature review above. However, Chuttur (2009) cautioned that the BI-usage link might be inappropriate. Wu and Du (2012) critically examined the appropriateness of relationships between BI and the different categories of usage. Referencing several meta-studies, the researchers cautioned that BI has been taken with little empirical evidence to be a proxy for usage. Comparing analyses with BI as the ultimate dependent variable rather than actual usage, Wu and Du (2012) found that insignificant results tripled when usage was the final independent variable. This suggests that usage should be studied directly. Further, Wu and Du (2012) found that actual usage was least correlated with BI compared with assessed usage and reported usage.

### 2.7.1 Individual Differences

Since UTAUT2 notes a substantial improvement in predictive strength with demographic moderators, a discussion of individual differences is appropriate. Venkatesh et al. (2012) found that gender and age moderated the effect of HM on behavioural intention such that it was stronger for younger men. Price value was found to be moderated by age and gender – stronger for older woman indicating the effect of gender and age. Gender and age show a moderating influence on habit, with older men having usage experience, relying more on this construct to drive usage. Shin (2009) found significant moderating effects of age and gender on mobile wallet adoption using UTAUT. While age and gender differences have been discussed, the effect of an individual's relationship with technology is a further point of difference.

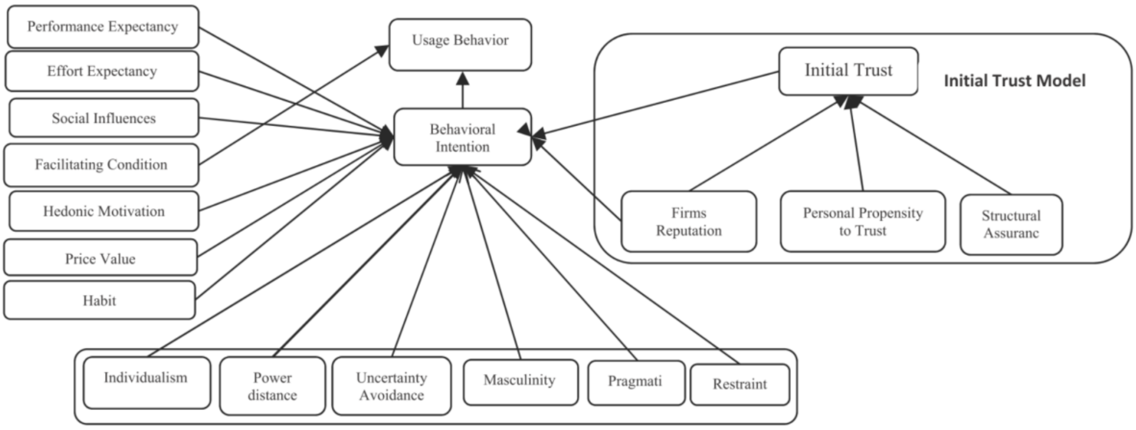
Rogers (1995) classified users according to the time of their adoption. Agarwal and Prasad (1998) sought to define the concept of Personal Innovativeness in the Domain of Information Technology (PIIT) based on IDT theory and in order to capture the effect of personality traits. IDT, however, premised innovators as early adopters which was an after-the-fact assertion on behaviour rather than a hypothesis on what produced that early adoption. Agarwal and Prasad (1998) wanted to capture why some individuals were more likely to adopt technology innovations earlier, i.e. the personality traits of early adopters. According to IDT, these early adopters are a crucial stepping stone towards mass adoption. Therefore PIIT is worthy of study. Agarwal and Prasad (1998) found that PIIT moderated the effect of compatibility on BI, and of BI on actual usage. In explaining the non-significant result for hypothesising moderating effects on PU (~PE) and PEOU (~EE), the authors postulated that due to popular attention and media buzz around the Web (on which the study was based), the effect on PIIT was diminished. This is to say that PIIT did not moderate these factors as these perceptions were more dependent on external influence rather than personal traits in the particular concept of Web adoption in the late nineties. A later study by Lu et al. (2008) found that PIIT had a significant effect on PEOU (as a predictor) in their study on Wireless Mobile Data Services adoption. Yang et al. (2012) found that PIIT had a significant effect on BI for mobile payment services. Yang et al. (2012) opined that higher PIIT scores lead to greater BI due to individuals with this trait having higher risk-taking behaviour and the ability to visualise more readily potential benefits of use.

Yang et al. (2012) studied differences between potential adopters and current users of mobile payment services in China. For potential adopters, both positive and negative factors were significant. Specifically, compatibility (related to facilitating conditions) was found to be an important consideration for potential adopters. PIIT, behavioural beliefs and social influences were also significant. For initial adopters without prior experience with the service, SI had a stronger effect both directly on BI and indirectly through lowering perceived risk and increasing relative advantage. For current adopters, compatibility (~FC) was reduced in effect strength. Interestingly for current users, the study found that the perceived fee was non-significant. Explanations offered are (1) that once other benefits were understood through direct experience the consideration of fees were not applicable as they are adjudged against value, and (2) the actual costs incurred were not large for mobile payments. The latter postulate may refer to costs calculated as a proportion of transactions by consumers rather than a holistic calculation of all costs – both monetary and other. Kim et al. (2010) found that for early adopters the technical characteristics of the service had no effect on the PU (~PE) as their expectations on usability were low, to begin with. The study further found significant differences between groups with different PIIT scores. The key contribution is the necessity to target early and late adopters with different strategies.

Individual differences lead to the question of group differences at the centre of the identity pyramid (Davidson, 2002). In fact, group differences, both in the intra-national and international context, are more practically operationalised. Much research has focused on cultural differences at a national level. House, Hanges, Javidan, Dorfman, and Gupta, (2004) defined culture "as shared motives, values beliefs, identities, and interpretations or meanings or significant events that result from common experiences of members of collectives and are transmitted across age generations" (p. 15). In the conception of national culture, Hofstede et al. (2010) define layers of culture to include social classes, generational, gender, regional and ultimately national. There are a variety of dimensions, of which Hofstede's has found the most wide-scale application. Hofstede (2011) defined six dimensions: power-distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence, the definitions of which are beyond the scope of this research. Hofstede, through various quantitative studies then scored countries on these dimensions. Ignoring some of the criticisms regarding the level of aggregation, i.e. the national level, these dimensions present a potentially moderating influence on BI and usage construct antecedents in adoption theory. Mahfuz et al. (2017) integrated

Hofstede's dimensions, UTAUT2 and the initial trust model (ITM) as shown in Figure 13. Cultural dimensions were studied as direct antecedents of BI. PV, masculinity, and power distance were the only significant variables predicting BI.

Figure 13: Adoption model integrating UTAUT2, ITM, and culture by (Mahfuz et al., 2017).

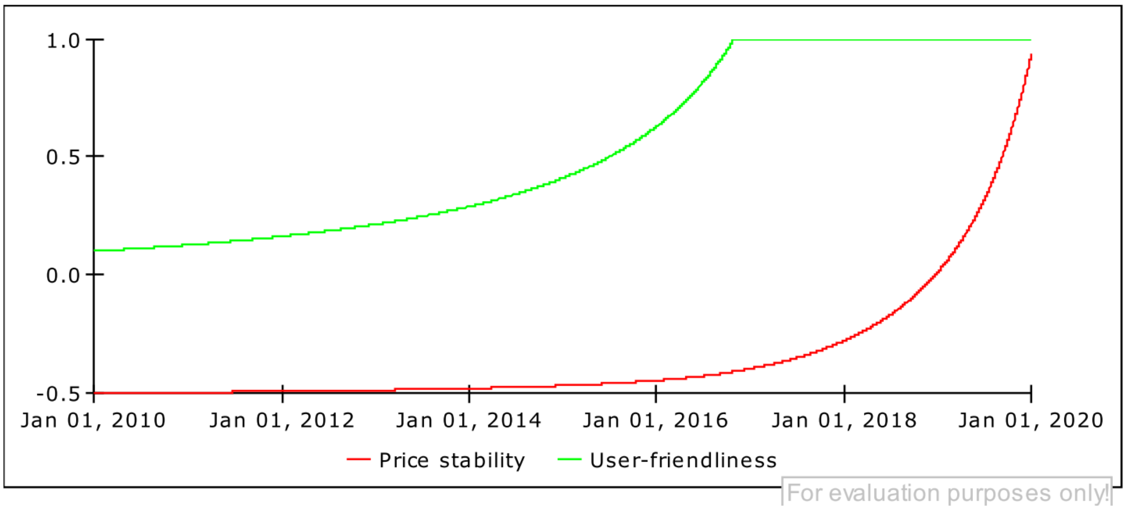



### 2.7.2 Cryptocurrency Domain

In the specific domain of cryptocurrency adoption, there are few studies, all of which are qualitative. Baur et al. (2015) used semi-structured interviews to quantify the perceptions of advantages and disadvantages of cryptocurrency, the long-term outlook of consumers and merchants, and pertinently the factors driving adoption. Using the open-coding technique, the constructs from TAM2: PEOU, PE and subjective norm were assessed. From a PEOU perspective, interviewees in general perceived the technology difficult to use noting that training (~FC) was required. Convenience was a major factor especially the ability to use Bitcoin at point-of-sale (POS) in brick and mortar stores. From a PU perspective, consumers ranked the advantages of security and anonymity highly. Regarding subjective norm, the effect of peer influence on initial usage was validated. After attitude, PEOU was found to be the strongest effect. Weaker effects from social factors and self-efficacy were found.

Spenkelink (2014) produced one of the few studies to date in his master's thesis on adoption of cryptocurrency using technology adoption theory - IDT. The study used a qualitative methodology using semi-structured interviews. The interviewees – 15 in total – included persons from banks, cryptocurrency service providers, academia, incumbent payment providers, consultants, and retailers. A conceptual model was synthesised and tested with subject-matter experts. The study does not, however, appear in a peer-reviewed journal. Furthermore, the final output was a systems dynamic model also beyond this study's scope. Spenkelink (2014) divided his research into advantages (benefits), disadvantages, and extra factors emergent from the interview analysis according to whether there was general or little consensus. He found that there was general consensus amongst interviewees on the benefits of low cost which is related to PV. There was little consensus on the publicness of transactions or anonymity. Consensus on disadvantages was related to ease of use (related to EE), volatility (PE and risk). This is supported by Penfold's (2015) study where price stability was cited as the primary factor in determining not to adopt cryptocurrency. There was little consensus on whether the lack of government oversight was a disadvantage (related to trust). Extra factors identified were related to the knowledge required to use cryptocurrency pointing to FC. It is important to note that it is not the consensus on advantages or disadvantages but whether interviewees felt these were important constructs they considered in whether to adopt or use cryptocurrency. Spenkelink (2014) concluded that PEOU, price stability and governance were the most critical factors for mass adoption. These relate to EE, PE, and TR respectively. While the systems dynamic model – analysing time-based effects on usage – is beyond this scope, it showed that price stability would follow ease of use - Figure 14.

Figure 14: User friendliness and price stability modelled using a systems dynamic model (Spenkelink, 2014).




## 2.8 Conclusion

In the preceding literature review, an overview of the fundamental operation of cryptocurrencies was described. Of salience is the peer-to-peer nature and the mechanism through which ownership of cryptocurrency holdings is determined. The seeming complexity of the technology is an important consideration in developing hypotheses around intention to use and actual usage. The unique benefits and disadvantages are listed based on this discussion. Since cryptocurrency was conceived as a financial transactional technology, the question of whether it is money is discussed highlighting the aspect of money as a social contract. This informs the study of what users do with cryptocurrency and what their expectations are of the technology. The question of whether cryptocurrency is money is left open with the conclusion being that classification is based on usage which is still evolving.

Following the review of cryptocurrency as a technology, the theoretical framework through which adoption will be studied – technology adoption theory – is reviewed. The evolution of the study of technology adoption starts with a look into Innovation Diffusion Theory before delving into the first theoretical model of technology adoption –TAM. TAM and the models developed after it are based on instrumental and emotional constructs driving intention which subsequently converts into usage. The evolution of the field is shown to be the development of models incorporating more and more independent constructs in order to increase explanatory power. UTAUT2 is one of the more recent iterations of adoption models and incorporates explicitly a consumer context. For this reason, UTAUT2 is chosen as the basis for the conceptual model used in this study.

After selecting UTAUT2, other constructs are reviewed for possible expansion of the model to better serve the objectives and context of the study. Of these, trust was found to be an often included construct in the financial services domain. Gender differences and their possible implications for this study are reviewed and found to be significant. Finally, applications of UTAUT2 and related adoption theory is reviewed to inform the development of this study's hypotheses and the related conceptual model. In this review, the cryptocurrency field is found to have had few prior quantitative studies necessitating the inclusion of other studies in related fields – most notably mobile financial services. The literature reviewed shows that there is little consistency in which constructs to use and non-significant findings are prevalent for all effects posited. Based on these applications, this study's hypotheses can now be formulated.

# Chapter 3: Research Propositions

Having studied the literature available on cryptocurrencies, the study by Alalwan et al. (2017) is adjudged to be the most suitable research on which to base this study with some modification. The research propositions below are thus adapted from Alalwan et al. (2017) which is largely based on the original conception of UTAUT2 by Venkatesh et al. (2012) with the addition of the trust construct from Gefen et al. (2003). The rationale for this decision is that the Alalwan et al. (2017) is only a minor departure from the original UTAUT2 framework and has already proven construct validity and item validity for the instrument used. Due to the complexity and emergent nature of the cryptocurrency domain, this lower risk approach to the study is deemed suitable as opposed to a completely new conceptual model and related research instrument.

## 3.1 Hypotheses

Using the review provided in section 2.7, hypotheses appropriate for the cryptocurrency domain are synthesised here. In keeping with the rationale provided by Alalwan et al. (2017) and Koenig-Lewis et al. (2015) habit is not considered due to the novelty of the technology and the potentially spurious results. Adding additional terms would only serve to complicate the the research instrument. Experience, like habit, is neglected in this model since the number of respondents with sufficient experience was hypothesised to be small. Unlike Alalwan et al. (2017), and in line with the original conceptual model by Venkatesh et al. (2012), the moderating effects of age and gender are considered. Since a small sample size is expected, the study of age and gender may not be practical. For similar reasons, the practical consideration of sample sizes for each group: potential adopters, early adopters, and experienced users, the effect of PIIT is not considered. The analysis technique – described later – seeks to establish the magnitude of theorised effects on relationships found in the literature study. Causality is therefore not specifically studied only insofar as it is theorised that for example, trust has an effect on behavioural intention to use. Also, it is noted that causality cannot be studied solely by statistical techniques (Kline, 2011). The below hypotheses are theorised on prior research using UTAUT2 and its predecessors. The statistical tests applied will, therefore, be confirmatory in nature (Kline, 2011).

Since cryptocurrency usage categories represent a competing offer to traditional existing services, it would stand to reason that performance expectancy (PE) would be a driver of behavioural intention (BI). Furthermore, PE was found to consistently significantly predict BI.

H1. Performance expectancy will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

Cryptocurrency usage in its current forms requires some technical know-how due to the complex nature of the technology and the recency of commercial offerings. This means that usage requires individuals to navigate an immature landscape of different cryptocurrencies each with their own idiosyncrasies, different exchanges, and different wallet types. In addition, for some services those traditional businesses recognizing cryptocurrencies – such as retail stores, investment houses, and governments, mean that some knowledge as to which organisations accept or deal with cryptocurrency is required. It is expected therefore that difficulty in using cryptocurrency will feature prominently.

H2. Effort expectancy will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

In line with prior research, effort expectancy is also found to interact with performance expectancy potentially through an explicit or implicit trade-off by the individual (Alalwan et al., 2017; Venkatesh et al., 2012).

H3. Effort expectancy will positively influence performance expectancy of cryptocurrencies.

The very nature of cryptocurrencies, i.e. the peer-to-peer transaction system and socialised blockchain and consensus mechanism point to social influence (Dickinger, Arami, & Meyer, 2008). Indeed, the success of any cryptocurrency depends largely on network effects and users are encouraged by the community to advocate for increased adoption and acceptance. Money, in general, is a social contract in which participants exchange goods with intrinsic value for promissory notes expected to have future value in exchange (Bjerg, 2016; Salemi, 2012). Therefore, SI in adoption at least from a currency perspective is relevant. Social factors have been found to be influential for financial services such as m-payments and mobile banking as indicated above. Therefore, social influence should positively influence behavioural intention.

H4. Social influence will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

The inclusion of hedonic motivation (HM) stems from its strong predictive influence in customer-related research. Even though cryptocurrencies may be a utilitarian technology, prior research indicates that HM plays a contextually dependent role on intention to use. Since this research is focused on consumer adoption, a positive influence is hypothesised.

H5. Hedonic motivation will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

Consumer technology, unlike in an organisational context, involves some cost consideration. Price value was found to be a strong explainer of behavioural intention in prior studies. Again, the technology competes directly with incumbent services, with cost being touted as a primary advantage achieved through disintermediation.

H6. Price value will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

Trust was found to be a significant factor in studies relating to mobile banking, and online commerce (Alalwan et al., 2017; Gefen et al., 2003; Yan & Pan, 2015; Zhou, 2012), and is attributable to the financial nature of the technology. Further, the cryptocurrency ascent into the mainstream has been dogged by various scandals. Trust should therefore positively influence intention to use cryptocurrency. This study deals with trust as a unitary construct and neglects any potential antecedents since research is focused on broad mechanisms rather than specifically the trust construct.

H7. Trust will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

In the study by Alalwan et al. (2017), trust was found to interact significantly with performance expectancy again involving a potential trade-off similar to what is hypothesised for effort expectancy. Similarly, other studies have found interacting effects with perceived ease of use (similar to EE) and perceived usefulness (similar to PE) (Yan & Pan, 2015; Zhou, 2012).

H8. Trust will show a positive effect on performance expectancy for cryptocurrencies.

Again the nature of cryptocurrencies requires that other systems and structures are in place to facilitate their use. Therefore, facilitating conditions (FC) should be a key factor in influencing actual usage. Therefore in line with Alalwan et al. (2017) study of banking, a positive relationship is hypothesised with usage.

H9. Facilitating conditions will positively influence a consumer's behavioural intention to adopt cryptocurrencies.

Accepting Wu and Du's (2012) caution that measuring intention cannot be considered to predict usage directly, this study opts to measure both, with BI as a predictor of usage.

In most prior adoption theory, including TAM and UTAUT, behavioural intention is a strong predictor of actual usage. In keeping with the UTAUT2 model, this model hypothesises a positive influence.

H10. <u>Behavioural Intention</u> will positively influence a consumer's adoption of cryptocurrencies.

Age and gender were found to be a strong moderating influence on facilitating conditions, hedonic motivation and price value (Shin, 2009; Venkatesh et al., 2012). Based on prior research of new high technology products, the population of interest will be heavily weighted to young males, the influence of age and gender may not be possible to elicit from the sample. In addition, income was found to be a confounding variable that could make interpretation difficult (Venkatesh, Morris, & Ackerman, 2000).

H11. <u>Age and Gender</u> will moderate the effect of <u>price value</u> on behavioural intention such that the effect will be stronger for older women.

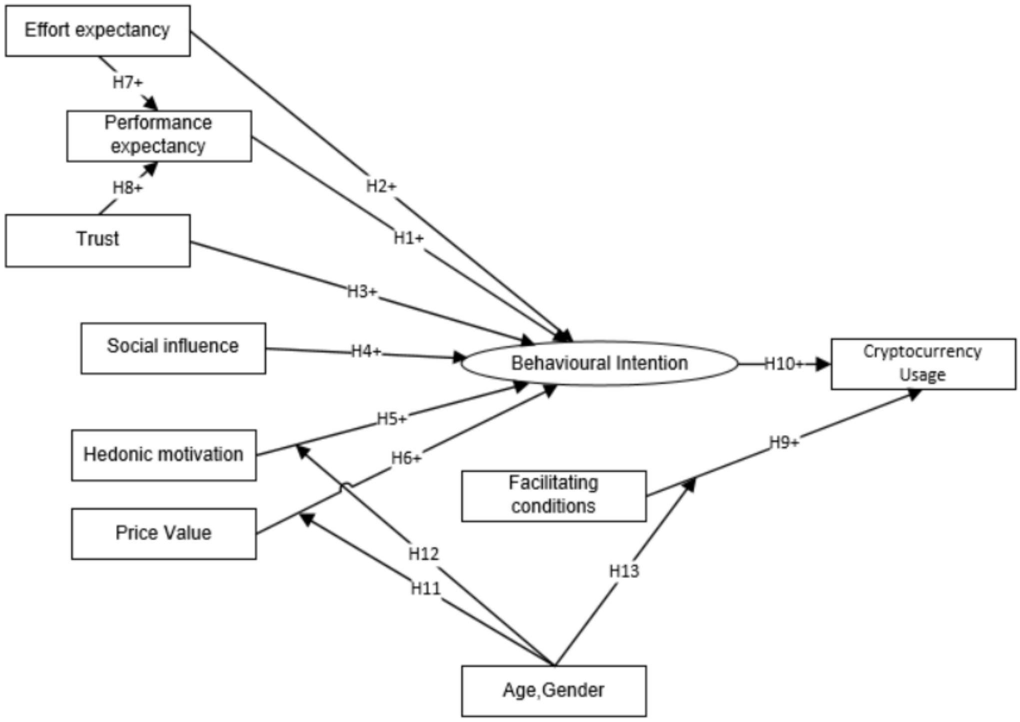
H12. <u>Age and Gender</u> will moderate the effect of <u>hedonic motivation</u> on behavioural intention such that the effect will be stronger for younger men.

