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End-consumer trust and adoption of smart contracts in life insurance in South Africa

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Abstract

Blockchain technology has received a disproportionate share of technology news reporting in recent years. As the database technology that solves the double-transaction problem for cryptocurrencies, blockchain has conventionalised digital ledger technology thinking and is envisaged to represent the future of financial platforms. Smart contract technology, the blockchain containers for processes and rules, is positioned to expedite automation in the post-trade infrastructure of financial systems.

Fintech disruptors discern blockchain's potential as a mechanism for disintermediation of the insurance value chain as an opportunity for innovation. Industry counter-measures to this threat include coalitions of financial institutions to evaluate potentially disruptive technologies. The fundamental questions facing the insurance industry are the end-consumer's trusting beliefs and propensity to use these emerging technologies in policy servicing systems.

We harness technology adoption theories, trust in technology research and the task-technology fit model to measure policyholder perceptions of blockchain among consumers in the life insurance industry. Responses from a sample of life insurance policyholders (n = 199) were used to measure concepts from three IS adoption theories. Our research finds evidence of policyholder trust in the reliability of blockchain technology, an understanding of the benefits of the technology and a willingness for it to be used in policy servicing.

Keywords

Blockchain, smart contract, cryptocurrency, trust, technology adoption.

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.

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1. Introduction to the Research Problem

As of 2016 there were approximately 710 online tradeable cryptocurrencies together with the open-source Bitcoin currency, the first decentralised digital currency (Brito, Shadab & Castillo, 2015), having subsequently produced 667 derivatives of itself (mapofcoins.com, 2017). Cryptocurrencies were designed around the notion that money is an object and that trade is possible by virtue of an enforceable consensus principle. With Bitcoin's market capitalisation estimated at US$ 21.5bn in 2017 (coinmarketcap.com, 2017) corporations are showing increasing interest in utilising the Bitcoin platform for the transactional benefits it offers (Brito & Castillo, 2013). Notwithstanding the regulatory challenges faced by cryptocurrencies, the increasing popularity of Bitcoin and other digital currencies are driving the innovation of peripheral technologies related to cryptocurrencies. One such technology is the blockchain database which secures cryptocurrency transactions. Blockchain databases provide the decentralised, tamper-resistant digital ledgers that solve the double-transaction problem of trading in digital assets (Swan, 2015c).

A promising application of blockchain databases is smart contract technology which extends its native transactional architecture from the traditional buy and sell use-case to include self-executing algorithms. These computer algorithms represent real-world processes associated with a contract or transaction. This enables the blockchain to become the intermediary between two parties, effectively providing the trust relationship due to its innate characteristics of being decentralised, self-sufficient and autonomous (Swan, 2015a). Cryptocurrencies, by virtue of the underlying blockchain technology, eliminates the need for intermediaries in financial transactions including those of a more complex nature such as trade in financial instruments (Brito et al, 2015). Blockchain-driven smart contract technology is anticipated to do the same for contracts and our research explores consumer trust and technology adoption of these technologies in the life insurance industry in South Africa.

Life insurance premiums have stagnated in the post-financial crises economies of developed countries (Swiss Re, 2016). Western Europe and North America is quoted as having negative life premium growth despite above-average premium growth rates in 2014 and 2015. Emerging markets have followed suit and life insurance premiums have struggled to match the growth rates experienced before the global financial crises in 2008. Among emerging markets South Africa boasts the highest insurance penetration rate at 15% (Swiss Re, 2016) and the sixth highest in total premiums written. South

African life insurers recorded a 2.3% growth rate in premiums in 2015, down from 4.6% in 2014 due to weak economic activity, and the near-term outlook for the life insurance industry in South Africa is that it will remain a challenging sector for insurers (Swiss Re, 2016).