H13. <u>Age and Gender</u> will moderate the effect of <u>facilitating conditions</u> on actual usage with the effect being stronger for older women.

## 3.2 Conceptual Model

Based on the above hypotheses, a conceptual model is shown in Figure 15 below.

Figure 15: Conceptual model proposed for research into cryptocurrency adoption.



## 3.3 Conclusion

In this chapter, the research hypothesis is listed based on the extensive literature review presented in chapter 2. Using the UTAUT2 framework with trust added, the antecedents of behavioural intention to adopt and actually use cryptocurrency can be studied. The independent variables hypothesised to affect usage are facilitating conditions and behavioural intention. Those independent variables affecting behavioural intention are trust, performance expectancy, effort expectancy, social influence, hedonic motivation, and price value. The potential problems of attempting a study including moderating effects are highlighted even though the effects of age and gender are included in the conceptual model. Experience and habit are excluded explicitly due to the immaturity of the technology and the low probability of finding varied experience in the population of interest. The next chapter details how the conceptual model can be quantitatively assessed.

# Chapter 4: Research Methodology

In this chapter, the methodology followed is outlined. This is based on the overall structure provided by Saunders and Lewis (2012). The description begins with a choice of the overall research design, including the philosophy, approach and research strategy. The population of interest is then defined together with the sampling technique. Having opted for a quantitative study, the survey instrument chosen is described together with the data analysis techniques applicable to testing the hypotheses synthesised in the previous chapter. Finally, research limitations based on the research methodology are listed.

## 4.1 Research Design

The novelty of cryptocurrencies in the market affects the research design. Since familiarity with cryptocurrencies is hypothesised to be low amongst the general consumer population, a more targeted approach was required. Further, the underlying technology is complex to understand, and thus the unique aspects of cryptocurrency may not be easily explained. This affects the quality of data collected, and was therefore taken into account in the research design.

Saunders and Lewis (2012) stated that the quality of research is determined in large part by the consistency and alignment of the research design. The authors further propose a framework for ensuring this consistency – referred to as the research onion. The following sections use this framework to arrive at a research design.

### 4.1.1 Philosophy

A research philosophy centred around positivism is followed (Saunders & Lewis, 2012). In line with a positivist philosophy, the research looks for general inferences that can be drawn from data with regards to cryptocurrency adoption. The resultant findings are presupposed to be widely applicable across subgroups in the population while noting the potential effect of contextual variables. These variables must therefore be controlled for example country location.  Research further aimed to identify causal links using tests for prediction on cryptocurrency adoption.

### 4.1.2 Approach

A quantitative deductive approach was used to test the existing theory proposed by UTAUT2 (Venkatesh et al., 2012), on adoption using the relationships between variables intention and cryptocurrency usage. Using data collected as described in the following sections, the research aimed to discover the major drivers of adoption amongst cryptocurrency users. The research is therefore explanatory in nature (Saunders & Lewis, 2012).

### 4.1.3 Strategy

The research strategy employed was an electronic survey. Direct measurement of cryptocurrency users is difficult due to the pseudo-anonymous architecture of the technology (Bohr & Bashir, 2014), making surveys with self-reported values appropriate. The length and complexity of the survey are important and affect response rates and quality. The survey was pilot tested amongst a small group of cryptocurrency users to ensure that content is valid to the testing of the above hypotheses.

### 4.1.4 Time Horizon

The time horizon is determined by both the constraint of academic submission deadlines and the strategy employed above – i.e. a survey. Since less than a year was available in which to do the research, only a cross-sectional study was practicable. As indicated above, technology adoption models are based on social-cognitive aspects. Thus, it is hypothesised that while cryptocurrency adoption may be happening at a fast rate, social and cognitive aspects will not change appreciably. Resultantly, in this epoch changes in the influence factors of adoption will not be material to the proposed research.

## 4.2 Population and Sampling

### 4.2.1 Population and Unit of Analysis

The study further limits the population to those with some knowledge of cryptocurrencies of which the most prevalent is Bitcoin. Since cryptocurrencies are fundamentally an internet technology, the population was further limited to internet users. It could be argued that this limits the studies relevance to offline consumers who may adopt cryptocurrency as a payment method. However, including the wider population would create complexity in explaining results, i.e. adoption of internet technologies compared to adoption of cryptocurrency. Additionally, those who intend to use or have used cryptocurrency would by the very nature of the technology be internet users. The requirement for familiarity with cryptocurrencies follows logically from the research questions, i.e. influencing variables driving adoption, intention to use, and usage. Similarly, the unit of analyses is the individual respondent since consumers are the target.

### 4.2.2 Sampling Technique

The initial technique used was self-selection sampling – a non-probability sampling technique. Self-selection sampling is effective when the population under study has distinct characteristics, for instance, cryptocurrency familiarity. However, self-selection sampling introduces biases due to those opting to participate potentially having strong opinions on the subject (Saunders & Lewis, 2012). The survey was posted on websites, forums, company intranets, and text messaging groups.

Following the initial sampling effort, snowball sampling was used. Snowball sampling is a non-probability sampling method where earlier respondents identify and distribute to further respondents (Saunders & Lewis, 2012). Snowball sampling is appropriate to populations in which the sampling units are difficult to identify (Saunders & Lewis, 2012). This is true for cryptocurrency users due to the anonymity aspects of the technology. There are no known public databases of users and access to proprietary databases would be close to impossible to obtain. Also, actual cryptocurrency users are hypothesised to be a specific niche community of early adopters. From adoption research, social influence processes imply a network effect amongst early adopters, further supporting the appropriateness of snowball sampling. Considering the other group of individuals under study, i.e. potential adopters also lend itself to snowball sampling. Alternative methods of achieving the reach required to build a large enough sample would be to advertise the survey on sites dealing with cryptocurrency. However, this could lead to significant costs without the surety of an increase in a representative sample of both users and potential users. Snowball sampling is also linked to the strategy employed – an electronic survey – since electronic surveys are easily distributed via electronic means. The downsides of snowball sampling are related to selection bias in initial respondents resulting in a potentially homogenous sample.

### 4.2.3 Sampling Size

The sample size for the survey is a minimum of 30 for each condition (Wegner, 2007). Furthermore based on the statistical technique – described in section 4.5 – a 20:1 ratio of samples to interactions estimated is required. Since 13 hypotheses are studied, this implies a sample size of 260. To account for potential unusable cases, the sample size targeted is rounded up to 300. Based on consumer awareness in studies performed in the US (Carr, Marsh, Dunn, & Grigorescu, 2015; Schuh & Shy, 2016) a low response rate was expected. A conservative estimate of a 20% response rate is used. This means for a minimum samples size of 300 responses, a total of 1500 respondents was targeted. This target was also chosen in light of time limitations and previous studies conducting similar research.

## 4.3 Research Instrument and Measurement

The base UTAUT2 model by Alalwan et al. (2017) selected above as the most appropriate theory for the proposed study also includes a survey instrument. The survey instrument was specific to mobile internet technology but was adaptable to cryptocurrency adoption. Also, the review of the extant literature in the personal finance domain noted trust as an important variable in predicting usage intention. The Alalwan et al. (2017) instrument is based on the initial survey instrument by Venkatesh et al. (2012) with the addition of the trust construct. This study, therefore, adopts the instrument from Venkatesh et al. (2012) with the addition of trust as per the implementation by Alalwan et al. (2017). Adaptation of the study was partially based on Schuh and Shy's (2016) findings related to the difficulties related to survey comprehension when dealing with cryptocurrencies.

A summary of the variables measured is presented here (Table 5), with the actual survey discussed next. The nature of the measured variables dictate the statistical tests that can be applied.

Table 5: Data types of response variables

| Variable | Data Type |
|---|---|
| Usage Frequency | Ordinal |
| Mobile Banking Usage | Ordinal |
| Age | Ratio |
| Gender | Dichotomous, Nominal |
| Income | Continuous |
| Education | Nominal |
| Country | Nominal |
| Psychological Measures | Likert, Ordinal |
| Technology Relationship | Ordinal |
| Services Used | Nominal |

## 4.4 Survey Design

Even though specific variables are not directly used in the proposed model – such as those related to demographics, these variables were relevant to the analysis. Some of these data points were therefore collected but were non-mandatory. The survey instrument content is found in Appendix A. Variables related to the constructs were operationalised as done by Alalwan et al. (2017) with modification for the domain under study, i.e. cryptocurrency and not mobile banking.

Demographic variables were first asked. Due to the sensitivity of information requested, some of these variables were optional. This affected the ability to quantify the moderating effects of age and gender. Furthermore, it was expected, along with other online technology research that respondents will be skewed towards males between the ages of 20 to 40 (Alalwan et al., 2017; Roos, 2015). However, gender and age effects are not central to answering the research questions (in section 1.1). Five age brackets were used: 18 -24; 25-34; 35-44; 45-54; and lastly 55 and over. The decision to exclude under 18s was to ensure that out of population groups were not included – under-18s do not have legal authority over their finances in most jurisdictions.

Questions targeting exogenous constructs that directly influence intention to use were mandatory. These constructs were PE, EE, SI, FC, HM, PV and TR. A full list of survey items appears in Appendix B. Each question had a five-point Likert scale from "strongly agree" to "strongly disagree". The choice between five or seven-point scales was found to be inconsequential on statistical analysis (Dawes, 2008). The Likert scale is coded from one to five for strongly disagree" to "strongly agree" respectively.

Behavioural intention and usage are the dependent or endogenous constructs in this study. Behavioural intention was tested using survey items as detailed in Appendix B. Usage is captured as a frequency of use scale item as is the case in the original research by Venkatesh et al. (2012) and as used in Alalwan et al. (2017). Usage was quantified according to a seven-point time scale: never, once a year, several times a year, once a month, several times a month, several times a week, several times a day (Alalwan et al., 2017; Venkatesh et al., 2012).

Usage type was also a question and therefore is self-reported. This is due to the difficulty of accessing actual usage data due to privacy and the anonymity of the cryptocurrency system. Included in this group of questions was the purpose of use in order to answer research question one (RQ1).

The survey was administered in English. The questionnaire was also piloted amongst five MBA students who are users of cryptocurrency from GIBS University. Due to the anonymous nature of the survey, the pilot group's participation in the final survey cannot be ruled out with certainty. However, due to the small size of the pilot group, contamination of results in the main survey is not considered. Ethical clearance was received from the university and is included in Appendix C.

## 4.5 Data Analysis

Descriptive statistics are performed in order to determine the statistical validity of the data as well as subsequent test application. The discussion below proceeds by outlining two methods. The first method discusses what is more prevalent in the extant literature. The second discusses the more robust and widely applicable technique of multiple linear regression.

### 4.5.1 Structural Equation Modelling (SEM)

In the original conception of UTAUT2, Venkatesh et al. (2012) used partial least squares regression (PLS) to test the model since the research was directed at determining all interaction between terms. Some form of structural equation modelling (SEM) is used in most studies reviewed in this research (Alalwan et al., 2017; Rondan-Cataluña et al., 2015; Venkatesh et al., 2012). Kline (2011) describe three areas of application for SEM: strictly confirmatory (testing existing models on a binary accept or reject basis), alternative model testing, and lastly model generation (where an initial model is adapted by the research for better fit with observations). There are two classes of SEM based on covariance and variance respectively. PLS-SEM is a variance technique. Svensson (2015) describes PLS-SEM as theory building and CB-SEM as theory testing.

This study tests documented relationships between variables in the domain of cryptocurrency and is therefore model testing. This research, therefore, is theory-testing indicating that CB-SEM is more appropriate.  SEM is similar to regression analysis to test the strength of relationships between dependent and independent variables. In the SEM nomenclature, variables are defined as observed (measured data – e.g. survey) and latent – continuous variables that cannot be observed directly (Kline, 2011). In the model being tested (in Figure 15), behavioural intention is a latent variable. Indicators are a subset of observed variables with the additional requirement that they are used as an indirect measure of some other model construct. For instance, trust in the model tested here is an observed variable used as an indicator of both behavioural intention – a latent variable and performance expectancy – another observed variable. A specific advantage of SEM is the ability to analyse these latent variables compared with other regression techniques such as analysis of variance (ANOVA) and multiple regression. An additional advantage and limitation is the ability to study the entire model rather than individual effects (Kline, 2011). The limitation arises in making assertions of validity between individual model parameters. The first step in a SEM analysis is to determine reliability, discriminant validity, and convergent validity of the measurement model. Discriminant validity is achieved when constructs are adequately distinguishable from related constructs (Agarwal & Prasad, 1998). Convergent validity tests how different indicators relate to the same construct. Average variance extracted (AVE) is calculated to determine discriminant validity with the threshold being the square of the correlations. Common method variance (CMV) was cited as a potential source of measurement error when using cross-sectional data in a single survey when studying latent variables (Luo et al., 2010). To ensure CMV is not a problem, the correlation matrix is examined for correlations between latent variables.

In SEM, unexplained variance – partly due to measurement error – is represented by error (or residual) terms. This is another advantage over first-generation techniques such as multiple regression where an unrealistic assumption of zero measurement error is required. This leads to a discussion on the limitations of SEM since a large sample is required. With small samples, standard errors may not be accurate (Kline, 2011). Jackson (2003) suggested a ratio of cases to the number of parameter estimates of 20:1 for implementations employing maximum likelihood estimation. Below a ratio of 10:1, results cannot be trusted. Bootstrapping is a resampling technique that creates more data sets by randomly sampling with replacement of the original dataset – the case of nonparametric bootstrapping (Kline, 2011). Kline (2011) however, cautions that bootstrapping is not a panacea for small samples, or non-normal distributions and may magnify problems in a small sample.

### 4.5.2 Multiple Linear Regression

As mentioned above, SEM is a second generation technique that is used for much of the same purposes as multiple linear regression (Kline, 2011). Due to the more onerous requirements on sample size for SEM, multiple linear regression presented another viable option. As discussed above, this has the disadvantages of not being a complete view of the interactions and mediating effects will have to be accepted if either a large enough sample is not collected, or non-normality or collinearity is detected. These aspects have been elaborated on in the preceding section on SEM. In much of the prior adoption research, SEM was the favoured technique. However, multiple regression has been used in research such as I. Brown et al. (2003) study of cell phone (mobile) banking adoption in South Africa and in the original TAM model by Davis (1989).

Multiple linear regression is a commonly used technique due to the simplicity of its application and the ease of which the results may be interpreted. The analysis involves a linear curve fitting in its simplest form determining the gradient and constant for a single line equation in the form of $y=mx+c$, where y is the independent variable and x the dependent variable (Wegner, 2007). The variable “m” then represents the proportion of variance in y explained by x. In multiple linear regression, there are multiple independent variables. There are a number of assumptions that must be met in order to use multiple regression (Chiba, 2015; Tompkins, 1991):

- A linear relationship between dependent and independent variables.
- Multivariate normality where residuals are assumed to be normally distributed.
- The absence of multicollinearity, i.e. no highly correlated independent variables. This can be tested using Variance Inflation Factor (VIF). Multicollinearity can lead to incorrect interpretations of the contribution of predictor variables to the variance in the dependent variable.
- Homoscedasticity where there are no large differences in the variance in error terms across the independent variables.

## 4.6 Research Limitations

An obvious limitation of the work is the use of self-reported usage rather than actual usage. However, self-reported usage was found to be a valid indicator of actual usage as indicated in Venkatesh and Davis (2000). When studying pro-social behaviour such as charitable giving, the tendency to over-report desirable behaviour, social-desirability bias, was found (Krumpal, 2013). It is, however, unlikely that respondents overstated usage as the context was non-mandatory and cryptocurrencies are not necessarily a pro-social behaviour. Image amongst early adopters may, however, play a role.

Chuttur (2009) provided an overview of adoption models. In it, he highlights the concerns of other researchers in the behavioural-usage link underpinning TAM that UTAUT2 inherits. Citing Bagozzi (2007), he explained that intention to use and behaviour is not an appropriate link since users intention is based on a more fundamental need or want. In the case of cryptocurrencies, this would be to invest or transact. This is supported by Wu and Du's (2012) meta-study on the linkages between BI and usage.

## 4.7 Conclusion

Much of the choices on methodology were made in light of the characteristics of the technology under study which are maturity, complexity, and consumer awareness. Therefore, the research followed a positivist philosophy aiming to identify the general variables driving adoption. The approach was deductive using a quantitative study of primary cross-sectional survey data. The population under study was defined as those internet users with familiarity of cryptocurrency. The sampling technique used was self-selection and snowball sampling primarily for the practical reality of reaching cryptocurrency users and potential adopters. The researcher maintains an understanding of the limitations of this technique which are discussed further in later chapters. To ensure flexibility in analysis techniques, a relatively large sample of 300 respondents was targeted. The instrument used in the study of Alalwan et al. (2017) is used since it is based largely on the original UTAUT2 work by Venkatesh et al. (2012) and has been validated. Two options for the data analysis section were proposed contingent on the sample achieved. The first, structural equation modelling (SEM) is the tool of choice in the adoption theory applications reviewed in chapter 2, and represents a more robust analysis but with more onerous requirements on the sample. A second option, multiple-linear regression has been less frequently applied but offered less onerous conditions on the sample collected and less complexity in drawing valid and non-spurious statistical conclusions. Finally, the limitations of the study are listed as determined by the methodology choices described. In the next chapter, the results obtained using the methodology discussed in this chapter are presented before discussing their implications in Chapter 6.

# Chapter 5: Results

The statistical analysis was performed using the software package from IBM called the Statistical Package for Social Sciences (SPSS) version 24. This section begins with a description of the sample. Tests for validity and reliability of the data is then presented. The results of three multiple linear regressions are then presented based on the dependent variable modelled i.e. BI, PE, and CU.

## 5.1 Data Transformations

The only data transformations were to convert text entry fields for income into the corresponding numeric value. For income, data had to be manually transformed into South African Rand (ZAR) using the exchange rate at the time of analysis (12 September 2017). The exact exchange rate is not particularly important due to the low response rate for non-South African residents. In addition to currency conversions, the survey question allowed text entry which meant that all data had to be converted from thousands, millions and decimal format into the appropriate Rand value.

## 5.2 Sample Description

This section presents the descriptive statistics. There were a total of 323 respondents to the online survey, of which 280 were in the population of interest, i.e. those individuals with some knowledge of cryptocurrencies or the various incarnations, most notably Bitcoin. A summary of the demographic profile appears in Table 6 below with "frequency" referring to the number of respondents for the question and "valid percent" referring to the proportion or percentage of the total responses.

Table 6: Demographic and usage profile of respondents.

| | Frequency | Valid Percent |
|---|---|---|
| **Cryptocurrency Usage Frequency (CCUF)** | | |
| Never | 168 | 60,0 |
| Once a year | 20 | 7,1 |
| Several times a year | 25 | 8,9 |
| Once a month | 13 | 4,6 |
| Several times a month | 27 | 9,6 |
| Several times a week | 18 | 6,4 |
| Several times a day | 9 | 3,2 |
| Total | 280 | 100,0 |
| **Internet Usage Frequency (IUF)** | | |
| Never | 1 | 0,4 |
| Several times a year | 2 | 0,7 |
| Once a month | 6 | 2,1 |
| Several times a month | 98 | 35,0 |
| Several times a week | 121 | 43,2 |

| | | |
|---|---|---|
| Several times a day | 52 | 18,6 |
| Total | 280 | 100,0 |
| **Technology Comfortableness (TC)** | | |
| Very comfortable | 201 | 71,8 |
| Comfortable | 64 | 22,9 |
| Neutral | 8 | 2,9 |
| Very uncomfortable | 7 | 2,5 |
| Total | 280 | 100,0 |
| **Age** | | |
| 18 - 24 | 14 | 5,0 |
| 25 - 34 | 178 | 63,6 |
| 35 - 44 | 64 | 22,9 |
| 45 - 54 | 20 | 7,1 |
| 55 and over | 4 | 1,4 |
| Total | 280 | 100,0 |
| **Gender** | | |
| Male | 239 | 86,0 |
| Female | 39 | 14,0 |
| Total | 278 | 100,0 |
| Missing values | 2 | |
| Total | 280 | |
| **Level of Education (LOE)** | | |
| No schooling completed | 1 | 0,4 |
| High school graduate | 33 | 11,8 |
| Bachelor's degree | 63 | 22,5 |
| Honours degree | 97 | 34,6 |
| Postgraduate degree | 86 | 30,7 |
| Total | 280 | 100,0 |

### 5.2.1 Cryptocurrency Usage Frequency and Services Used or Planned

For Cryptocurrency Usage Frequency (CCUF), of the 280 respondents, an overall majority of 60% had never used a cryptocurrency even though they had knowledge of it. This means that only 40% or 112 respondents had used a cryptocurrency at least once a year. The full breakdown appears in Table 7 below, together with gender breakdown. Only seven female respondents have ever used a cryptocurrency. For comparison, 99.06% of respondents had used internet banking at least once a year with 96.8% using it at the minimum several times a month. From the respondents, 94.7% stated they were comfortable with technology – defined as the latest gadget or smartphone.