Smart contract technology offers a new transactional mechanism for insurers (IAIS, 2017, p. 36) which in turn offers opportunities for distribution channel innovation for extant life insurance products. By implication smart contract technology affords life insurers a rare opportunity for business model innovation in an industry that has seen little change since the advent of e-commerce. The relationship between a firm's information technology (IT) related investments and its effect on profitability has been studied extensively and in many cases found conclusively that IT investments have greater bearing on sales and profitability than advertising and research & development expenditure (Mithas, Tafti, Bardhan & Mein Goh, 2012). Furthermore, Mithas & Rust (2016) conceptualised a firm's IT-related investments in terms of revenue focus and cost focus. The authors argued that firms with a dual emphasis on strategic and cost-saving IT strategies tend to have more sustainable and accelerated cash flows due to the duality of performance targets the firm sets for itself. Mithas et al (2016) concluded that IT investments by a firm and its IT strategy jointly influences firm performance. For insurance companies this implies a requirement to investment in IT in the form of new technologies and form cohesive strategies in order to appropriate value from such investments.

Financial institutions face significant pressure from investors to drive cost-reduction programmes and earn higher returns from capital investments in technology. It is not only the vibrant technology start-up scene that will provide such technology but also large technology firms such as Google and Microsoft (Skan, Dickerson & Gagliardi, 2016) supplying platforms for a variety of use-cases. Platforms provide financial institutions the opportunity to innovate feature-level implementations of new technologies to serve niche and specific business needs. Investment in new technologies and platforms enable banks to maintain vertically integrated operating models (Skan et al, 2016) and higher degrees of responsiveness to technology demands within the organisation. It requires an IT investment strategy concentrated on strategic outcomes rather than the cost-saving. Industry lexicology collated such technological strategies into the terms fintech and insurtech.

The International Association of Insurance Supervisors provides this definition of fintech (IAIS, 2017):

> The term Financial Technologies or "Fintech" is used to describe "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services" and covers a broad array of technical innovations that are finding their way into the financial industry. (p. 5).

PayPal, Square, WorldPay and First Data were some of 2015's successful fintech initial public offerings (IPO) (Skan et al, 2016). Coincidentally, 2015 also saw the demise of some legendary fintech companies such as mobile payment vendor Powa, once revered as one of the United Kingdom's start-up success stories (Skan et al, 2016). It is a testament to the unforgiving pace of fintech innovation.

The spectrum of emerging technologies with transformational potential available to insurance companies are referred to as insurtech. Venture capital invested in insurtech totalled US$ 800 million in 2014 globally and US$ 2.5 billion in 2015, a threefold increase within 12 months (IAIS, 2017; Skan et al, 2016). This was, however, growth off a very low base. Analysing fintech deal volumes from 2015, 78% of deals went to fintech companies focussing on the banking sector, 9% to wealth & asset management technology and only 1% to the insurance industry (Skan et al, 2016).

Arnold (2017) confirmed the trend that insurtech investment is catching up with fintech by stating that fintech investment and merger & acquisition activity have nearly halved from a record high of US$ 47.7 billion in 2015 globally to US$ 24.7 billion in 2016. The author cited geopolitical events such as Brexit and the Trump administration in Washington, but also expressed a concern that the fintech industry may be losing its appeal for investors (Arnold, 2017). Only in Asia did total fintech investment in 2016 increase and largely due to a single deal involving Ant Financial to the value of US$ 4.5 billion. Shubber (2016) theorised that the banking industry is quite likely perceiving the unprecedented transparency afforded by digital ledger technologies (DLT) such as blockchain as a risk rather than a technological advantage. Feature-level implementation of DLTs in bank treasury departments would allow trades to be viewable and verifiable by anyone using the platform. So-called fat-finger trades, where trades are made using erroneous values, usually due to human mistakes, would become irreversible on digital ledgers and smart contracts would exacerbate this problem through automatic processing of trading events (Shubber, 2016).

Fintech has traditionally received the lion share of venture capital funding but insurtech investment is steadily increasing. The 2017 IAIS report on fintech and insurtech shared some insightful trends, firstly that insurers are adopting innovative new technologies predominantly in the areas of premium pricing and underwriting functions. These organisational functions within insurance companies are experiencing the adoption of software-as-a-service (SaaS) platforms, big data and artificial intelligence, internet-of-things (IoT), roboadvisory and gamification & social media (IAIS, 2017). Secondly, blockchain and distributed ledger technologies (DLT) scored poorly in this regard and was generally perceived as a platform for product development. A surprising conclusion was that blockchain and smart contracts are not being considered as innovative platform technologies in either the distribution & sales or policy servicing functions of the insurance value chain (IAIS, 2017). This is contrary to the vociferous media surrounding these technologies. By way of illustration, Swan (2015c) described how attestation could be executed on a blockchain for proof of insurance or proof of liability.

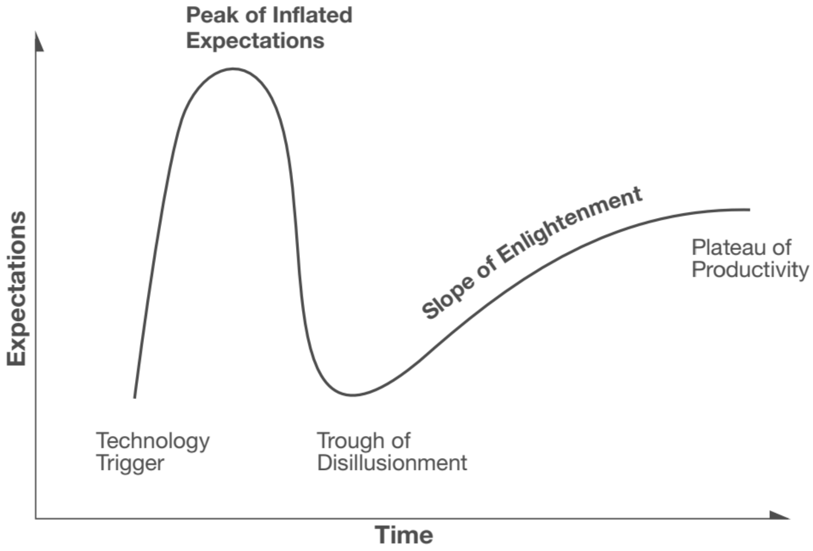
In contrast to the insurance industry's stance towards blockchain, insurtech technology start-ups are formulating business plans to transform insurance distribution using digital ledger technology (Arnold, 2017). Their value propositions include technologies aimed at improving operational efficiencies and cost effectiveness, while at the same time creating more customer-centric products. Considerable value can be derived from the exploitation of traditionally poor customer interaction in the policy lifecycle, from issuance to servicing (IAIS, 2017) and provides insurtech start-ups the opportunity to build customer centric distribution channels (Skan et al, 2016). Of great concern to insurers should be the loss of control over customer interactions to third-party distribution and policy servicing platforms.

Hesitation to incorporate blockchain in policy lifecycle platforms are likely due to that fact that, despite numerous potential applications for blockchain technology in suitable insurance contexts, much of what has been written remains theoretical (Collomb & Sok, 2016, p. 99). Swan (2015a), for instance, proposed a variety of future applications for blockchain-driven smart contracts including one for contract law which may also be applicable to annuity life insurance contracts. Life insurers are noticing the tentative research into cryptocurrencies and blockchain technology by the banking sector, sensing hesitation on behalf of the banks (Shubber, 2016), and weighing up their options. As with the banking industry, insurers grapple with understanding the commercial viability of blockchain (Arnold, 2017).

The information technology research company Gartner pioneered the hype cycle research report. The Gartner hype cycle is a generalised graph illustrating the market maturity of a technology by plotting public expectations against time (Gartner, 2016).