Table 7: Cryptocurrency usage with gender breakdown.

| Row Labels | % of n | n |
|---|---|---|
| **Never** | **61.43%** | **172** |
| Female | 11.07% | 31 |
| Male | 50.36% | 141 |
| **Once a year** | **7.14%** | **20** |
| Female | 0.36% | 1 |

| | | |
|---|---|---|
| Male | 6.79% | 19 |
| **Several times a year** | **8.57%** | **24** |
| Female | 1.07% | 3 |
| Male | 7.50% | 21 |
| **Once a month** | **4.64%** | **13** |
| Female | 0.71% | 2 |
| Male | 3.93% | 11 |
| **Several times a month** | **8.93%** | **25** |
| Female | 0.36% | 1 |
| Male | 8.57% | 24 |
| **Several times a week** | **6.07%** | **17** |
| Male | 6.07% | 17 |
| **Several times a day** | **3.21%** | **9** |
| Male | 3.21% | 9 |
| **Grand Total** | **100.00%** | **280** |

Of the total, 266 respondents chose one of the survey offered options for usage categories. The results are shown in Table 8 below, noting that multiple selections were possible. Predominantly usage is for investments, and payments or transactions. Investment for growth is the outright leader with 73.9%.

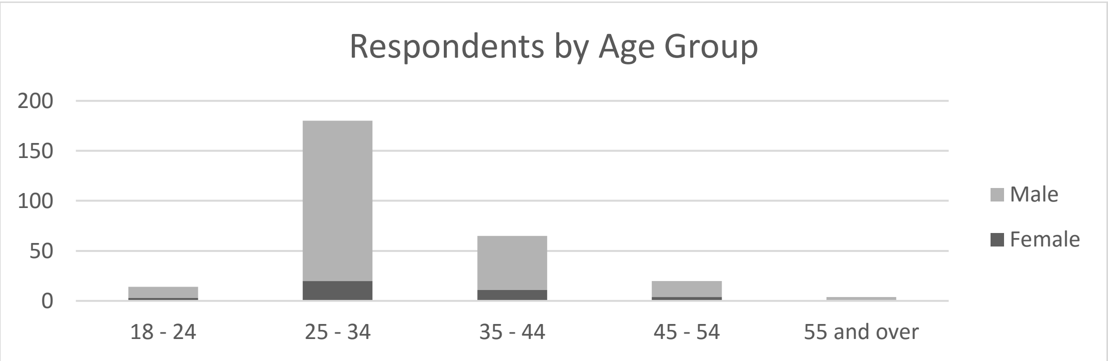
Table 8: Proportion of respondents per use case.

| Investment | Payments | International Transfers | Savings | Currency Hedge | Total Users |
|---|---|---|---|---|---|
| 195 | 156 | 134 | 115 | 120 | 264 |
| 73.9% | 59.1% | 50.8% | 43.6% | 45.5% | 100% |

### 5.2.2 Age and Gender

The largest proportion of respondents were in the 25-34 age group with 63.6% followed by the 35-44 age group with 23.1% as shown in Figure 16 below. In this sample these age groups together, i.e. 25-44 account for 86.5% of the respondents.

Figure 16: Frequency plot of respondent age category




The statistics for gender are shown per usage frequency in Table 7. Of the 280, 239 identified as male (86%). Two respondents identified as other and were removed. The low number of female respondents makes the study of gender effects unrealistic – although this study did not seek to achieve an understanding of gender effects primarily.

### 5.2.3 Level of Education

In level of education, the two largest groups accounting for 65% of responses were those with an honours degree (34.4%) and those with a post-graduate degree (30.9%) indicating a highly educated sample. Only 12% of respondents were without any tertiary qualification – bachelor's degree or higher.

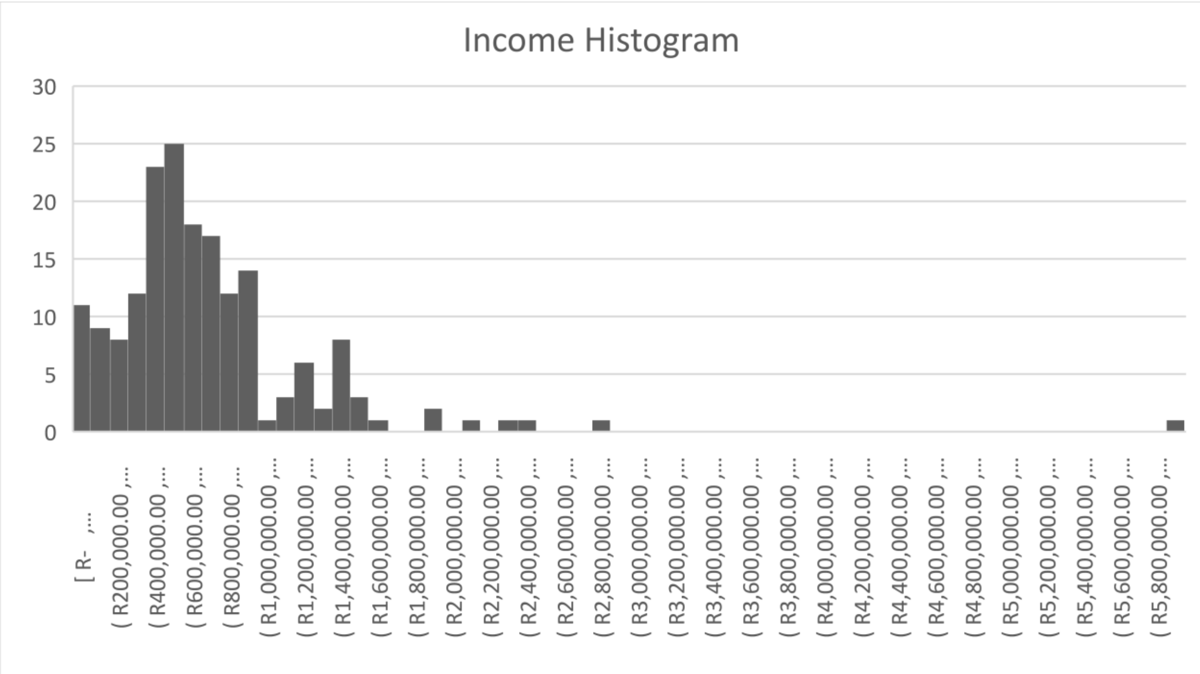
### 5.2.4 Country of Respondents

Respondents were asked to select their country of residence rather than nationality. Regarding the respondent's location, 88.6% of all respondents were based in South Africa, with some minor numbers (between 1 and 2%) from the United States of America, United Kingdom, Australia and Germany.

### 5.2.5 Income Levels

The histogram in Figure 18 below shows the frequency distribution of annual incomes in R100,000 buckets.

Figure 17: Income histogram for respondents in the sample.




Since a continuous variable was used to measure annual income, means and standard deviations are calculated. A mean income of R483,514 (34,402 USD) is observed, taking note of the high standard deviation of R615,945 (43,825 USD) indicating a significant spread of income values amongst respondents. The median income was R400,000

(28,460 USD). All conversions to USD are based on an exchange rate of 0.071 R/USD at 3 November 2017 (XE.com, 2017).

Table 9: Descriptive statistics for income variable.

**Annual Gross Income**

| | |
|---|---|
| Mean | 483 514.71 |
| Median | 400 000.00 |
| Std. Deviation | 615 944.509 |
| Minimum | 0 |
| Maximum | 6000000 |

## 5.3 Validity and reliability

### 5.3.1 Rejection of the SEM Method

The SEM model was attempted despite the small sample size using the bootstrapping technique to artificially inflate the sample size. However, this study had only 280 responses and much fewer responses for each pair-wise construct due to missing values, throwing some doubt on the statistical validity of the findings. Errors may be introduced through the use of the bootstrapping technique as discussed in section 4.5.1. A clean-up of some of the items resulted in a better model fit, however PE, EE and FC were still problematic due to AVE scores below 0.5. Costello and Osborne (2005) indicated that smaller sizes are tolerable however the requirement is that the data be "strong". Strong data indicates high communalities without cross-loadings. Due to the criticality of these terms in the analysis and the concerns outlined above regarding sample size and bootstrapping, it was decided to conduct a series of multiple linear regressions in SPSS. This is the analysis that follows.

### 5.3.2 Multiple Regression Assumptions

In order to perform a valid multiple regression analysis, certain assumptions must be met. In addition, a sample size of at least 20 cases per dependent variable is required (Wegner, 2007). The sample size here exceeds the minimum. The assumptions of normality and presence of outliers, a linear relationship, homoscedasticity, and multicollinearity need to be verified.

Normality is required to ensure that biases are not introduced in the data analysis. Using SPSS skewness and kurtosis scores are calculated as shown in Table 10 below. According to Field (2013), magnitudes of each statistic should not exceed 2. From the table, all values are within the recommended range.

Table 10: Skewness and Kurtosis statistics.

| | Skewness | Kurtosis |
|---|---|---|
| | Statistic | Statistic |
| **PE** | -1,083 | 1,128 |
| **EE** | -0,719 | 0,451 |
| **SI** | -0,168 | -0,341 |
| **FC** | -0,589 | 0,248 |
| **TR** | -0,332 | 0,012 |
| **HM** | -0,292 | -0,128 |
| **BI** | -0,568 | -0,015 |

The data were visually inspected for outliers using SPSS boxplots. Some outliers were identified, however since the mean does not appreciably differ from the trimmed mean, these are adjudged to not affect the data (Field, 2013; Pallant, 2013). This analysis is presented in Appendix D. The data used to check validity is summarised in Table 11 below. The Variance Inflation Factor (VIF) and tolerance scores below indicate no multicollinearity, i.e. independent variables are not highly correlated. Multicollinearity refers to the correlation between the predictor variables themselves and is assessed by VIF and the tolerance statistic. VIF should be below 10, and the tolerance statistic should be above 0.1 (Field, 2013; Pallant, 2013).

Table 11 below shows that all predictor variables are within the recommended ranges indicating that the assumption of multicollinearity is met. A normal distribution of residuals around the predicted scores demonstrates that the assumption of multivariate normality holds. For testing whether there is a linear relationship between BI and its antecedent variables, the normal P-P plot was inspected to ensure that the assumption of linearity is met. Lastly, the assumption of homoscedasticity is checked through inspection of a scatter plot. The rectangular shape indicates that the variances of error terms are equally distributed across all values for the independent variables. Therefore, the assumption of homoscedasticity is met.

Table 11: Validity data for the sample.

| PE | BI | Usage |
|---|---|---|

**Multicollinearity statistics**

PE

| | Tolerance | VIF |
|---|---|---|
| *EE* | 0,512 | 1,954 |
| *TR* | 0,322 | 3,104 |

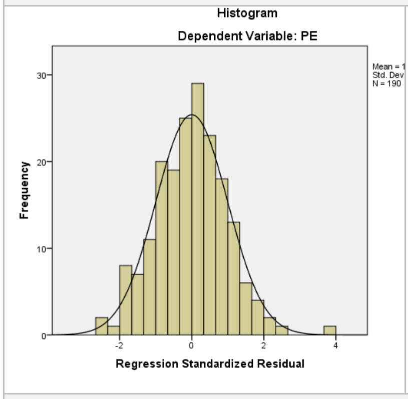
BI

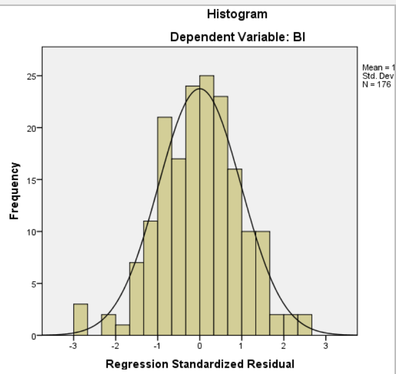
| | Tolerance | VIF |
|---|---|---|
| *PE* | 0,351 | 2,846 |
| *EE* | 0,512 | 1,954 |
| *SI* | 0,773 | 1,293 |
| *HM* | 0,367 | 2,725 |
| *TR* | 0,322 | 3,104 |

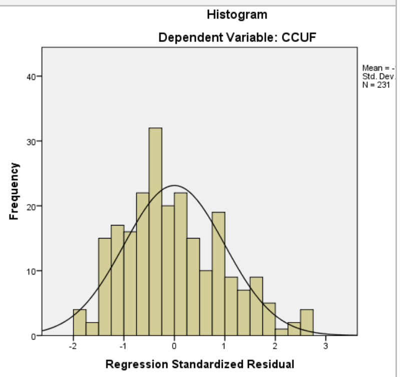
Usage

| | Tolerance | VIF |
|---|---|---|
| **FC** | 0,696 | 1,436 |
| **BI** | 0,696 | 1,436 |

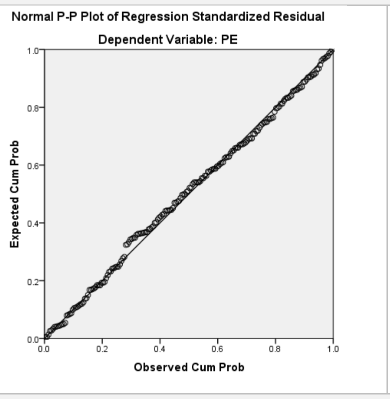
**Normality**

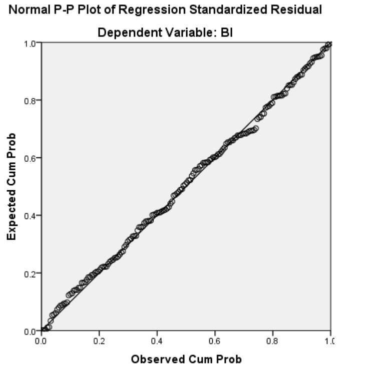


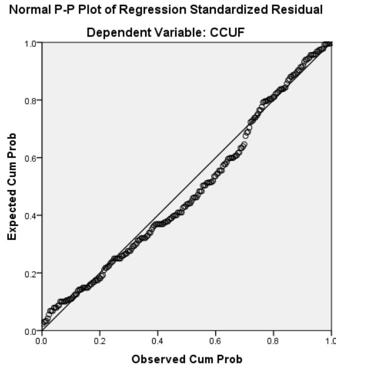



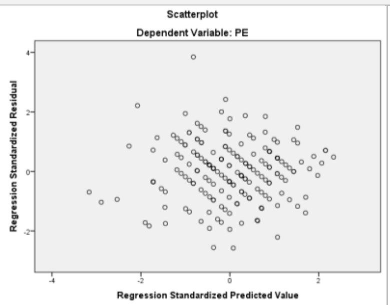

**Linearity**

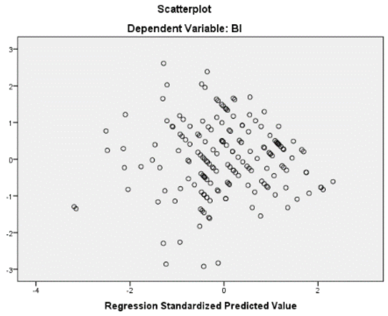


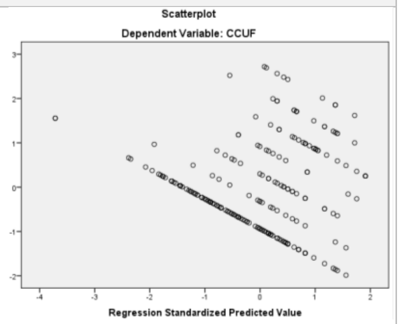




**Homoscedasticity**



### 5.3.3 Reliability

Assessing reliability involves checking for internal consistency. Table 12 below shows Cronbach's Alpha coefficients for each of the constructs. For reliability, Cronbach's Alpha should be above 0.7 (Field, 2013). Scores for PV are below this level and are therefore excluded from further analysis. Remaining scores range from 0.738 to 0.891 indicating adequate internal consistency of the measurement instrument.

Table 12: Reliability statistics for model constructs

| Constructs | Cronbach's Alpha |
|---|---|
| **PE** | 0.747 |
| **EE** | 0.810 |
| **SI** | 0.891 |
| **FC** | 0.738 |
| **TR** | 0.793 |
| **HM** | 0.779 |
| **BI** | 0.887 |
| ~~**PV**~~ | *0.589* |

### 5.3.4 Convergent Validity

In order to ensure scales are reliable (i.e. exhibit internal consistency) correlation between each scale and the total construct score is analysed. A score of 0.5 indicates a 50% correlation. The corrected item-total correlation should be above 0.5 with 0.4 being marginally acceptable (Pallant, 2013). Correlations for each survey item is shown in the table below with most items exceeding 0.5 and a few only exceeding the 0.4 limit indicating good loading. There is therefore convergent validity of the scale.

Table 13: Item-total statistics

| Items (statements) | Corrected Item-Total Correlation |
|---|---|
| **Performance Expectancy** | |
| PE1 | 0,589 |
| PE2 | 0,624 |
| PE3 | 0,548 |
| PE4 | *0,412* |
| **Effort Expectancy** | |
| EE1 | 0,671 |
| EE2 | 0,582 |
| EE3 | 0,626 |
| EE4 | 0,632 |
| **Facilitating Conditions** | |
| FC1 | 0,606 |
| FC2 | 0,581 |
| FC3 | 0,518 |

| | |
|---|---|
| FC4 | *0,427* |
| **Social Influence** | |
| SI1 | 0,841 |
| SI2 | 0,734 |
| SI3 | 0,779 |
| **Hedonic Motivation** | |
| HM1 | 0,663 |
| HM2 | 0,730 |
| HM3 | *0,448* |
| **Behavioural Influence** | |
| BI1 | 0,842 |
| BI2 | 0,537 |
| BI3 | 0,836 |
| BI4 | 0,809 |
| **Trust** | |
| TR1 | 0.586 |
| TR2 | 0.599 |
| TR3 | *0.493* |
| TR4 | *0.404* |
| TR5 | 0.676 |
| TR6 | 0.528 |

## 5.4 Results Per Hypothesis

The study seems to find predictor variables of usage intention and usage behaviour in consumers. The various constructs have been described in chapter 2 and are an arithmetic mean of the items in the construct, e.g. PE = (PE1 + PE2 + PE3 + PE4)/4. CCUF refers to usage frequency and is not computed but is simply a scale from one to seven where one refers to no previous cryptocurrency usage (CU) and seven usage multiple times a day. Descriptive statistics for these constructs are provided in Table 14 below.

Table 14: Descriptive statistics for all variables.

| **Descriptive Statistics** | | |
|---|---|---|
| | **Mean** | **Std. Deviation** |
| PE | 3,16 | 0,75 |
| EE | 3,46 | 0,79 |
| FC | 3,55 | 0,78 |
| SI | 2,89 | 0,92 |
| HM | 3,38 | 0,84 |
| TR | 3,15 | 0,73 |
| BI | 3,74 | 0,85 |
| CU | 2,29 | 1,87 |

The table indicates that most respondents agreed with the statements (with means above a neutral response of 3). In terms of actual usage, a mean of 2.29 indicates low usage (std. dev = 1.87) in the sample.

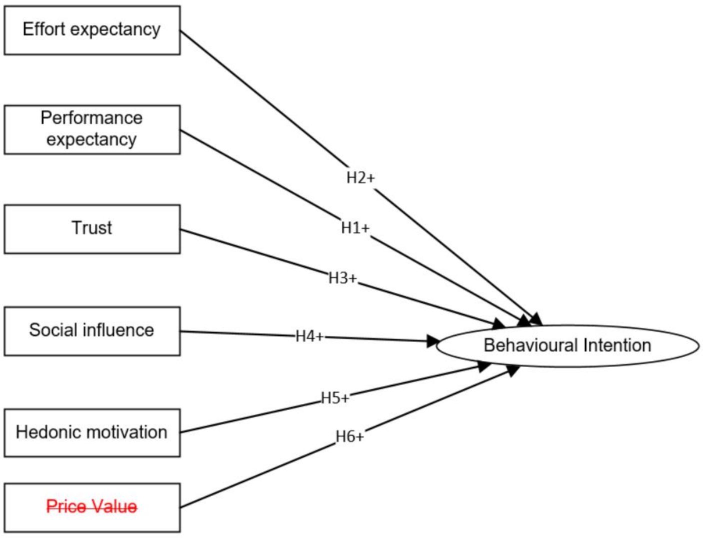
The model hypothesised includes three outcome variables, and so three multiple linear regressions are performed. The three outcome variables are PE predicted by EE and TR, BI predicted by PE, SI, HM, TR, EE, and CU predicted by BI and FC. The sections below are presented according to the dependent variable.