The hype cycle is widely used to assess adoption of information technologies, platforms and applications. It is divided into stages reflective of the IT market's general attitude towards adoption of the technology as measured empirically by Gartner. These stages are named technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment and plateau of productivity (Gartner, 2016). Mainstream media often cites the Gartner hype cycle either directly or indirectly (Shubber, 2016; Arnold, 2017).

Figure 1: Gartner Hype Cycle (Gartner, 2016)



A promising technological innovation initiates a new hype when its underlying theory is introduced to the IT market. Much excitement and media attention usually surround the new technology and its possible applications, although generally there is little to no demonstrable commercial viability in its application. The peak of inflated expectations stage signifies rising expectations of first-generation products that might be highly specialized or even difficult to use. Quite often these products and feature-level applications are very expensive as technology providers attempt to recover research and development costs (Gartner, 2016). Innovative organisations recognise the potential competitive advantage of the new technology during this phase and bespoke solutions are created for their niche requirements. At its highest point the peak of inflated expectations sees many new providers rush into the technology as organisations prototype new solutions to existing business problems.

As the inflated expectations are discredited by failed implementations and negative media, the trough of disillusionment sets in. During this phase the technology vendor landscape moves from highly fragmented to consolidated as vendors exit the market. The slope of enlightenment sees second and third generation products being launched and use cases are expanded to include a greater breadth of business problems, culminating in the plateau of productivity as the technology enters mainstream adoption. During the final phase the technology's market relevance becomes apparent and the hype diminishes (Gartner, 2016).

Arnold (2017) suggests that in 2017 blockchain has entered the trough of disillusionment in the Gartner hype cycle. Issues with first-generation products, or feature-level applications of the technology, have emerged (Swan, 2015c, p. 85). Prototyping of blockchain solutions are continuing but scepticism of its value to financial institutions are surfacing (Arnold, 2017). Of real interest to insurers are the potential second- and third-generation blockchain products in the hype cycle's slope of enlightenment. Those solutions will feature measurable return on investment outcomes, implemented by a reduced number of specialised vendors and at reduced costs (Gartner, 2016). Feature-level applications in insurance would include operational simplification, counterparty risk reduction and improved information governance (IAIS, 2017).

The banking industry's interest in blockchain, in general, concerns the disintermediation of its supply chains and the potential benefit of blockchain in banking's post-trade infrastructure (Collomb et al, 2016). Post-trade infrastructure in banking includes clearing and settlement systems and activities, generally to persist transactions in a sustainable way. In insurance the post-trade infrastructure may include proof of insurance capability and is regarded as a viable implementation for blockchain (Swan, 2015c).

South Africa's banking sector has convened a twenty two organisation committee entitled The South African Financial Blockchain (SAFBC) to research blockchain in financial services with a focus on transaction integrity, operational efficiency and long-term cost savings (Naidoo, 2017). The efficiency and cost-cutting focus by banks in regards to blockchain, and the proven benefit IT-related investment has to firm profitability (Mithas et al, 2016), may be able to convince the South African insurance industry to pursue similar research initiatives in order to achieve desired growth targets through the establishment of shared platforms.

Digital platforms are the foundational building blocks for innovations such as complementary products, new services and distribution models (Yoo, Boland, Lyytinen & Majchrzak, 2012, p. 1400). Industry-wide digital platforms have become increasingly more important to maintain competitive advantages as demonstrated by the establishment of the South African Financial Blockchain (Naidoo, 2017). Yoo et al (2012) theorised that the purpose of establishing industry platform initiatives is to take advantage of the generativity of digital technology and the convergence it offers. At the core of our research question is the survival instinct of the insurance industry and its willingness to embrace a shared blockchain platform.

Investment in insurtech is surging, life insurance premium growth is low and insurers are facing competition for their customer's relationship. Our research explores aspects of end-consumer beliefs and attitudes towards technology adoption, trust in digitisation of physical policy artefacts and the consumer's perception of the cognitive fit of blockchain in policy servicing functions. Our research is cognisant of the fact that there are very few reference implementations of second- and third-generation blockchain applications to inform or benchmark consumer adoption beliefs. In order for the South African life insurance sector to pursue the industry-wide blockchain initiatives in the same way the banking sector has, it is essential to understand end-consumer beliefs in blockchain and the effect they have on trust.