**NOTE** on missing values: The selection used in SPSS was to exclude cases pairwise so that per analysis (or variable) only cases with missing values were excluded for that specific variable.

### 5.4.1 Behavioural Intention (BI) – H1 to H6

BI antecedents deal with hypotheses H1 (PE), H2 (EE), H3 (TR), H4 (SI), H5 (HM), H6 (PV). The hypothesised effects are all positive, i.e. increasing BI. The model in Figure 18 below summarises the subset of the hypothesised model analysed in this section.

Figure 18: Independent predictor variables of behavioural intention in the hypothesised model.




The bivariate Pearson correlations are shown in Table 15 below indicating statistically significant positive correlations at a 99% confidence level for all constructs. The bivariate correlation values are all less than 1. This indicates that a study of predictive influence is valid – analysed below using multiple linear regression.

Table 15: Correlation matrix for behavioural intention as the dependent variable.

**Correlations**

| | PE | EE | SI | HM | TR | BI |
|---|---|---|---|---|---|---|
| PE | | | | | | |
| EE | 0.614** | | | | | |
| SI | 0.440** | 0.168* | | | | |
| HM | 0.700** | 0.629** | 0.314** | | | |
| TR | 0.746** | 0.624** | 0.383** | 0.754** | | |
| BI | 0.664** | 0.562** | 0.433** | 0.713** | 0.709** | |

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

The model is summarised in Table 16 below and indicates that the six predictor variables explain 60.5% of the variance in BI using the adjusted R-squared value. An adjusted R-squared value is one where the variance is modified to include the effect of increased R-squared scores due to chance (Chiba, 2015).

Table 16: Summary statistics of regression model with behavioural intention as the dependent variable.

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .785[a] | .616 | .605 | .53337 |

Predictors: TR, SI, EE, HM, PE

Next, a test for significance is necessary using the ANOVA technique (Chiba, 2015). The ANOVA table below indicates that the result above is a good fit for the data and is statistically significant with a p-value less than 0.001 (F = 57.740).

Table 17: ANOVA results for regression model with behavioural intention as the dependent variable

**ANOVA**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 82.129 | 5 | 16.426 | 57.740 | .000[b] |
| | Residual | 51.206 | 180 | .284 | | |
| | Total | 133.335 | 185 | | | |

a. Dependent Variable: BI

b. Predictors: TR, SI, EE, HM, PE

The effect of each predictor can be analysed using the table of coefficients below:

Table 18: Regression coefficient results and hypothesis decisions with behavioural intention as the dependent variable.

| Coefficients | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Unstandardized Coefficients | | Stand. Coeffs | t | Sig. | Hypotheses Decision |
| | | B | Std. Error | Beta | | | |
| | (Constant) | 0,476 | 0,208 | | 2,291 | 0,023 | |
| | PE | 0,121 | 0,088 | 0,107 | 1,379 | 0,170 | H1 Rejected |
| | EE | 0,113 | 0,070 | 0,104 | 1,615 | 0,108 | H2 Rejected |
| | SI | 0,155 | 0,048 | **0,168** | **3,207** | **0,002** | H4 Accepted |
| | HM | 0,334 | 0,077 | **0,332** | **4,349** | **0,000** | H5 Accepted |
| | TR | 0,291 | 0,095 | **0,249** | **3,063** | **0,003** | H3 Accepted |
| **Dependent Variable: BI** | | | | | | | |

The regression equation is, therefore,

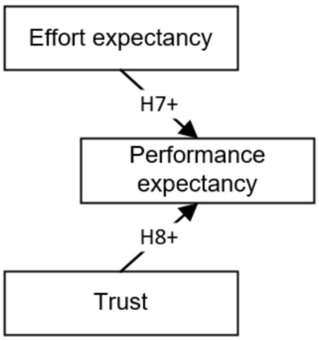
$$BI = 0.476 + 0.121(PE) + 0.113(EE) + 0.155(SI) + 0.334(HM) + 0.291(TR) + 0.208$$

with a standard error of 0.208 – the last term. From Table 18 above, PE and EE do not have a statistically significant effect at the 95% confidence interval ($p > 0.05$) and these hypotheses H2 and H1 are rejected. Of the statistically significant effects, HM is the strongest predictor followed by TR and then SI. These hypotheses – H3, H4, and H5 are therefore accepted.

### 5.4.2 Performance Expectancy (PE) – H7 and H8

PE antecedents were hypothesised to be effort expectancy (H7) and trust (H8) with a positive effect, i.e. to increase PE (Figure 19). The analysis below follows similarly to what was presented in the section above.

Figure 19: Independent predictor variables of performance expectancy in the hypothesised model.




The regression analysis is summarised in Table 19 below. The R-squared value indicates that TR and EE explain up to 58.9% of the variance of PE in the sample.

Table 19: Summary statistics of the regression model with performance expectancy as the dependent variable.

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .770[a] | .593 | .589 | .48158 |

Predictors: TR, EE

An ANOVA – shown in Table 20 – indicates that the model is a good fit for the data and is significant with p-value < 0.001.

Table 20: ANOVA results for regression model for performance expectancy as the dependent variable.

**ANOVA**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 64.900 | 2 | 32.450 | 139.918 | .000[b] |
| | Residual | 44.529 | 192 | .232 | | |
| | Total | 109.429 | 194 | | | |

a. Dependent Variable: PE

b. Predictors: (Constant), TR, EE

A table of coefficients is shown in Table 21 below indicating both predictors are significant. TR is the stronger predictor at β=0.594 (p-value <0.001) with EE having a β of 0.243 (p-value < 0.001). The analysis, therefore, fails to reject hypotheses H3 and H8.

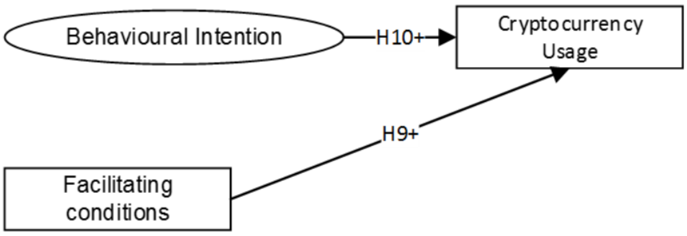
Table 21: Regression coefficient results and hypothesis decisions with performance expectancy as the dependent variable.

| | **Unstandardized Coefficients** | | **Standardized Coefficients** | **t** | **Sig.** | **Decision on hypotheses** |
|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | | |
| **(Constant)** | 0,414 | 0,171 | | 2,418 | 0,017 | |
| **EE** | 0,233 | 0,056 | 0,243 | 4,132 | 0,000 | H7 Accepted |
| **TR** | 0,614 | 0,061 | 0,594 | 10,093 | 0,000 | H8 Accepted |

### 5.4.3 Usage (CU) – H9 – H10

Usage is hypothesised to be affected positively in hypotheses H9 (FC) and H10 (BI). The third regression analysis is summarised in the model in Figure 20 below.

Figure 20: Independent predictor variables of usage in the hypothesised model.




A correlation matrix is shown in Table 22 below indicating statistically significant correlations

Table 22: Correlations matrix for usage as the dependent variable.

| Correlations | | | |
|---|---|---|---|
| | FC | BI | CCUF |
| FC | | | |
| BI | .551** | | |
| CCUF | .492** | .462** | |
| **. Correlation is significant at the 0.01 level (2-tailed). | | | |

From the multiple regression results inTable 23, BI and FC explain 28.8% of the variance in usage (CU).

Table 23: Summary of regression model with usage as the dependent variable.

| Model Summary | | | | |
|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
| 1 | .543[a] | .295 | .288 | 1.579 |
| Predictors: BI, FC | | | | |

The ANOVA – shown in Table 24 below – indicates that the model is significant.

Table 24: ANOVA results for regression model for Usage as the dependent variable.

**ANOVA**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 237.407 | 2 | 118.704 | 47.609 | .000[b] |
| | Residual | 568.473 | 228 | 2.493 | | |
| | Total | 805.880 | 230 | | | |

a. Dependent Variable: CCUF

b. Predictors: (Constant), BI, FC

The table of coefficients appears in Table 25 below.

Table 25: Regression coefficient results and hypothesis decisions with usage (CU) as the dependent variable.

**Coefficients**

| Model | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. | Decision on the Hypotheses |
|---|---|---|---|---|---|---|
| (Constant) | -2,876 | 0,540 | | -5,329 | 0,000 | |
| FC | 0,817 | 0,160 | 0,341 | 5,109 | 0,000 | H9 Accepted |
| BI | 0,606 | 0,147 | 0,275 | 4,123 | 0,000 | H10 Accepted |

a. Dependent Variable: CU

Both predictors are significant and positive. FC has the strongest influence on CU.

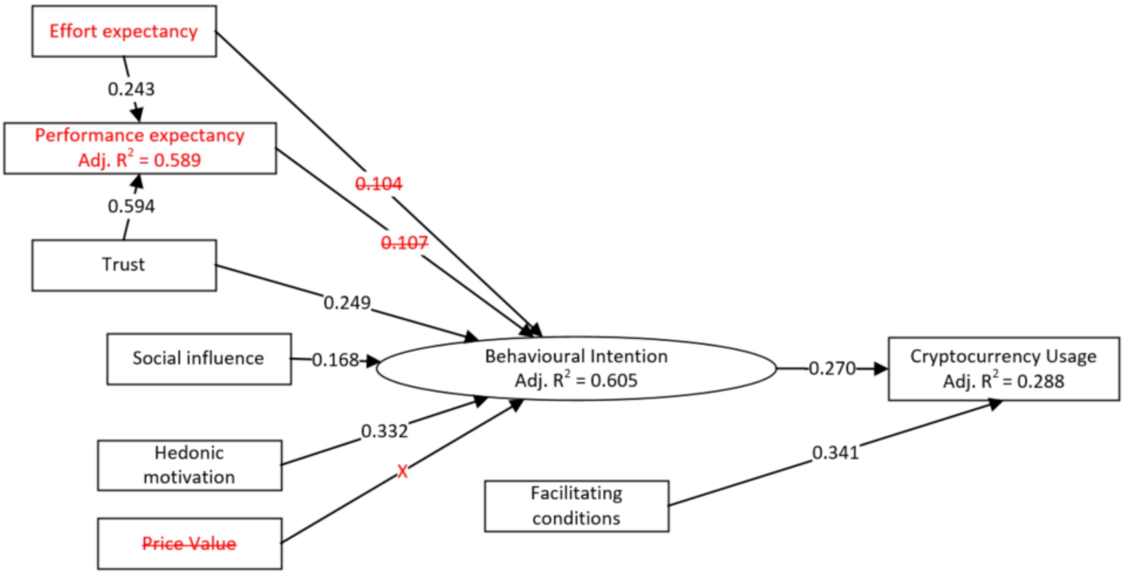
### 5.4.4 Moderating Variables, Age and Gender – H11 to H13

Due to the low sample size and number of respondents in each group, a statistical analysis of moderating effects was deemed not to be valid. Therefore, H12, H13, and H14, i.e. the moderating effects of age and gender on the relationship between FC and usage, and the moderating effects of age and gender on HM and PV on BI.

## 5.5 Summary of Results

Overall the model was able to explain 60.5% of the variance in behavioural intention and 28.8% of actual usage. All three regressions are significant (p-value < 0.05). It is noted that the validity of usage construct suffers from a small sample when interpreting the results.

Figure 21: Resultant model including non-valid and non-significant effects.




In addition, effort expectancy and trust together explained 58.9% of the variance in performance expectancy. However, performance expectancy as well as effort expectancy was not found to have a significant effect on behavioural intention and is therefore excluded from the final model. This departure from the technology adoption literature is discussed further below. Price value was not found to display item validity. A tabulated summary of the results per hypotheses appears in Table 26 below.

Table 26: Summary of findings per hypothesis.

| H# | Description | Result |
|---|---|---|
| H1 | Performance expectancy will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Rejected |
| H2 | Effort expectancy will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Rejected |
| H3 | Effort Expectancy will positively influence performance expectancy of cryptocurrencies. | Accepted |
| H4 | Social influence will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Accepted |
| H5 | Hedonic motivation will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Accepted |
| H6 | Price Value will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Not Valid |
| H7 | Trust will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Accepted |

| | | |
|---|---|---|
| H8 | Trust as a mediator of performance expectancy will show a positive effect on performance expectancy for cryptocurrencies. | Accepted |
| H9 | Facilitating conditions will positively influence a consumer's behavioural intention to adopt cryptocurrencies. | Accepted |
| H10 | Behavioural Intention will positively influence a consumer's adoption of cryptocurrencies. | Accepted |
| H11 | Age and Gender will moderate the effect of facilitating conditions on actual usage with the effect being stronger for older women. | Not studied |
| H12 | Age and Gender will moderate the effect of price value on behavioural intention such that the effect will be stronger for older women. | Not studied |
| H14 | Age and Gender will moderate the effect of hedonic motivation on behavioural intention such that the effect will be stronger for younger men. | Not studied |

## 5.6 Conclusion

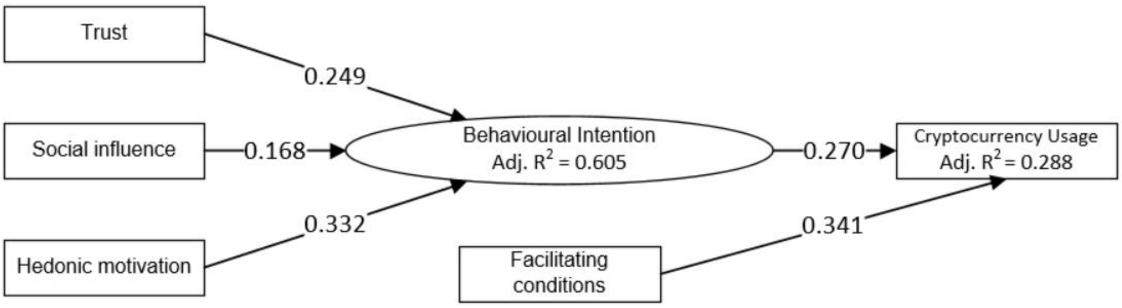
The results in this chapter are presented without any insights drawn. First, the description of the sample is given, indicating young, affluent, tertiary educated, male, respondents who report regular use of internet banking and being comfortable with the latest technology. The sample is also heavily biased toward South African respondents. The homogeneity found with regards to gender and age means that between-group differences are not studied further. Hypotheses H11 to H14 are therefore not tested.

The sample is checked for validity and reliability finding both to be adequate for the purposes of multiple linear regression. PV is found to be unusable due to a Cronbach Alpha score under 0.7. Therefore, hypothesis H6 cannot be tested statistically. Three multiple linear regression analyses are then run, each with BI, PE, and CU as the dependent variable. With BI as the dependent variable, PE and EE are found to be non-significant. Hypotheses H1 and H2 are therefore rejected. HM is found to be the strongest predictor of BI. For CU, FC is found to be the strongest predictor ahead of BI. Hypotheses H3-H5 and H7-H10 are accepted. The combined model is able to predict 60.5% of the variance in BI and 28.8% in CU. These results present the basis for the discussion that follows in Chapter 6.

# Chapter 6: Discussion of Results

The model presented above indicates that hedonic motivation (β=0.332; t=4.349; p-value<0.01), trust (β=0.249; t=3.063; p-value<0.01) and social influence (β=0.168; t=3.207; p-value<0.01) have a significant positive effect on behavioural intention (p-value<0.01) explaining 60.5% of the variance in BI. In this study, a 95% confidence interval is used. Hedonic motivation is the strongest predictor. In turn, facilitating conditions (Beta = 0.270) and behavioural intention (Adjusted $R^2$ = 0.341) significantly affect actual cryptocurrency usage (p-value < 0.01) explaining 28.8% of the variance in usage (CU). For comparison, Alalwan et al. (2017) were able to explain 65% of the variance in BI for mobile banking adoption and 31% for actual usage. Of the other studies reviewed, R-squared values ranged from 59% to 81% for BI and approximately 30% to 40% for usage (Koenig-Lewis, Marquet, Palmer, & Zhao, 2015; Mahfuz, Khanam, & Wang, 2017; Shin, 2009). Alalwan et al. (2017) is the closest model to which a comparison can be made if any – since it used UTAUT2 with TR added and no moderating or interacting effects. The model presented here, therefore, exhibits comparative predictive strength. The final model is shown Figure 22 below.

Figure 22: Final model showing only significant and valid effects.




Both performance expectancy (p-value = 0.170) and effort expectancy (p-value = 0.108) were found to be non-significant (p-value > 0.05). These results are discussed per hypothesis below before analysing non-valid and non-significant results.

## 6.1 Sample Achieved

The population targeted were those with internet access and some knowledge of cryptocurrency. The sample size achieved of 280 and specifically pairwise sample size without missing variables was not large enough to perform SEM reliably. Multiple linear regression was therefore chosen.

The respondent demographics and usage profile of respondents are mostly expected given previous surveys on consumers (Carr, Marsh, Dunn, & Grigorescu, 2015; Christian et al., 2014; Schuh & Shy, 2016). In a 2014 study, only 6% of consumers were aware of cryptocurrencies, and only 3% used cryptocurrency in the preceding year (Carr, Marsh, Dunn, & Grigorescu, 2015). In the second study in 2015, 4.7% were more than slightly familiar. In this study, only 39.8% used cryptocurrency at least once in the last year – a large jump over PWC's 2014 (published in 2015) study, noting the geographical difference in sample respondents, i.e. the US vs South Africa. This may be reflective of local conditions with regards to trust in government and currency volatility experienced during the same period.

Of the total in this sample, only 67 (23.8%) respondents had used cryptocurrency at least once a month. This is much larger than was found for a study in the US where 1-1.5% had ever owned cryptocurrency in 2015 (Schuh & Shy, 2016). This may be due to the adoption curve effects as shown in Spenkelink's (2014) system dynamic model where adoption is exponential and the general adoption s-curve in Innovation Diffusion Theory (IDT). Furthermore, as shown by awareness metrics, South Africa is a leader in terms of interest in cryptocurrencies (Google, 2017). Contrary to cryptocurrency usage a majority of respondents indicated that they used internet or mobile banking (IUF) at least once a month (96.8%) and were comfortable or very comfortable with technology (TC) (94.7%). This is expected since Schuh and Shy (2016) found that adopters were most likely to be users of internet banks and online payment services. This indicates a sample of tech-savvy respondents by these measures. This also shows that adopters and potential adopters are drawn from existing user bases for internet and mobile banking. The homogeneity of the samples in terms of IUF and TC also means that between-group differences are not studied statistically.

Table 27: Summary of majority demographic and usage characteristics in the sample.

| **Variable** | **% of Sample** |
|---|---|
| Cryptocurrency usage frequency, at least once a month | 23.8 |
| Internet/Mobile banking, at least once a month | 98.9 |
| Comfortableness with technology, comfortable or very comfortable | 94.7 |
| Age groups, between 25 and 44 | 86.5 |
| Gender, male | 86.0 |
| Level of education, at least a bachelor's degree | 87.8 |
| Country of residence, South Africa | 88.6 |

Table 27 above, summarises the sample demographics. Income levels had a mean of R483,514 per annum and a median income of R400,000. Income levels correlate with other demographic variables such as level of education. Read together; the sample is dominated by relatively affluent South African males between the ages of 25 and 44 (with 63.6% between 25 and 34) with at least a bachelor's degree. Studies conducted by both Carr et al. (2015) and Schuh and Shy (2016) validate this result, having found that the majority of cryptocurrency adopters in the US were males with middle-class incomes and professional qualifications. Their study, however, did not find a significant age difference.

The age groups between 25 and 44 are over-represented in this sample since populations statistics for South Africa (88.6% of respondents) are a total of 33% of the population (Statistics South Africa, 2017). The age proportions are however in line with expectations, and other studies on technology adoption such as in the study by I. Brown et al. (2003) of mobile banking where 67% were between 18 and 30. The shift towards a slightly older group is indicative of discretionary spending that younger respondents may not have access to since a large proportion of respondents indicated investment as the primary use category. Bohr and Bashir (2014), in their analysis of the Bitcoin community, found that peak enthusiasm – measured as predicted long-term value of the cryptocurrency – was at the age of 35 to 40 with diminishing optimism for both older and younger individuals.

Geographic applicability is limited and cannot be said to be relevant beyond the South African context. The massive dominance of South African respondents is due to the sampling technique used, i.e. snowball sampling. Since snowball sampling was used, the response rate cannot be determined. In addition, the usual weaknesses of snowball sampling are noted, i.e. a bias towards those demographic characteristics in the initial survey distribution. This skew of the sample has implications for the research but may also be indicative of the overall user base within the South African population – of those familiar with cryptocurrency. Despite these problems, it could be inferred that this is reflective of actual users in South Africa in terms of age, gender, and income. For instance, Passport (2017) found that "Middle Youth" or those between the ages of 30 and 44 were the largest consumer group. The importance to the business context here may be to target this group in market penetration endeavours and to target untapped markets in those groups that fall outside these demographics such as women or low-income consumers. However, given the early stage of cryptocurrency developments, this latter aspect may be premature.

An extremely large gender gap is noted and cannot be explained by the sampling methodology used, but is expected due to the findings of prior research. For instance, Venkatesh et al. (2000) found differences in early-stage adoption and Goswami and Dutta (2016) showed similarly that men were more likely to adopt and use information technology initially. These results are also consistent with other studies in mobile payment and banking literature in which sample respondents were dominated by males (Alalwan et al., 2017; Yang et al., 2012). Schuh and Shy (2016) found that users were majority male in their US study. These findings were related to underlying mechanisms such as trust, facilitating conditions, price value and hedonic motivation (Venkatesh, Morris, & Ackerman, 2000; Venkatesh, Thong, & Xu, 2012). Those looking to apply the findings of this research should take cognisance of their target market but also of an underserved group of the population that may benefit from more niche products and services. The low response rate for women also means that interpretation of gender effects is inadvisable due to the low relative sample. Therefore, gender effects are not discussed beyond the descriptive statistics just mentioned.

Turning towards the use cases of the sample, the largest percentage indicated their usage was as an investment tool for growth. This data helps answer RQ1. Christian et al. (2014) found new users held Bitcoin pointing to an investment use case. This supports the assertion by Carr et al. (2015) that due to price volatility and the related potential for speculative investing, consumers trade cryptocurrency rather than use it as for transactional means. In the same survey, however, 81% of respondents used cryptocurrency for online shopping (Carr et al., 2015). Use for investments rather than transactions is supported by analysis of transaction volumes on the Bitcoin network, indicating that speculative investment was the largest share of volume (Hileman & Rauchs, 2017). This skew towards investments rather than transactions may also explain the removal of some of the independent variables form the model which may be more relevant to different usage contexts, i.e. payments, rather than in an investment context where there is a lower intensity of “usage” per se. In fact, all items in the survey for the PV construct related more to transactional services. Furthermore, due to the fuzziness of usage categories, and the immaturity of the vast array of technologies involved, the question of what constitutes costs for respondents is broad. While the data showed that the investment use case was the overall majority, the payment use case was a substantial minority at 59.1% in this survey. Even though transactional volume on the Bitcoin network is still low, the study by Spenkelink (2014) showed that adoption would lag price stability. Conversely, as price volatility decreases, the attraction of speculators should also decrease (ignoring causality), and will, therefore, reduce the investment use case with a concomitant rise in the transaction use case (Carr, Marsh, Dunn, & Grigorescu, 2015).

Usage frequency as indicated is particularly low in line with the novelty and immaturity of the technology and consumer understanding thereof. The majority of participants

(61.43%), while having heard of cryptocurrency had never used it. With only 9.28% using cryptocurrencies at least weekly, experience or habit effects may not be interpreted with any reliability, justifying their exclusion from this study. The low frequency of use may be inferred from the mechanisms discussed below as a way to understand the specific topics to be dealt with in order to increase usage and its precursor behavioural intention to use. The sections below deal with each of the dependent variables, BI and CU in turn.

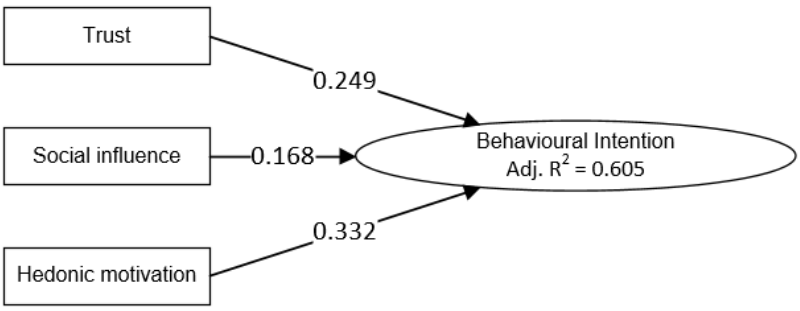
## 6.2 Primary Exogenous Variables

In comparing the results of this study, each construct is studied, specifically how it compares with prior research into other technology contexts. The section deals with the independent variables relating to BI: performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), and trust (TR). This helps answer RQ2. Finally, BI as an independent variable together with facilitating conditions (FC) on usage (CU) is discussed. This helps answer RQ3.

### 6.2.1 Predictors of BI

HM, TR and SI were found to be significant predictors of BI explaining 60.50% of the variance measured. The mode, therefore, exhibits a high degree of explanatory power without interacting or moderating effects. Venkatesh et al. (2012) were able to explain 44% of the variance in BI in their original study with UTATU2 on mobile internet technology. Unexpectedly, PE and EE were found to be non-significant. These results are discussed in the sections that follow.

Figure 23: Predictors of BI in the resultant model.




#### *6.2.1.1 Hedonic Motivation*

In original model conception by Venkatesh et al. (2012), HM was found to correlate more highly with behavioural intention. In this study, HM is also significant and the strongest predictor of behavioural intention (β = 0.334, p-value < 0.01). Therefore, H5 is accepted.

HM was also found to be stronger the less utilitarian the context (Childers, Carr, & Carson, 2001). Since in this study it is the strongest predictor of BI the result seems counter-intuitive. However, Morosan and DeFranco (2016) in their study of NFC payments – an instrumental use – found that HM was the second strongest predictor of BI after PE. Koenig-Lewis et al. (2015) in their study of enjoyment as a predictor of m-payment adoption found that HM (through PE) was a strong factor in financial services adoption. The study which focused on young people found perceived enjoyment increased model explanatory power from 44% to 62%. They further postulated that this might be due to the way younger individuals interact with technology expecting an enjoyable experience and instant gratification. In understanding the link to SI, discussed later, there might be interacting effects. For instance, prior research by Dickinger et al. (2008) would suggest that much of the drivers behind initial adoption were SI factors and that being part of the conversation was a motivator amongst early adopters. In line with this, Koenig-Lewis (2015) found interacting positive effects between HM and SI. This result, validated in prior research, would indicate that enjoyment (~HM) plays an important role. This study, however, did not look at moderating factors specifically age and gender which were found to have strong effects, i.e. stronger for younger males. Since the sample achieved is heavily weighted towards younger males this result is somewhat expected.

Gourville and Norton (2014) defined one of four frameworks for the consumer buying process as the cognitive versus emotional decision-making process. Taken together with the result on price value, PE, and EE, it may be postulated that cognitive instrumental evaluations of the technology are at least as important as emotional evaluations. The consumer is therefore not a purely rational agent within the context of cryptocurrency adoption. Further, Gourville and Norton (2014) assert that instrumental decisions are made over time while emotional decisions based on HM are made quicker on initial interaction with the product or service. The implications for businesses and therefore developers are to realise the importance of the emotional part of the decision in addition to the cognitive or instrumental decision. Therefore, an enjoyable, immersive experience when interacting with the services provided around cryptocurrencies should be prioritised. While investments or transactional platforms may be seen as purely instrumental or utilitarian pursuits, the study indicates that having "fun" while seeking these contexts is an important driver of intent to adopt cryptocurrencies. These findings could be operationalised in terms of 'gamifying' the experience on wallets as an example or driving engagement through rewards programs.

#### *6.2.1.2 Trust*

Trust was a significant predictor in seven of nine studies reviewed by Slade et al. (2013). Alalwan et al. (2017) found that trust was the most significant predictor of customers' BI to use mobile banking (β = 0.26). Based on the nature of cryptocurrencies, i.e. an amorphous grouping of products and services in the personal finance domain, it was hypothesised that trust would have a significant and strong effect on BI. In this study, trust was found to have a significant positive effect on BI (β = 0.25, p-value < 0.005) and was second to HM in strength of effect. Therefore, H7 is accepted. Trust was also found to be a significant positive driver of PE (β = 0.594, p-value < 0.001) even though in this study PE was non-significant to BI. Therefore, H8 is accepted. Trust as a predictor of PE was found in (Alalwan et al., 2017) study as well. Together with EE, trust explained 58.9% of the variance in PE. This indicates that trust may have multiplicative effects in contexts where PE is significant as is the case in most adoption literature on mobile banking as well as other technologies. The non-significant result for PE is discussed later.

Carr et al. (2015) note that consumer protection is a barrier to more widespread adoption together with knowledge and confidence in using the technology. Consumer protection speaks to trust. The implication for management is that the use and marketing of technical safeguards (e.g. Secure Sockets Layer (SSL) encryption and two-factor authentication), as well as legal or other assurances and recourse (e.g. guarantees, security audits, and third-party trust seals), will translate into increased behavioural intention to adopt cryptocurrencies. The use of structural assurances such as trust seals is based on Yan and Pan's (2015) findings that structural assurance had the largest effect on trust for mobile payments. Further trust may be enhanced through other pathways not studied here but also found to have a significant effect on behavioural intention. PEOU and PU were found to affect trust positively. While the model presented here hypothesises no causal interactions in the direction of trust, a focus on usability may have multiple positive effects on intention to use. Additionally, understanding that continuance trust (based on prior experience) may translate into increased adoption, as well as perceived ease of use, organisations offering end-to-end solutions may have an advantage.

Perceived risk has been found to interact strongly with TR in many studies. While trust is an external assignment, i.e. the belief in the benevolence or integrity of others, risk is a more internally focused belief. Perceived risk refers to belief in one's own exposure to negative events occurring. While, adopters and potential adopters believe there is trust in the network – designed to be 'trust-less' – or counterparty, they may have completely different views on risks inherent in cryptocurrency participation. Therefore, the study of perceived risk would further enlighten how users' perceptions translate into BI.

#### *6.2.1.3 Social Influence*

Social influence (SI) had the weakest effect on BI from all valid and significant predictors. Hypothesis H4 is therefore accepted. Venkatesh et al. (2012) in their original conception of UTAUT2 found that SI was a driver of behavioural intention and is confirmed in this study. This result is expected insofar as cryptocurrency is money which is a social contract between people (Salemi, 2012). The value of the coin is in the size of the network antecedent on an unstated social contract in which each user accepts the coin as having value (Bjerg, 2016). As indicated in the literature review above, social norms (or subjective norms) were found to be stronger for peer-to-peer technologies which also display network effects (Dickinger, Arami, & Meyer, 2008; Koenig-Lewis, Marquet, Palmer, & Zhao, 2015). This is again true with cryptocurrency since its value is in the number of people using it and accepting it as payment. Its value in investment is also driven by social attention. Rogers (1995) defined diffusions as a special form of communication where the social system and communication channels were key components beyond the technology itself. Venkatesh et al. (2012) found that social influence was moderated stronger for older women which may explain its weaker effect, as seen in this study. Since cryptocurrencies are a peer-to-peer network technology and the sample is skewed to younger individuals, social influence, i.e. the social pressures to use a particular technology, is expected to have an effect albeit a muted one on BI. Finally, since HM was found to have a strong effect, the expectation is that SI will correlate to a degree based on previous studies (Koenig-Lewis et al., 2015).

Gourville and Norton (2014) define the decision-making unit (DMU) as a “set of individuals who affect, influence, and take part in a decision to buy” (p. 15). This brings focus on the other actors within the decision-making process. The DMU consists of the buyer, influencer, gatekeeper, and approver. The effect of the influencer is naturally moderated higher in the case where SI is found to be a predictor of BI. Taken together with IDT’s diffusing effect (Rogers, 1995), this finding puts an emphasis on word-of-mouth effects from initial adopters to those with intent to use. Initial adopters were also found to be tech savvy or rather had high personal innovativeness in technology (PIIT) scores (Agarwal & Prasad, 1998; Lu, Liu, Yu, & Wang, 2008; Yang, Lu, Gupta, Cao, & Zhang, 2012). Those with high PIIT would also be expected to set trends in technology choices and adoption and to interact more intensely with a technology or service as indicated by their readiness to adopt new technology and their risk-taking attitude. Services and technologies that will make the jump into mass adoption are not only those that have technical proficiency but which are marketed by early adopters expressing their opinion to potential adopters who are in the evaluation stage of the decision-making process. This has implications for the type of marketing strategy adopted which would place a heavier emphasis on facilitating peer-to-peer sharing of experiences rather than mass media marketing. Prahalad and Ramaswamy (2000) draw attention to a new wave of consumers and the potential to co-create value by co-opting them into the development and direction of products and services as well as the marketing thereof. This implies an inbuilt mechanism to allow this co-creation and the ability to have conversations with these initial adopters would produce multiplicative positive effects.

#### *6.2.1.4 Price Value*

The items relating to price value could not demonstrate construct validity. However, previous studies such as by Venkatesh et al. (2012) found that price value was a significant driver of behavioural intention moderated higher for older women, i.e. aligned with contemporary social roles.

Price value in this study was not found to be valid due to low Cronbach Alpha scores. Costello and Osborne (2005) recommend at least three items per factor and five for strong loadings with any less resulting in unstable loading. PV in this study had only three items. The problem with too few items may be exacerbated by consumer understanding. It is questionable that respondents had the ability to understand price value in the context of cryptocurrency and separate the different categories of costs, i.e. those related to services enabling cryptocurrency usage, compared to inherent costs such as those related to volatility. The survey item construction may, therefore, be problematic. This is due to the mixed nature of use and the survey items trying to deal with both possibilities, i.e. investment and transactions. In the latter case, the price value trade-off is more clear in terms of transaction fees and subscription costs, whereas in the investment case these costs are relatively small compared to the investment amount. Further, the survey items required a relative assessment of price value, and since usage is not well defined, it may have been difficult for respondents to compare costs to other traditional channels such as investment products or transactional services. This last aspect is in line with the rationale forwarded by Koenig-Lewis et al. (2015) in their study of m-payment adoption. In the South African context, Passport (2017) found that the primary motivation for online consumers (of which a large majority of the sample is assumed to be) was convenience rather than price.

#### *6.2.1.5 Performance Expectancy and Effort Expectancy*

Both PE and EE were non-significant predictors in the results for this sample. However, the study validated the significant effect of trust and EE on PE as is theorised (Venkatesh, Thong, & Xu, 2012). In the original validation of the UTAUT2 model, both PE and EE had a significant effect on BI (Venkatesh et al., 2012). These findings are therefore in contrast to the theoretical evolution of adoption research in which PE (and in TAM perceived usefulness), as well as EE (and in TAM perceived ease of use), were consistently found to have a significant effect on behavioural intention (Abdullah, Dwivedi, & Williams, 2014; Slade, Williams, & Dwivdei, 2013). It is therefore pertinent to posit reasons for these contrarian findings.

The non-significant finding may relate to the conception of cryptocurrency in the minds of consumers as opposed to the conception of a more concrete technology such as a wallet application. Cryptocurrencies are both a financial technology and a technology-enabled financial service. Furthermore, the fact that most respondents indicated their objective was investments may be part of the reason these predictors were non-significant. Investments may require less knowledge to operate as opposed to transactions as exchanges mostly require one point of contact. Baur et al. (2015) found that PEOU (similar to EE) was considered low. Therefore, the expectation of extreme complexity as a trade-off for exceptional returns may have been internalised. This posited mechanism in behaviour is based loosely on the finding that habit moderated the effect of BI on usage (Venkatesh, Thong, & Xu, 2012). This is due to behaviour becoming automatic and not requiring intent. Therefore, the internalisation of complexity may result in an under-represented EE in line with the findings of Kim et al. (2010) that for early adopters PU was non-significant as expectations were already low. Similarly, PE may be the bias in consumer's positivity towards price increases in the investment use case. Again, the optimism around investment returns, would result in PE not being a factor in driving BI. From a transaction perspective, PU (similar to PE) was found to relate to the potential for lower transaction fees (Baur, Bühler, Bick, & Bonorden, 2015). Since PV items could not be validated, this interaction could not be tested.

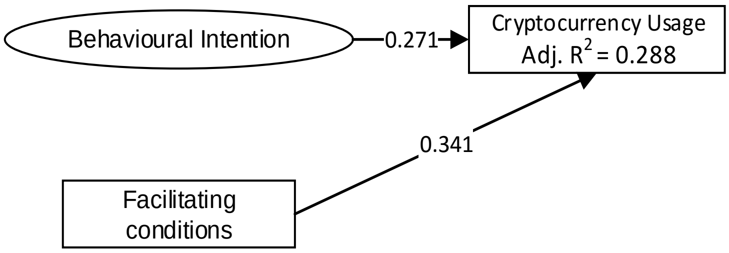
A further consideration is the effect of media attention during the study period. As discussed above, South Africans, the bulk of respondents, display a disproportionate interest in cryptocurrencies globally (Google, 2017). Agarwal and Prasad (1998) postulated that PU and PEOU did not show interacting effects with PIIT due to media attention resulting in external factors driving these variables rather than individual factors. From the investment use context, large media attention, and drastic gains that cryptocurrencies have made in the last year may lead to motivations of financial gain moderating the effect of EE and PE from a technology usage perspective. It is unclear if the performance in performance expectancy would refer to the objective of being able to make a positive return on investment rather than just the ability to invest. To expand, it is questionable as to whether the goal is to make an investment or to make money and whether this is clearly separable. Future survey design will need to respond to this complication. It is the researcher's conclusion therefore that the reason for a non-significant effect by these two variables requires further study and their effect cannot be summarily dismissed.

Finally, the researcher cannot ignore the potential for the survey instrument to have been inadequately adapted for the cryptocurrency context compared to its use in (Alalwan, Dwivedi, & Rana, 2017; Venkatesh, Thong, & Xu, 2012). However, in support of the non-significant result being non-spurious, both PE and EE were both non-significant and in prior studies were found to be strongly related (Alalwan et al., 2017). It would, therefore, require both EE and PE to be inadequately operationalised in the survey instrument. Koenig-Lewis et al. (2015) also found EE to be a non-significant predictor of BI in understanding m-payment adoption.

### 6.2.2 Predictors of Usage

In this study usage is predicted by both FC and BI, with 28.8% of the variance in CU explained – see Figure 24. In the original UTAUT2 model, 26% of usage of mobile banking was explained using FC and BI (Venkatesh, Thong, & Xu, 2012). In Alalwan et al. (2017), 31% of the variance in adoption behaviour was explained using the same UTAUT2 constructs. At 28.8%, this model offers comparative predictive strength.

Figure 24: Multiple regression results for usage (CU).




#### *6.2.2.1 Facilitating Conditions*

Venkatesh et al. (2012) found that facilitating conditions (FC) was a driver of actual usage, and was moderated by age and gender. Other studies also validate FC as a significant predictor of BI (Abdullah, Dwivedi, & Williams, 2014; Alalwan, Dwivedi, & Rana, 2017; Koenig-Lewis, Marquet, Palmer, & Zhao, 2015; Mahfuz, Khanam, & Wang, 2017; Zhou, 2012). In this study, Facilitating Conditions (FC) was found to have a significant effect (p-value < 0.001) with a positive effect and regression coefficient of 0.341, as shown in Figure 24. This result is the opposite of the findings by Alalwan et al. (2017) for mobile banking. In their study, FC was the weaker predictor of usage, with a coefficient of 0.153 (p-value<0.021) compared to BI with 0.467 (p-value<0.001).

FC was the strongest predictor of CU ahead of BI. This implies that actual usage requires that consumers perceive that they have the necessary support and systems in place to use the technology such as online guides, training, and customer support. Therefore, providers of cryptocurrency services need to ensure not only that these systems are in place but need to make sure that awareness of support systems is driven. This point is important when considering that it is not reality but the perception of support systems that is measured. Further, Venkatesh et al. (2012) showed that the effect of FC was weakest for younger males. This sample is weighted more heavily to the 25-34 age group (64%) and to men (86%). The implication is that FC could have a stronger effect when other groups such as women and older customers eventually adopt cryptocurrency. This effect could be indicative of the complexity of using cryptocurrency since FC is required in response to it. Also, it implies that focusing on FC could be the most important consideration in driving actual usage. Importantly, this effect is independent of intent, implying greater business impact.

Since FC may be more important in driving intent for potential users (Yang, Lu, Gupta, Cao, & Zhang, 2012), future research should be conducted to understand this interaction through BI. Further, Yang et al. (2012) posit that the effect of FC attenuates with experience and for higher PIIT scores. Since experience, as measured by frequency of use, is low this study should not see significant attenuation of FC in predictive power. However, without having measuring PIIT– based on prior research (Agarwal & Prasad, 1998; Kim, Mirusmonov, & Lee, 2010; Yang et al., 2012) – it may be assumed that initial adopters constitute a large proportion of the sample. Conversely, the effect of FC could, therefore, be moderated higher for adopters later in the IDT curve.

#### *6.2.2.2 Behavioural Intention*

In the resultant model, behavioural intention (BI) is an antecedent of usage together with facilitating conditions (FC). This is in line with much of the previous adoption studies specifically in mobile payments where, in all four studies reviewed, BI was a significant predictor (Slade, Williams, & Dwivdei, 2013). In a more general study of mobile technologies, six out of seven studies found BI to be a significant predictor of usage (Abdullah, Dwivedi, & Williams, 2014).

BI had a lower regression coefficient ($\beta = 0.270$, p-value $< 0.001$) compared with FC. The relatively low regression weights are unexpected compared to previous studies. This may indicate that actual intent is less important to usage than other factors such as FC and latent variables not studied. However, Wu and Du (2012) found that the translation from BI to actual usage may be over-reported in some studies due to the differences in how usage is measured. In addition, many studies reporting high R-squared values when studying BI without studying usage directly, implicitly assume a correlation between BI and usage. In this study and those referenced for comparison, usage is actually measured – albeit self-reported. A possible limitation is also that BI as a predictor of usage is meant to be as an immediate antecedent to the intended behaviour and not a intent to behave sometime in the future (Fishbein & Ajzen, 1975). The low regression coefficient for usage is therefore in line with Wu and Du's (2012) finding that BI does not convert well into usage. In addition, research participants were found to anchor their reported usage based on their intended use (Wu & Du, 2012). Since most respondents were potential adopters in this sample, this effect should be understated, explaining some of the lower correlation scores measured.

The implication of this finding is that at this early stage of adoption, focus on those with an intent on use, may not yield the best results. Instead, setting up the conditions to facilitate usage may see a better return in terms of adoption.

## 6.3 Nature of Use

The study also sought to identify the primary usage category for cryptocurrency users and potential adopters. The primary usage category identified by the majority of respondents was as an investment (73.9%). Christian et al. (2014), in their data-based model, found that most users were holding rather than trading their Bitcoin. Badev and Chen (2014) used a wider sample of exchange data and found similarly that transactions were negligible.

Despite investments being the overall majority, a large minority (59%) indicated that they used or intended to use cryptocurrency for transactions. Carr et al. (2015) reported that 81% of consumers who used cryptocurrency to transact expected their usage to increase over the next three years. This means that the transaction use case, while low in volume on the network, is still salient for consumers.

The media frenzy around the price of cryptocurrencies during the study may skew results towards specific categories. For instance, Schuh and Shy (2016) opined that the volatility and the potential for windfall gains was a primary reason for holding cryptocurrency for some respondents in a survey of US consumers. This result does, however, support previous data that show cryptocurrency as a transactional medium being minuscule compared with speculative investments (Carr, Marsh, Dunn, & Grigorescu, 2015; Yermack, 2013). Christian et al. (2014) in their study using primary data, found that most new users held their Bitcoin indicating an investment use case. Contrary to these studies, Schuh and Shy (2016) found in the US that two-thirds of respondents' primary reason for adoption was transactions. Despite this, the same study found that a consumer's adoption decision was influenced by an expectation of an appreciating BTC to USD exchange rate. This supports the view that cryptocurrency cannot at this stage be considered money both from an economic perspective (Yermack, 2013), and a behavioural one (Bjerg, 2016). However, usage is evolving, and as indicated by Penfold (2015) and Spenkelink (2014), usage as money will follow price stability which is both a primary driver and result of speculative investment.

## 6.4 Conclusion

The sample is dominated by young, affluent, well educated, South African men who use internet banking regularly and consider themselves comfortable with technological developments. The sample correlates with other studies validating the profile on gender, education and income dimensions. The gender and age imbalance in the sample, while expected, is severe and both indicate the target for businesses as well as the potential to reach unserved segments. South African usage statistics appear significantly higher than found in other national studies and may be indicative of local context – such as institutional trust and currency volatility. The South African skew to the sample implies that results cannot be generalized globally without further qualification. An outright majority of respondents indicated that they used cryptocurrency as an investment tool, although other categories had large minorities, most notably payments. This is in line with much of the previous research indicating that speculative investment was a primary use category driven by significant increases in price and optimism that the trend will hold.

This study aimed to identify the primary factors driving individual consumer's behavioural intention toward and usage of cryptocurrency. For the sample achieved, BI was most strongly predicted by HM. This is an interesting result indicating that even though investment was the primary use case – a purely utilitarian pursuit – consumers valued enjoyment during the experience. Most providers of cryptocurrency services are targeting their ease of use (~EE). However, these results may indicate an acceptance of the complexity of cryptocurrency mitigating its effect on BI. While performance expectancy and effort expectancy cannot be disregarded based on previous studies, this research may indicate that these are necessary but no longer sufficient conditions for adoption. Trust was also found to be a significant predictor of BI and is in line with much of the prior research into consumer financial services. Social influence was the only other significant predictor of BI and follows the networked peer-to-peer nature of cryptocurrencies. This also follows closely the diffusion theory in IDT where the influence of individuals cumulatively increases to influence innovators and early adopters into majority adoption.

Surprisingly, BI is not the strongest predictor of actual usage. This is contrary to much of the extant literature. However, it supports the view by Wu and Du (2012) that BI is not a surrogate for usage. FC is found to be the strongest predictor of usage indicating that if the systems and processes are in place to help guide users, usage will increase. The low adjusted R-squared score – 28.8% - indicates that more research is required to adequately explain usage.

In the following chapter, the implications of the principal findings of this study are discussed together with the limitations of the research.

# Chapter 7: Conclusion

This study sought to understand the factors driving behavioural intention (BI) as well as usage of cryptocurrencies in order to inform business models and services strategies that seek to improve adoption. In addition, the study seeks to inform policymakers and incumbent institutions on their response to cryptocurrencies at this early stage of their potentially disruptive path. The section begins with a summary of the principal findings before presenting the study's managerial implications. This chapter concludes with a critical look at the limitations of the research and the consequent directions for future studies.

## 7.1 Principal Findings

The study set out to answer the questions of the purpose of cryptocurrency adoption (RQ1), the factors driving behavioural intention to use cryptocurrency (RQ2) and finally the drivers of actual usage (RQ3). The literature review resulted in a critical selection of possible antecedent variables based on prior research to arrive at salient factors for the cryptocurrency domain. A survey was used to collect data on current and potential users. On analysing the data, certain variables were found to affect intent and usage significantly. The sample achieved is highly weighted towards the South African context and these findings are therefore limited to this country. This section summarises the principal findings as follows:

1. Both potential and current users (more so for the latter group) consist of males, holding at least a bachelor's degree, with a mean income of R484,000 between the ages of 25 and 34 with a significant group up to age 44.
2. The primary usage type was investment both for current and potential users. However, the transaction use case was a large minority.
3. The hypothesised model, with non-significant predictors removed, was able to explain 60.5% of the variance in behavioural intention and 28.8% of the variance in actual usage. No interacting or moderating effects were considered.
4. Facilitating conditions is the strongest predictor of actual usage. Simply creating the environment for usage will see the greatest impact on cryptocurrency usage.
5. Compared with facilitating conditions, the intent to use (BI) was secondary to driving actual usage.
6. Hedonic motivation is the strongest predictor of BI. Focusing on driving enjoyment or an affective response will show the greatest return for businesses trying to drive intent. This is a somewhat counter-intuitive result.

7. Social influence is a significant predictor of intent and may be due to the networked nature of the technology as well as the mass media attention received by cryptocurrency at the time of the study.
8. Trust, as expected, is a significant predictor of BI. This indicates that installing security measures, as well as legal guarantees and the marketing thereof will increase BI. In addition, this provides an advantage for established businesses with a proven record that consumers trust.
9. Performance expectancy and effort expectancy are both non-significant in driving behavioural intention to use cryptocurrency. This may indicate that potential users have already crafted an idea of PE and EE in their intent which has reduced the effect on BI.

## 7.2 Managerial Implications

The extensive interest of consumers in cryptocurrencies, and consequently the level of private and public investment into a plethora of services and novel applications, make the understanding of the drivers of consumer adoption key. In the last 12 months alone, funds poured into Bitcoin, and various alt-coins have resulted in a 13 times gain in price as of 24 October 2017 (CoinMarketCap, 2017b). This frenzy has resulted in a large number of players including institutional investors, banks, 'fintech' startups, and venture capitalists devoting a significant amount of resources into capitalising on consumer interest. This presents an opportunity for business albeit in a crowded market. In order to maximise return on investments, it is crucial that strategies focus on those few aspects that are significant to the target segments. The implications for management based on the principal findings above are discussed here.

The respondent profile, at least at this early stage of adoption implies that a focus on professional males between the ages of 25 and 34 would see the greatest impact. This has implications for marketing spend. Naturally, the converse applies, in that some segments, for instance, women are underserved. However, previous studies on gender differences would suggest that this is characteristic of the evolution of new technology adoption and that female participation will follow wider adoption.

The high median salary, as well as the high variance in income of respondents, suggest that cryptocurrencies are not just a tool for tech-savvy youngsters but are seeing interest amongst high net worth individuals as well. The technology is therefore salient for businesses such as wealth managers and investment houses catering to these groups. In fact, 74% of respondents indicated their use or planned use as an investment.

From a usage category perspective, investment is the outright leader, as indicated above. However, transactions were second, and the effect of increased investment may be increased experience which according to research will moderate down perceived risk. This could imply that cryptocurrencies as money, i.e. a transactional medium, could follow the investment use closely. Other uses such as savings and currency hedge were also significant and indicates that incumbent financial services providers cannot ignore the ascent of cryptocurrency and its implications for their product and service offerings. Banks for instance – who are already focused on blockchain – cannot outright dismiss cryptocurrencies and will need to monitor demand closely. As discussed in the philosophical viewpoint on cryptocurrency as money – it is not the underlying character of the technology but rather the perceptions of it that matters. Cryptocurrencies have value in use because users potentially perceive it to be this way. However, its nature as money is not yet apparent, but there are strong indications that this will change going forward. This is an important consideration for not only business but governments as well.

Facilitating conditions (FC) was found to be the strongest predictor of actual usage. FC is therefore discussed first, before dealing with the antecedents of BI. This can be operationalised by management in the following ways:

- Development efforts should explore creating resources and support infrastructure that facilitates adoption. Focusing on early adopters may see multiplicative benefits through the social influence (SI) mechanism. Penfold (2015) in his study on cryptocurrencies as competitive money, showed that mass adoption is predicated on the presence of a supportive value chain.
- Industry bodies that collectively promote consumer understanding of cryptocurrencies will result in increased resource support while moderating perceived risks.

Hedonic motivation (HM) was the strongest predictor of BI. This may seem like a surprising result since cryptocurrency adoption may on the surface be seen as a purely instrumental endeavour employing cognitive evaluations. However, this finding is supported by prior research – such as by Morosan and DeFranco (2016) in NFC payment use – that showed emotional evaluations are fundamental to driving intent. Implications for business strategies are to ensure that the experience is as painless as possible which relates to the recommendations of facilitating conditions above. In addition, strategies such as gamification of cryptocurrency wallets, exchanges, and other consumer-facing services may drive increased intent. For instance, anecdotal evidence suggests that as an investment tool, much of the conversation is centred around outperforming one's peers in the market. In order to bridge the trust deficit and increase HM, providers could market and develop zero cost simulators in which potential users could trial in a risk free simulated environment that tracks the cryptocurrency market.

Trust (TR) and the related concept perceived risk has been found to be significant in many studies of financial technologies and related fields (Gefen, Karahanna, & Straub, 2003; Shin, 2009; Slade, Williams, & Dwivdei, 2013; Yan & Pan, 2015; Zhou, 2012). Since trust was found to have a significant effect on BI for cryptocurrencies, companies championing their technical safeguards and guarantees will lead to increased intent to adopt. Companies providing cryptocurrency services have many choices on how to secure users' credentials and ensure the security of their coins. These include those where the provider takes responsibility and those where the user does. The latter involves the use of offline wallets, encrypted physical keys (as on USB drives), or simply writing one's private key on a piece of paper. However, shifting responsibility to users may counter the finding on FC as stated above as it adds complexity relative to existing financial services like internet and mobile banking. Therefore, it seems that if businesses want to leverage the effects of both FC and TR, a provider-side solution is the best option. This involves the use of encrypted channels (e.g. SSL), two-factor-authentication, guarantees, and the use of third-party trust seals. This last point potentially attenuates some of the touted benefits of cryptocurrency, i.e. reduced cost through deprecating the need for third-party trust providers. Guarantees on funds may be key as Martins et al. (2014) found that financial risk was a strong predictor of overall perceived risk as related to TR. Therefore structural assurances, i.e. potential legal recourse or regulations, may be a key aspect in driving trust (Zhou, 2012). In fact, Yan and Pan (2015) found that structural assurances had the largest effect on predicting trust. Penfold (2015) found that regulation will increase the trustworthiness of cryptocurrencies. In addition, based on the concept of continuance trust, companies with proven track records in the consumer financial services sector may have a distinct advantage. The aspect of trust also leads to a discussion on increased regulation. This is again counter to the philosophical tenets of early proponents including some developers.

The social influence (SI) construct was found to be significant in driving intent. Focusing on driving the conversation between potential adopters using current adopters will increase these effects. Businesses need to recognise the importance of word-of-mouth marketing compared to traditional advertising. Previous studies have identified SI to interact with both TR and HM which therefore portends a multiplicative effect. It would, therefore, be wise to have an active and engaging presence on online platforms and forums where influencers – specifically early adopters – form and shape their opinions. Further, cryptocurrency technology benefits from network effects, and therefore, focusing on SI may result in an early lead for businesses. The gamification potential is pertinent here and will harness SI effects which feed into the recommendation for HM above. In the low-income group, those businesses developing products for collectivist cultures could harness group savings (known as 'stokvels' in South Africa) to serve those segments more effectively.

Lastly, PE and EE were found to be non-significant. The discussion on this potential spurious result appears in section 6.2.1.5 above. However, allowing for interpretation, this implies that management should focus on other aspects such as FC, HM, TR, and SI rather than EE and PE. Baur et al. (2015) in their qualitative study of cryptocurrency adoption, found that most providers were highlighting ease of use and compatibility on their websites. The results presented here potentially imply that the FC should be the focus rather than the EE.

## 7.3 Limitations of the Research

The demographics of the respondents represent a key limitation to the research. Applicability of the research to a wider population is, therefore, ill-advised. However, this limitation may not be serious since it may represent the bias in users of cryptocurrency, i.e. young, male, professionals with tertiary education and middle-class incomes. In fact, a US study found the same demographics using annual reserve bank survey data (Schuh & Shy, 2016). The geographic applicability cannot be dismissed easily and the research findings should be confined to the South African context.

The biases in the sample obtained could also be due to the sampling technique used, i.e. snowball sampling. This could also be a source of the demographic skew in the sample with resulting homogeneity in gender, income, country of residence, and age group.

The number of actual users (self-reported) is low compared to those without usage experience. This means that the study of what translates into usage is based on a smaller sample than the study of behavioural intention. This is an important consideration since each regression is combined into a single model from which inferences are drawn. In future, a more homogenous study into users or potential users by themselves may display a more statistically robust result. Also, increasing BI may not translate into actual usage as was found in a study of the relationship across studies (Wu & Du, 2012).

This study excluded the moderating demographic variables due to low variability in respondent demographics. Demographic variables were found to increase the predictive ability of the UTAUT2 model (Venkatesh et al., 2012). Again, this may be unimportant in terms of managerial implications with no real increase in R-squared given that the sample group demographics may be indicative of the actual user base as validated by other studies. However, even if this postulate is true, the research cannot be used for strategies that aim to serve untapped segments such as women or older users.

Media and consumer attention on cryptocurrency is at its peak as measured by Google search data. This attention may skew results to increased behavioural intention to use through socio-cognitive biases such as availability bias, anchoring bias and the contrast effect (Robbins & Judge, 2015). Coupled with this is the potential for respondents misinterpreting what cryptocurrency familiarity means. For instance, Schuh and Shy (2016) found that 75% of respondents to a national survey in 2014 incorrectly identified cryptocurrencies with some mistaking online payment services like PayPal for cryptocurrency. Future research should, therefore, test for actu,al familiarity in the survey. Furthermore, the timing of the study is at the height of consumer interest in cryptocurrency – a fact more acute for South Africa – means that the study's findings are specific to this point in the adoption curve and may not be generalizable once mass adoption begins.

The quality of the research instrument design is in question since in attempting the SEM model validation, correlations between items were found. Multiple studies have used UTAUT2 without major validation problems reported and in at least two studies where the instrument is listed and validated (Alalwan, Dwivedi, & Rana, 2017; Venkatesh, Thong, & Xu, 2012). Therefore, the actual construction of the questions may be problematic. However, as indicated in section 2.7, multiple studies have found invalid constructs. This could be indicative of the instrument as a whole or as indicated by Schuh and Shy (2016) due to the fuzzy understanding of the cryptocurrency ecosystem amongst consumers. For instance, Wentzel et al. (2013) stress that the difference between a technology and a technology-enabled financial service. Cryptocurrency in current form includes both. As Schuh and Shy (2016) note, there is as much confusion as to what it is as there is about how it works. Carr et al. (2015) state that its characteristics span multiple categories – as a currency, financial asset, and enabling technology protocol. In either event – inadequacies in the survey instrument or consumer comprehension thereof – more care in developing the survey instrument should be taken when designing questionnaires for cryptocurrency at this stage. Further, the increase in items per construct may allow the researcher a more robust data set where unreliable items can be excluded without severely affecting the predictive ability of constructs.

Specification error is always a potential problem when applying regression techniques and refers to predictors omitted, also known as left-out-variable-error (Kline, 2011). This research omitted potential effects of habit, experience and perceived risk which has been identified by prior research as significant. Further price value was omitted for validity reasons. Specification error increases for increasing correlations between omitted predictors and those included in the model (Kline, 2011). Since habit is related to experience and perceived risk related to trust, the specification error may throw into doubt some of the correlation coefficients in the model – either overestimation or underestimation of the predictive power of the included predictors. Since in general researchers are limited in their ability to include all possible predictors, this shortfall is common in all regression techniques.

Much of the theory building has been based on the work of the most prolific researchers in the adoption field, i.e. Venkatesh (S. A. Brown & Venkatesh, 2005; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012, 2016). This is expected since Venkatesh conceived both TAM extensions and UTAUT and its various iterations. The models and mechanisms proposed in this study are therefore heavily weighted on the theoretical frameworks developed by a single author albeit validated and applied by a plethora of other authors. This last aspect allays most fears about the potential for undetected biases and errors of Venkatesh propagating through the research but is worth noting.

This study has used assessed usage, i.e. as reported on an ordinal scale and not actual usage. Wu and Du (2012) found that actual usage should be studied rather than assessed or reported usage. Further, Davis (1989) cautioned that intensity of usage was potentially more useful than the frequency of use. Intensity could be measured as total time spent with a system (Davis, 1989).

## 7.4 Suggestions for Future Research

To deal with demographic skew in the respondent sample, stratified or quota sampling may be employed so that the effect of age and gender could be studied with more statistical validity. Despite the sample potentially being reflective of actual user demographics an understanding of moderating variables due to subgroup differences would be useful. Further, demographic variables could be studied with more resolution, for example, the type of education – technical or other would be useful (Davis, 1989).

Since cryptocurrency is a nascent technology research into the various stages of adoption would be useful in understanding the technology's potential evolution. A look at between-group differences particularly for early and late adopters or based on the frequency of usage may provide more distinct results such as in the studies conducted for mobile payments (Kim, Mirusmonov, & Lee, 2010; Yang, Lu, Gupta, Cao, & Zhang, 2012). This type of study will assist in understanding the distinct differences between early adopters who are influencers and consequently affect the social influence predictor identified in this study.

The technology requires some understanding of the underlying workings for consumers to use as demonstrated in the technical description in section 2.1. However, prior experience with the internet shows that as products and services mature this requirement will attenuate. Nevertheless, at this early stage toward mass adoption, innovators and early adopters (in the IDT nomenclature) may be important to study as a sub-population of adopters. This deals with the criticisms of Wu and Du (2012) by studying usage directly and will have more statistical validity by studying a more homogenous group. Based on Rogers' (1995) diffusion effect, these groups are relevant for driving mass adoption through word-of-mouth and peer influence. Therefore, research focusing on only these groups and the factors driving usage rather than intent would be useful.

The above suggestion of a study into early-stage adopters potentially warrants the inclusion of PIIT as an independent variable. PIIT as a personality level determinant of intent and usage was found to be significant and statistical differences in the time of adopters were found (Agarwal & Prasad, 1998; Yang, Lu, Gupta, Cao, & Zhang, 2012). Therefore, early adopters should tend to have a higher predictive strength of PIIT for BI and CU – a quantification of which could lead to insights into catering for these powerful groups.

The inclusion of individual differences such as PIIT, leads to a potential analysis on a cultural level. Cultural factors have most notably been operationalised by Hofstede (2011) and have been shown to have an effect on a multitude of social contexts. Agarwal & Prasad (1998) postulated that more collectivist cultures might moderate the effect of social influence higher.  Research focusing on how culture moderates the model proposed may be useful so as to craft strategies for different national contexts.

National differences are of course not limited to culture. For instance, while investment was the primary usage category in our sample, Schuh and Shy (2016) found that 66% of US consumers adopted cryptocurrency for transactions. As postulated above, interest in cryptocurrency (as measured by search results on Google Trends) may correlate with countries experiencing currency volatility. In this study, 45.5% indicated cryptocurrency as a currency hedge. Investment and currency hedge may be inter-related, and a study of emerging markets and national differences would be useful for both governments' regulator policies and those providing international money transfer services.

Gefen et al. (2003) identified four significant factors affecting trust with the strongest effect from institution-based structural assurances. Also, they found interacting effects with other TAM constructs. Similarly, Zhou (2012) and Yan and Pan (2015) found that structural assurances had the largest effect of all antecedents on trust in mobile banking adoption. Since cryptocurrency's maturity level and its distributed nature indicate an aversion to regulation, assurances are based on community members and their technical ability to analyse mostly open-sourced code for malicious intent. However, this relies on a large base of technically competent and engaged users. As Bitcoin is challenged by more alt-coins, this reliance cannot be sustainable. Further, the initial community is ideologically aligned with libertarian views championing disintermediation and the lack of central control. Therefore, future research into the effect of structural assurances on trust will provide insight into whether increased oversight will increase adoption and behavioural intention.

A broader look at adoption of cryptocurrency would be useful since this research, and much research using existing adoption theory focuses on studying factors identified in the extant research. However, the novelty of cryptocurrencies and the social nature of the technology may be sufficiently unique to warrant conceiving an entirely new model so far as independent variables BI and CU go. As the literature review has identified, there is a large number of factors that could be useful in predicting BI and usage. It may, therefore, be prudent to use a mixed-method design such as was conducted in Dickinger et al. (2008). Mixed method designs may assist in focusing the quantitative research by conducting ethnographic research prior to survey instrument design, increasing the return on the data collection effort (Saunders & Lewis, 2012). The specification error – discussed above – that arises from excluded predictors can also be resolved by exploring alternate models with other predictors included. Further research is therefore required to test alternate models.

Kim et al. (2010) included m-payment knowledge as an independent variable in their model. This may be useful since there is a wide band of experience in the sample based on an analysis of the frequency of use. This may also be the cause of the difference in pilot survey data validity and the actual survey, i.e. the pilot group may have had more knowledge of cryptocurrency.

As noted above, using the SEM technique provides distinct advantages over traditional regression analyses. It is therefore prudent to repeat this study – with or without changes to the model structure – using the SEM technique. This would require a revision of the data collection process – particularly a larger sample would be required.

## 7.5 Concluding Remarks

To the author's knowledge, this study represents the first quantitative assessment of the factors driving consumer adoption of cryptocurrencies using technology adoption theory. The study is, therefore, a first step in quantitatively analysing a new breed of consumer technology with little resemblance to previous technologies. The results presented are therefore taken in the context of the point in cryptocurrency's evolution.

The study sought to explain: (RQ1) what consumers are using cryptocurrency for, (RQ2) what are the factors driving intention to use cryptocurrency, and (RQ3) what are the factors driving actual usage. In the first instance, data supported the view of other researchers that investments were the primary use-case. Consumers, therefore, do not primarily treat cryptocurrency as money, with implications on the perceived nature of the technology. In answering RQ3, the data showed that creating the support mechanisms around usage – known as facilitating conditions – is potentially the most effective means of driving adoption. In answering RQ2, the findings indicate that an enjoyable experience most strongly predicted intention to use cryptocurrency. Both these findings are somewhat contrary to the findings of the majority of studies in related fields of financial technology adoption in so far as the strength and ranking of these effects go. The findings, therefore, provide novel insights into this unique and emergent technology. However, much more research is required in order to increase the explanatory power of the model by exploring alternate models and additional factors.

## References

Abdullah, B., Dwivedi, Y., & Williams, M. (2014). Adopting an extended UTAUT2 to predict consumer adoption of m-technologies in Saudi Arabia. In *UK Academy for Information Systems Conference Proceedings* (pp. 1–25).

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 204–215. http://doi.org/10.1287/isre.9.2.204

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99–110. http://doi.org/10.1016/j.ijinfomgt.2017.01.002

Ametrano, F. M. (2016). Hayek money: The cryptocurrency price stability solution. http://doi.org/10.2139/ssrn.2425270

Arestis, P., & Sawyer, M. C. (2006). *A handbook of alternative monetary economics*. Edward Elgar Publishing.

Badev, A. I., & Chen, M. (2014). Bitcoin: Technical background and data analysis. *SSRN Electronic Journal*. http://doi.org/10.2139/ssrn.2544331

Baur, A. W., Bühler, J., Bick, M., & Bonorden, C. S. (2015). Cryptocurrencies as a disruption? Empirical findings on user adoption and future potential of Bitcoin and Co. In M. Janssen, M. Mäntymäki, J. Hidders, B. Klievink, W. Lamersdorf, B. van Loenen, & A. Zuiderwijk (Eds.), *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 9373, pp. 63–80). Cham: Springer International Publishing. http://doi.org/10.1007/978-3-319-25013-7_6

Bech, M., & Garratt, R. (2017). Central bank cryptocurrencies. *BIS Quarterly Review*, (September), 55–70.

Bjerg, O. (2016). How is Bitcoin money? *Theory, Culture & Society*, *33*(1), 53–72. http://doi.org/10.1177/0263276415619015

Bohr, J., & Bashir, M. (2014). Who uses Bitcoin? An exploration of the Bitcoin community. *2014 12th Annual Conference on Privacy, Security and Trust, PST 2014*, 94–101. http://doi.org/10.1109/PST.2014.6890928

Boundless. (2016). *The four social revolutions*. Boundless. Retrieved from https://www.boundless.com/sociology/textbooks/boundless-sociology-textbook/social-change-21/sources-of-social-change-139/the-four-social-revolutions-761-3396/

Brown, I., Cajee, Z., Davies, D., & Stroebel, S. (2003). Cell phone banking: Predictors of adoption in South Africa - An exploratory study. *International Journal of Information Management*, *23*(5), 381–394. http://doi.org/10.1016/S0268-4012(03)00065-3

Brown, S. A., & Venkatesh, V. (2005). Model of adoption and technology in households: A baseline model test and extension incorporating household life cycle. *MIS Ouarterly*, *29*(3), 399–436. http://doi.org/10.2307/25148690

Carr, M., Marsh, C., Dunn, E., & Grigorescu, K. (2015). *Money is no object : Understanding the evolving cryptocurrency market*.

Chiba, M. D. (2015). Tests for prediction. Johannesburg.

Childers, T. L., Carr, C. L., & Carson, S. (2001). Hedonic and utilitrian motivations for online retail shopping behavior. *Journal of Retailing*, *77*, 511–535. http://doi.org/10.1016/S0022-4359(01)00056-2

Christian, M., Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M.

(2014). Bitcoin - Asset or currency? Revealing users' hidden intentions. *Twenty Second European Conference on Information Systems*, 1–14.

Chuttur, M. (2009). Overview of the Technology Acceptance Model : Origins, developments and future directions. *Sprouts: Working Papers on Information Systems*, *9*(37). Retrieved from http://sprouts.aisnet.org/9-37 Copyright:

CoinDesk. (2017). CoinDesk Bitcoin price index. Retrieved October 31, 2017, from http://www.coindesk.com/price/

CoinMarketCap. (2017a). Cryptocurrency market capitalizations. Retrieved October 31, 2017, from https://coinmarketcap.com/charts/

CoinMarketCap. (2017b). Global charts. Retrieved November 4, 2017, from https://coinmarketcap.com/charts/

Costello, A. B., & Osborne, J. W. (2005). Best Practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Education*, *10*, 1–9. http://doi.org/10.1.1.110.9154

CuriousInventor. (2013). *How Bitcoin works under the hood [Video file]*. *CuriousInventor*. Retrieved from https://www.youtube.com/watch?v=Lx9zgZCMqXE

Davidson, M. (2002). Primer on Social Identity: Understanding Group Membership.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. MIT. http://doi.org/oclc/56932490

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance. *MIS Quarterly*, *13*(3), 319–339. http://doi.org/10.2307/249008

Dawes, J. (2008). Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research*, *50*(1), 61–77. http://doi.org/Article

Dickinger, A., Arami, M., & Meyer, D. (2008). The role of perceived enjoyment and social norm in the adoption of technology with network externalities. *European Journal of Information Systems*, *17*(1), 4–11. http://doi.org/10.1057/palgrave.ejis.3000726

Edelman. (2016). *2016 Edelman trust barometer - Global results*. *Edelman Trust Barometer*. Retrieved from http://www.edelman.com/insights/intellectual-property/2016-edelman-trust-barometer/global-results/

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. SAGE Publications.

Fishbein, M. & Ajzen, I. (1975). *Belief, attitude, attitude, intention and behavior: An introduction to theory of research*. *Reading, MA : Addison-Wesley Addison-Wesley*.

Fishbein, M., & Ajzen, I. (1975). Chapter 8: Prediction of behavior. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. http://doi.org/10.1017/CBO9781107415324.004

Gantori, S., Donovan, P., Ganesh, K., DeMichiel, M., Dennean, K., Trussardi, F., & Klien, M. (2017). *Cryptocurrencies - Beneath the bubble*.

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, *115*(9), 1704–1723. http://doi.org/10.1108/IMDS-03-2015-0087

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: an integrated model. *MIS Quarterly*, *27*(1), 51–90.

Google. (2017). Explore - Google Trends. Retrieved October 25, 2017, from https://trends.google.com/trends/explore?date=all_2008&gprop=news&q=cryptocurrency

Goswami, A., & Dutta, S. (2016). Gender differences in technology usage — A literature review. *Open Journal of Business and Management*, *4*(January), 51–59.

http://doi.org/10.4236/ojbm.2016.41006

Gourville, J. T., & Norton, M. I. (2014). Consumer behavior and the buying process. Harvard Business Review.

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. *Hastings Sci. & Tech. LJ*, 50. http://doi.org/10.1145/2594288

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Wei, J. (2015). What catalyses mobile apps usage intention: an empirical analysis. *Industrial Management & Data Systems*, *115*(7), 1269–1291. http://doi.org/10.1108/IMDS-01-2015-0028

Hileman, G., & Rauchs, M. (2017). *Global cryptocurrency benchmarking study*. Cambridge. Retrieved from http://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2017-04-20-global-cryptocurrency-benchmarking-study.pdf

Hinds, D. (2004). Micropayments: A technology with a promising but uncertain future. *Communications of the Associaction of Computing Machinery*, *47*(5), 44. Retrieved from https://www.hsbc.com.my/1/2/personal-banking/online-internet-banking/mobile-banking

Hofstede, G. (2011). Dimensionalizing cultures : The Hofstede model in context. *Online Readings in Psychology and Culture*, *2*(1), 1–26. http://doi.org/http://dx.doi.org/10.9707/2307-0919.1014

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind*. (New York: McGraw-Hill., Ed.). New York.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V. (2004). *Culture, leadership, and organizations: The GLOBE Study of 62 societies*. SAGE Publications. Retrieved from https://books.google.co.za/books?id=4MByAwAAQBAJ

Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering*, *2015*. http://doi.org/10.1155/2015/603747

Huang, C. Y., Kao, Y. S., Wu, M. J., & Tzeng, G. H. (2013). Deriving factors influencing the acceptance of pad phones by using the DNP based UTAUT2 framework. In *2013 Proceedings of PICMET 2013: Technology Management in the IT-Driven Services* (pp. 880–887). Retrieved from http://www.scopus.com/inward/record.url?scp=84890815852&partnerID=8YFLogxK%5Cnhttp://www.scopus.com/inward/citedby.url?scp=84890815852&partnerID=8YFLogxK

Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N:q hypothesis. *Structural Equation Modeling*, *10*(1), 1–34. http://doi.org/10.1207/S15328007SEM1001

Kharpal, A. (2017, April 12). Bitcoin value rises over $1 billion as Japan, Russia move to legitimize cryptocurrency. *CNBC*. Retrieved from http://www.cnbc.com/2017/04/12/bitcoin-price-rises-japan-russia-regulation.html

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, *26*(3), 310–322. http://doi.org/10.1016/j.chb.2009.10.013

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. http://doi.org/10.1038/156278a0

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: predicting mobile payment adoption. *Service Industries Journal*, *35*(10), 537–554. http://doi.org/10.1080/02642069.2015.1043278

Kraljić, A., & Peštek, A. (2016). An application of UTAUT2 model in exploring the impact of quality of technology on mobile internet. *Journal of Economics and Busines*, *14*(2), 66–77.

Krumpal, I. (2013). Determinants of social desirability bias in sensitive surveys: A literature review. *Quality and Quantity*, *47*(4), 2025–2047. http://doi.org/10.1007/s11135-011-9640-9

Li, M. Y. (2017). How many bitcoins have been "lost" forever? Retrieved October 29, 2017, from https://seekingalpha.com/article/4082979-many-bitcoins-lost-forever

Limayem, M., Hirt, S. G., Limayem, M., & Hirt, S. G. (2003). Force of habit and information systems usage: Theory and initial validation. *Journal of the Association for Information Systems*, *4*(4), 65–97. http://doi.org/10.1016/j.actbio.2005.04.004

Lu, J., Liu, C., Yu, C. S., & Wang, K. (2008). Determinants of accepting wireless mobile data services in China. *Information and Management*, *45*(1), 52–64. http://doi.org/10.1016/j.im.2007.11.002

Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision Support Systems*, *49*(2), 222–234. http://doi.org/10.1016/j.dss.2010.02.008

Mahfuz, M. A., Khanam, L., & Wang, H. (2017). The influence of culture on m-banking technology adoption: An integrative approaches of UTAUT2 and ITM. *PICMET 2016 - Portland International Conference on Management of Engineering and Technology: Technology Management For Social Innovation, Proceedings*, 824–835. http://doi.org/10.1109/PICMET.2016.7806814

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, *34*(1), 1–13. http://doi.org/10.1016/j.ijinfomgt.2013.06.002

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation - A 25-year review. *International Journal of Forecasting*, *22*(3), 519–545. http://doi.org/10.1016/j.ijforecast.2006.01.005

Miles, D., Scott, A., & Breedon, F. (2012). *Macroeconomics: Understanding the global economy*. John Wiley & Sons.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. http://doi.org/10.1287/isre.2.3.192

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management*, *53*, 17–29. http://doi.org/10.1016/j.ijhm.2015.11.003

Mougayar, W., & Buterin, V. (2016). *The business blockchain*. Wiley.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Www.Bitcoin.Org*, 9. http://doi.org/10.1007/s10838-008-9062-0

Natalie Gerhart, Peak, D. A., & Prybutok, V. R. (2015). Searching for new answers: the application of task-technology fit to e-textbook usage. *Decision Sciences Journal of Innovative Education*, *13*(1), 91–111. http://doi.org/10.1111/dsji.12056

Neil Haran. (2017). What's keeping cryptocurrencies from mass adoption? Retrieved September 18, 2017, from https://techcrunch.com/2017/04/20/whats-keeping-cryptocurrencies-from-mass-adoption/

Pallant, J. (2013). *SPSS survival manual*. McGraw-Hill Education (UK) Ltd.

Passport. (2016a). *Digital consumer - Connected commerce: South Africa*.

Passport. (2016b). The New Connected Consumer Code: Unlocking Digital Commerce Opportunities. Euromonitor International.

Passport. (2017). *Consumer lifestyles in South Africa*. *Passport*.

Penfold, C. (2015). *Hayek's monetary denationalisation: A model for cryptocurrency competition*. Gordon Institute of Business Science.

Prahalad, C. K., & Ramaswamy, V. (2000, January). Co-opting customer competence. *Harvard Business Review*. Retrieved from https://hbr.org/2000/01/co-opting-customer-competence

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, *6*(7), 157–164. http://doi.org/10.5539/ies.v6n7p157

Rao, H., & Sutton, R. I. (2014). Bad to great: The path to scaling up excellence. *McKinsey Quarterly*, 1–11.

Raymaekers, W. (2015). Cryptocurrency Bitcoin: Disruption, challenges and opportunities. *Journal of Payment Strategy and Systems*, *9*(1), 30–40.

Robbins, S. P., & Judge, T. A. (2015). *Organizational behavior*. *Boston: Pearson*.

Rogers, E. M. (1995). *Diffusion of innovations*. *Macmillian Publishing Co.* http://doi.org/citeulike-article-id:126680

Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models. *Kybernetes*, *44*(5), 788–805. http://doi.org/10.1108/K-09-2014-0184

Roos, C. (2015). *The motivation and factors driving crypto-currency adoption in SMEs*. University of Pretoria.

Salemi, M. K. (2012). *Money and banking: What everyone should know*. *The Great Courses* (1st ed.). The Great Courses.

Saunders, M., & Lewis, P. (2012). *Doing Research in Business & Management* (1st ed.). Harlow: Pearson Education Ltd.

Schuh, S., & Shy, O. (2016). U.S. consumers' adoption and use of Bitcoin and other virtual currencies. *Federal Reserve Bank of Boston*. Retrieved from http://www.bankofcanada.ca/wp-content/uploads/2015/12/us-consumers-adoption.pdf

Shin, D.-H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior*, *25*(6), 1343–1354. http://doi.org/10.1016/j.chb.2009.06.001

Simnett, J. (2017). Bitcoin's surge past $1500 & its welcome in Japan suggest this is not a blip. Gold Made Simple News. Retrieved from http://www.goldmadesimplenews.com/analysis/bitcoins-surge-past-1500-its-welcome-in-japan-suggest-this-is-not-a-blip-13119/

Slade, E. L., & Williams, M. (2013). An extension of the UTAUT2 in a healthcare context. *UK Academy for Information Systems Conference Proceedings*, 1–14.

Slade, E. L., Williams, M., & Dwivdei, Y. (2013). Extending UTAUT2 to explore consumer adoption of mobile payments. *UK Academy for Information Systems Conference Proceedings*, *36*. Retrieved from http://aisel.aisnet.org/ukais2013/36/

Smith, A. (1976). *An inquiry into the nature and the causes of the wealth of nations*. *The Glasgow Edition of the Works and Correspondence of Adam Smith* (Digital Ed, Vol. 2). Amsterdam: MetaLibri. http://doi.org/10.1057/9780230291652

Spenkelink, H. (2014). *The adoption process of cryptocurrencies*. *University of Twente*.

Twente.

Statistics South Africa. (2017). *Statistical release: Mid-year population estimates 2017*. Retrieved from http://www.statssa.gov.za/publications/P0302/P03022017.pdf

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, *79*(2), 625–649. http://doi.org/10.3102/0034654308325896

Svensson, G. (2015). Contemporary process to test the theory of a research model through covariance-based structural equation modeling in business researchh: Is it science, quasi-science or just non-science …? *European Business Review*, *27*(4), 447–458. http://doi.org/10.1108

Tapscott, D., & Tapscott, A. (2016). *Blockchain revolution* (1st ed.). New York: Penguin Random House. http://doi.org/9781101980132

Tompkins, C. a. (1991). Using and interpreting linear regression and correlation analyses: Some cautions and considerations. *Clinical Aphasiology Conference*. Retrieved from http://aphasiology.pitt.edu/archive/00001435/

Velde, F. R. (2013). Bitcoin - A primer. *Chicago Fed Letter*, (December), 1–4. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=92563197&site=ehost-live

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. http://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. http://doi.org/WOS:000086130700002

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, *24*(1), 115–139.

Venkatesh, V., Morris, M. G., & Ackerman, P. L. (2000). A longitudinal field investigation of gender differences in individual technology adoption decision-making processes. *Organizational Behavior and Human Decision Processes*, *83*(1), 33–60. http://doi.org/10.1006/obhd.2000.2896

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. Retrieved from http://www.jstor.org/stable/30036540

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and user of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. http://doi.org/10.1111/j.1365-2729.2006.00163.x

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Informaiton Systems*, *17*(5), 328–376.

Vit, F. (2013). Bitcoin a peer-to-peer electronic cash system [Powerpoint slides]. University of Campinas. Retrieved from https://www.slideshare.net/flaviovit/bit-coin-p2pelectroniccashsystem

Wegner, T. (2007). *Applied Business Statistics: Methods and Excel-Based Applications*. Juta.

Wentzel, J. P., Diatha, K. S., & Yadavalli, V. (2013). An application of the extended Technology Acceptance Model in understanding technology-enabled financial service adoption in South Africa. *Development Southern Africa*, *30*(4–05), 659–673. http://doi.org/10.1080/0376835X.2013.830963

WillWoo. (2016). Bitcoin volatility will match major fiat currencies by 2019. Retrieved May 7, 2017, from http://woobull.com/bitcoin-volatility-will-match-major-fiat-currencies-by-2019/

Wong, C.-H., Wei-Han Tan, G., Loke, S.-P., & Ooi, K.-B. (2014). Mobile TV: A new form of entertainment? *Industrial Management & Data Systems*, *114*(7), 1050–1067. http://doi.org/10.1108/IMDS-05-2014-0146

Wu, J., & Du, H. (2012). Toward a better understanding of behavioral intention and system usage constructs. *European Journal of Information Systems*, *21*(6), 680–698. http://doi.org/10.1057/ejis.2012.15

XE.com. (2017). XE: Convert ZAR/USD. South Africa Rand to United States Dollar. Retrieved November 3, 2017, from http://www.xe.com/currencyconverter/convert/?Amount=1&From=ZAR&To=USD

Yan, H., & Pan, K. (2015). Examining mobile payment user adoption from the perspective of trust transfer. *International Journal of U- and E- Service, Science and Technology*, *8*(1), 117–130. http://doi.org/10.1504/IJNVO.2015.070423

Yang, S. (2013). Understanding undergraduate students' adoption of mobile learning model: A perspective of the extended UTAUT2. *Journal of Convergence Information Technology*, *8*(10), 969–979. http://doi.org/10.4156/jcit.vol8.issue10.118

Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior*, *28*(1), 129–142. http://doi.org/10.1016/j.chb.2011.08.019

Yermack, D. (2013). Is Bitcoin a real Currency? An economic appraisal. *National Bureau of Economic Research*.

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep Using My Health Apps: Discover Users' Perception of Health and Fitness Apps with the UTAUT2 Model. *Telemedicine and E-Health*, *21*(9), 735–741. http://doi.org/10.1089/tmj.2014.0148

Zhou, T. (2012). Examining mobile banking user adoption from the perspectives of trust and flow experience. *Information Technology and Management*, *13*(1), 27–37. http://doi.org/10.1007/s10799-011-0111-8

# A Survey

The basic survey contents are shown below. It must be noted that the survey will be created using an online eSurvey tool such as Google Forms.

## 5 Minute Cryptocurrency (e.g. Bitcoin) Survey

I am conducting research as part of my MBA studies at the Gordon Institute of Business Science (GIBS). This survey is in aid of my research on consumer adoption of cryptocurrency e.g. Bitcoin, Ethereum, Litecoin, Ripple.

The survey should take less than 5 minutes to complete.

**Disclaimer**

Your participation is voluntary and you can withdraw at any time without penalty. All data will be kept confidential, and no identifying information is stored. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact me or my supervisor. Our details are provided below.

Researcher Name: Nadim Mahomed

Contact: nadimm@gmail.com

Research Supervisor: Craig Penfold

Contact: cpenfold@tsebo.com

## Section 1 of 3

Are you familiar with cryptocurrencies e.g. Bitcoin?

- Yes/No

*(Questionnaire will end if a No answer is received)*

How often have you used Cryptocurrencies

- Never
- Once a year
- Several times a year
- Once a month
- Several times a month
- Several times a week

- Several times a day

How often do you use mobile or internet banking?

- Every day
- Once a week
- Once a month
- Less than once a month
- I have never used mobile or internet banking

How comfortable are you with technology e.g. the latest gadget or smartphone.

- Very comfortable
- Comfortable
- Neutral
- Uncomfortable
- Very uncomfortable.

## Section 2 of 3: Demographics

Age:

- 17 and younger
- 18-24
- 25-34
- 35-44
- 45-54
- 55 and over

Gender:

- Male
- Female
- Other [Tex Entry] *(Allows user to not disclose gender)*

Annual Gross Income (Please include currency) (*Optional*):

- [Text Entry]

Level of Education:

- No schooling completed.
- High school graduate.
- Bachelor's degree.
- Honours degree (4 years)
- Post graduate degree (e.g. Masters, PhD)

Country of residence (only one):

- [Selection Box]

## Section 3 of 3

This is the last section of the survey and requires less than 2 minutes to complete.

Cryptocurrency refers to digital coins such as Bitcoin, Litecoin, Ethereum and Ripple amongst others and should be read to include related services such as Wallets and Exchanges.

Please choose Not Applicable (N/A) if the question is not relevant to your experience with cryptocurrency.

**Please read each statement carefully and indicate your level of agreement.**

| | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree | Not Applicable |
|---|---|---|---|---|---|---|
| **Question 1** | | | | | | |
| I find Cryptocurrencies useful in my daily life. | | | | | | |
| Learning how to use Cryptocurrencies is easy for me. | | | | | | |
| I have trust in Cryptocurrencies. | | | | | | |
| I intend to use Cryptocurrencies in the future. | | | | | | |
| At the current price, using Cryptocurrencies and related services provides good value. | | | | | | |
| | | | | | | |
| **Question 2** | | | | | | |
| I find Cryptocurrencies and related services easy to use. | | | | | | |
| I have the resources necessary to use Cryptocurrencies. | | | | | | |
| People who influence my behaviour think that I should use Cryptocurrencies | | | | | | |
| Using Cryptocurrencies is fun. | | | | | | |
| Using Cryptocurrencies and related services (wallets, exchanges) helps me accomplish tasks more quickly. | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | |
| **Question 3** | | | | | | |
| People whose opinions that I value prefer that I use Cryptocurrencies. | | | | | | |
| I feel assured that legal and technological structures adequately protect me from problems with Cryptocurrencies. | | | | | | |
| It is easy for me to become skilful at using Cryptocurrencies. | | | | | | |
| Cryptocurrencies and related services are compatible with other technologies I use. | | | | | | |
| I plan to use Cryptocurrencies in future. | | | | | | |
| | | | | | | |
| **Question 4** | | | | | | |
| Using Cryptocurrencies is enjoyable. | | | | | | |
| Using Cryptocurrencies increases my productivity. | | | | | | |
| I can get help from others when I have difficulties using Cryptocurrencies and related services. | | | | | | |
| Cryptocurrencies services (e.g. wallets and exchanges) are reasonably priced. | | | | | | |
| I do not doubt the honesty of Cryptocurrencies their systems and related services. | | | | | | |
| | | | | | | |
| **Question 5** | | | | | | |
| People who are important to me think that I should use Cryptocurrencies. | | | | | | |
| I will always try to use Cryptocurrencies in my daily life. | | | | | | |
| Using Cryptocurrencies is entertaining. | | | | | | |
| I believe that Cryptocurrencies is trustworthy. | | | | | | |
| Cryptocurrencies services (e.g. wallets and exchanges) offer good value for money. | | | | | | |
| | | | | | | |
| **Question 6** | | | | | | |
| Cryptocurrencies have the ability to fulfil their task. | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| My interaction with Cryptocurrencies and related services is clear and understandable. | | | | | | |
| Using Cryptocurrencies increases my chances of achieving tasks that are important to me. | | | | | | |
| I have the knowledge necessary to use Cryptocurrencies. | | | | | | |
| I predict I would use Cryptocurrencies in the future. | | | | | | |
| Even if not monitored, I would trust Cryptocurrencies to do the job right. | | | | | | |

### Please select the reason(s) you use or plan to use cryptocurrency

[Check boxes]

- Investment for growth
- Transactions/Payments
- International money transfers
- Store of value or savings (similar to Gold)
- Hedge against local currency devaluation
- Other [Text Entry]

# B Survey Items

**Performance Expectancy**

| | |
|---|---|
| PE1 | I find Cryptocurrencies useful in my daily life. |
| PE2 | Using Cryptocurrencies increases my chances of achieving tasks that are important to me. |
| PE3 | Using Cryptocurrencies and related services (wallets, exchanges) helps me accomplish tasks more quickly. |
| PE4 | Using Cryptocurrencies increases my productivity. |

**Effort Expectancy**

| | |
|---|---|
| EE1 | Learning how to use Cryptocurrencies is easy for me. |
| EE2 | My interaction with Cryptocurrencies and related services is clear and understandable. |
| EE3 | I find Cryptocurrencies and related services easy to use. |
| EE4 | It is easy for me to become skilful at using Cryptocurrencies. |

**Social Influence**

| | |
|---|---|
| SI1 | People who are important to me think that I should use Cryptocurrencies. |
| SI2 | People who influence my behaviour think that I should use Cryptocurrencies |
| SI3 | People whose opinions that I value prefer that I use Cryptocurrencies. |

**Facilitating Conditions**

| | |
|---|---|
| FC1 | I have the resources necessary to use Cryptocurrencies. |
| FC2 | I have the knowledge necessary to use Cryptocurrencies. |
| FC3 | Cryptocurrencies and related services are compatible with other technologies I use. |
| FC4 | I can get help from others when I have difficulties using Cryptocurrencies and related services. |

**Hedonic Motivation**

| | |
|---|---|
| HM1 | Using Cryptocurrencies is fun. |
| HM2 | Using Cryptocurrencies is enjoyable. |
| HM3 | Using Cryptocurrencies is entertaining. |

**Price Value**

| | |
|---|---|
| PV1 | Cryptocurrencies services (e.g. wallets and exchanges) are reasonably priced. |
| PV2 | Cryptocurrencies services (e.g. wallets and exchanges) offer good value for money. |
| PV3 | At the current price, using Cryptocurrencies and related services provides good value. |

**Trust**

| | |
|---|---|
| TR1 | I believe that Cryptocurrencies is trustworthy. |
| TR2 | I have trust in Cryptocurrencies. |
| TR3 | I do not doubt the honesty of Cryptocurrencies their systems and related services. |
| TR4 | I feel assured that legal and technological structures adequately protect me from problems with Cryptocurrencies. |
| TR5 | Even if not monitored, I would trust Cryptocurrencies to do the job right. |
| TR6 | Cryptocurrencies have the ability to fulfil their task. |

**Behavioural Intention**

| | |
|---|---|
| BI1 | I intend to use Cryptocurrencies in the future. |
| BI2 | I will always try to use Cryptocurrencies in my daily life. |
| BI3 | I plan to use Cryptocurrencies in future. |
| BI4 | I predict I would use Cryptocurrencies in the future. |

## C Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

03 August 2017

Nadim Mahomed

Dear Nadim,

*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.*

*Kind Regards*

GIBS MBA Research Ethical Clearance Committee

**Gordon Institute of Business Science**
Reg. No. 99/19816/08

26 Melville Road, Illovo, Johannesburg
PO Box 787602, Sandton, 2146, South Africa

telephone **(+27) 11 771 4000**
fax **(+27) 11 771 4177**

website **gibs.co.za**
**University of Pretoria**

# D Outlier Analysis

The tables below show the mean and 5% trimmed mean of all the constructs. It clear that the mean does not significantly differ from the trimmed mean.

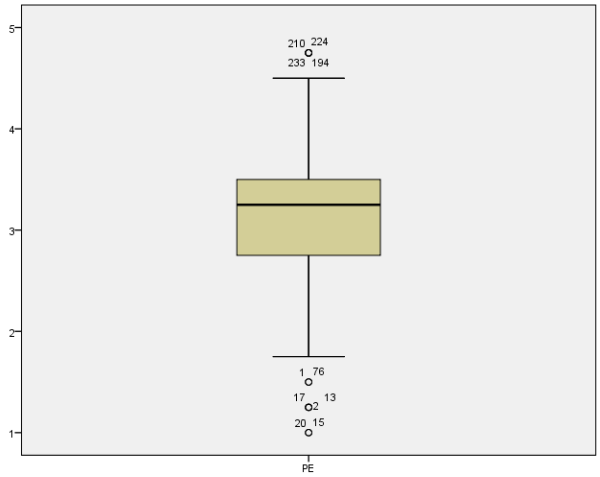
**Descriptives**

| | | | Statistic | Std. Error |
|---|---|---|---|---|
| PE | Mean | | **3,1567** | 0,05297 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,0523 | |
| | | Upper Bound | 3,2612 | |
| | 5% Trimmed Mean | | **3,1727** | |
| | Median | | 3,2500 | |
| | Variance | | 0,564 | |
| | Std. Deviation | | 0,75104 | |
| | Minimum | | 1,00 | |
| | Maximum | | 4,75 | |
| | Range | | 3,75 | |
| | Interquartile Range | | 0,88 | |
| | Skewness | | -0,331 | 0,172 |
| | Kurtosis | | 0,223 | 0,341 |
| EE | Mean | | **3,4585** | 0,05257 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,3549 | |
| | | Upper Bound | 3,5621 | |
| | 5% Trimmed Mean | | **3,4701** | |
| | Median | | 3,5000 | |
| | Variance | | 0,616 | |
| | Std. Deviation | | 0,78501 | |
| | Minimum | | 1,00 | |
| | Maximum | | 5,00 | |
| | Range | | 4,00 | |
| | Interquartile Range | | 1,00 | |
| | Skewness | | -0,290 | 0,163 |
| | Kurtosis | | -0,028 | 0,324 |
| FC | Mean | | **3,5467** | 0,05027 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,4477 | |
| | | Upper Bound | 3,6457 | |
| | 5% Trimmed Mean | | **3,5784** | |

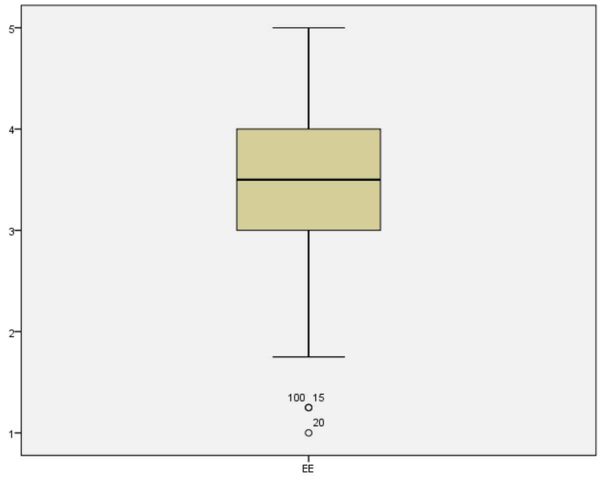
| | | | | |
|---|---|---|---|---|
| | Median | | 3,7500 | |
| | Variance | | 0,609 | |
| | Std. Deviation | | 0,78039 | |
| | Minimum | | 1,00 | |
| | Maximum | | 5,00 | |
| | Range | | 4,00 | |
| | Interquartile Range | | 1,00 | |
| | Skewness | | -0,569 | 0,157 |
| | Kurtosis | | 0,466 | 0,312 |
| SI | Mean | | 2,8875 | 0,06017 |
| | 95% Confidence Interval for Mean | Lower Bound | 2,7689 | |
| | | Upper Bound | 3,0060 | |
| | 5% Trimmed Mean | | 2,9009 | |
| | Median | | 3,0000 | |
| | Variance | | 0,847 | |
| | Std. Deviation | | 0,92037 | |
| | Minimum | | 1,00 | |
| | Maximum | | 5,00 | |
| | Range | | 4,00 | |
| | Interquartile Range | | 1,33 | |
| | Skewness | | -0,234 | 0,159 |
| | Kurtosis | | -0,493 | 0,317 |
| HM | Mean | | 3,3810 | 0,05639 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,2698 | |
| | | Upper Bound | 3,4921 | |
| | 5% Trimmed Mean | | 3,3942 | |
| | Median | | 3,3333 | |
| | Variance | | 0,712 | |
| | Std. Deviation | | 0,84393 | |
| | Minimum | | 1,00 | |
| | Maximum | | 5,00 | |
| | Range | | 4,00 | |
| | Interquartile Range | | 1,00 | |
| | Skewness | | -0,160 | 0,163 |
| | Kurtosis | | 0,026 | 0,324 |
| TR | Mean | | 3,1532 | 0,04866 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,0573 | |
| | | Upper Bound | 3,2491 | |

| | | | | |
|---|---|---|---|---|
| | 5% Trimmed Mean | | 3,1600 | |
| | Median | | 3,1667 | |
| | Variance | | 0,528 | |
| | Std. Deviation | | 0,72670 | |
| | Minimum | | 1,00 | |
| | Maximum | | 4,83 | |
| | Range | | 3,83 | |
| | Interquartile Range | | 1,00 | |
| | Skewness | | -0,140 | 0,163 |
| | Kurtosis | | 0,048 | 0,324 |
| BI | Mean | | 3,7440 | 0,05380 |
| | 95% Confidence Interval for Mean | Lower Bound | 3,6380 | |
| | | Upper Bound | 3,8499 | |
| | 5% Trimmed Mean | | 3,8001 | |
| | Median | | 3,7500 | |
| | Variance | | 0,721 | |
| | Std. Deviation | | 0,84896 | |
| | Minimum | | 1,00 | |
| | Maximum | | 5,00 | |
| | Range | | 4,00 | |
| | Interquartile Range | | 1,25 | |
| | Skewness | | -0,895 | 0,154 |
| | Kurtosis | | 0,827 | 0,307 |

**PE**

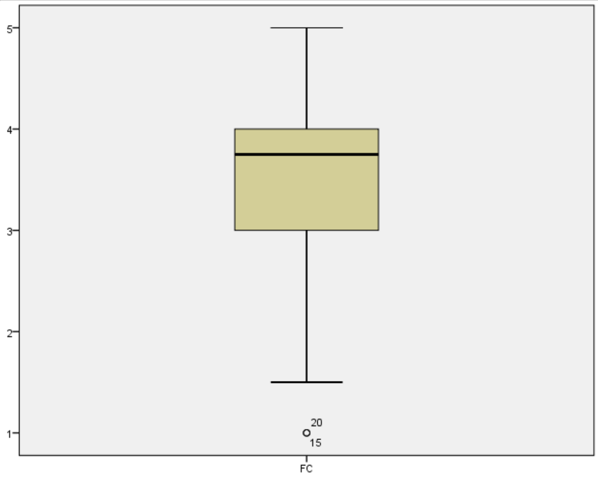


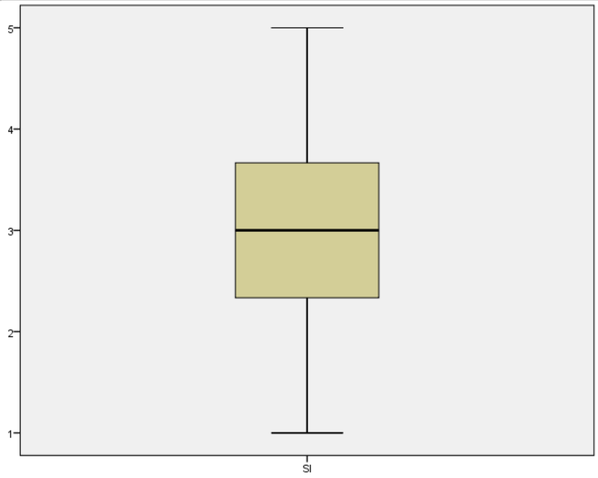

**EE**



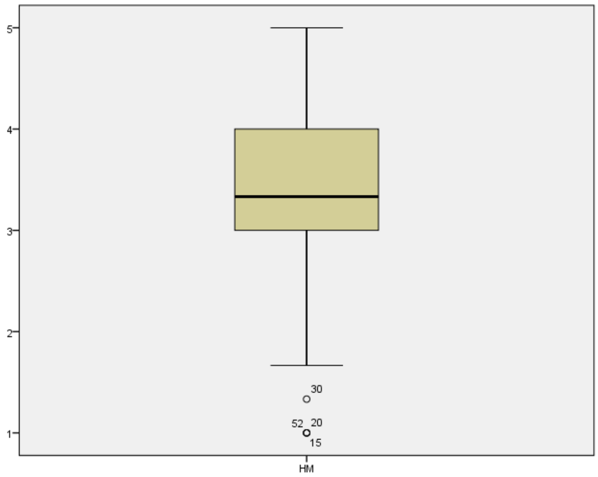

**FC**

**SI**

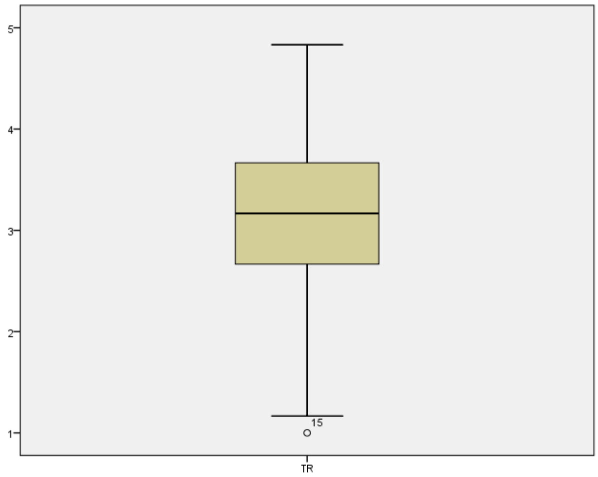

5
4
3
2
1
20
15
FC


5
4
3
2
1
SI

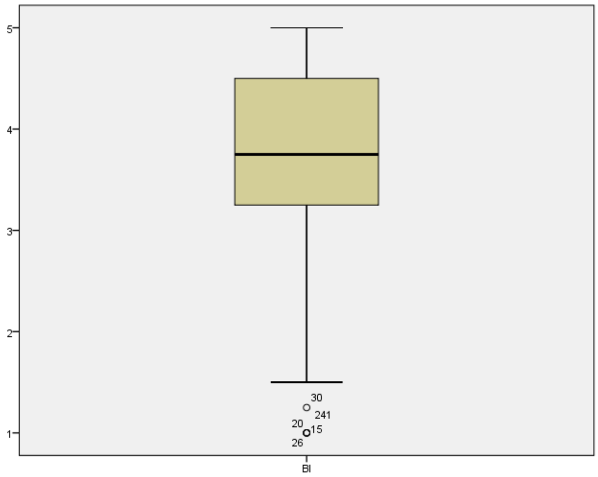
**HM**


5
4
3
2
1
30
52
20
15
HM

**TR**


5
4
3
2
1
15
TR

**BI**


5
4
3
2
1
30
241
20
15
26
BI