A digital proof of insurance application on blockchain in the life insurance industry would have to consider the policyholder and his or hers propensity to trust the technology (Collomb et al, 2016, p. 95). In academic literature, trust in technology constructs from the initial trust model (ITM) (McKnight, Choudhury & Kacmar, 2002) included structural assurances, defined as the measure of belief by a person that a specific technology can be used successfully. ITM also includes, among others, a measure for situational normality which has been defined as a person's level of comfort and familiarity with a technology. A study of consumer responses in life insurance, within the hypothetical context of a decentralised blockchain used to store and validate the life insurance policy, would serve to measure the aforementioned trusting beliefs of end-consumers. It would assist the industry in understanding their consumers' propensity to trust the new technology as well as how appropriate blockchain technology is deemed for proof of insurance functions.

By synthesising a research model from extant technology adoption models we aim to measure policyholder attitudes towards blockchain and smart contracts, thus providing the long-term insurance industry in South Africa with empirical research capable of tailoring effective digital strategies for competing decisively against fintech start-ups looking to insert themselves into the insurance distribution model. Insights derived from this research will be valuable for insurance industry coalitions to formulate strategies pertaining to disintermediation of the value chain, and distribution model innovation aimed at guarding against insurtech threats.

2. Theory and Literature Review

The preceding chapter outlined the competitive challenges faced by the insurance industry in South Africa from insurtech digital disruption driven by substantial financial investment from the technology industry. Blockchain and smart contract technology was cited for its transformational potential (Swan, 2015c) in the life insurance value chain (IAIS, 2017) with emphasis on policy servicing and proof of insurance requirements. In this chapter we assimilate the theories we will use to test salient end-consumer beliefs concerning these technologies whilst remaining cognisant of finding valuable insights for the long-term insurance industry for strategy formulation.

2.1 Blockchain and Smart Contracts

Blockchain is a new information technology that has the potential for revolutionising consensus models (Swan, 2015a) with its fundamental ability to solve the double-transacting problem. The double-spending problem was a principle hurdle for cryptocurrencies to overcome in order to achieve broad public adoption. The solution was proposed by Nakamoto (2012), a pseudo identify that remain anonymous to this day, in the original paper theorising Bitcoin. A decentralised digital ledger of all Bitcoin transactions prevents double transacting using the same digital asset. The technological innovation that made this possible was the blockchain and hash-based proof-of-work algorithms at its core (Rosenfeld, 2012). Rosenfeld's explanation of blocks in blockchain was succinct:

> Computational effort (consisting in the calculation of hashes) is spent on acknowledging groups of transactions, called blocks; and a transaction is considered final once sufficient work has gone into acknowledging the block that contains it. (p. 2)

Blocks are linked to form a chain and represents the transactional history of one unit of cryptocurrency (Rosenfeld, 2012). The blockchain digital ledger is largely considered durable and secured by consensus among the transaction participants (Peters, Panayi & Chapelle, 2015), which is consistent with Swan's argument that it has the potential of revolutionising consensus models. Unsurprisingly, Peters et al (2015) reported interest from the Euro Banking Association in cryptocurrency's distributed ledger technology to achieve governance by consensus and stated that regulators are likely to favour blockchain more than cryptocurrencies itself.

Blockchain technology may provide the bedrock for cohesive human existence in digital societies. Swan (2015b) argued that the decentralised nature of block technology will provide opportunities for large-scale digital coordination and as an equality technology. Blockchain-based smart contracts may be able to serve as a conveyance attorney in the legal transfer of title in real estate. This is one of a number of use-cases proposed by Swan (2015b) as the author discussed blockchain-based legal advocates. Blockchain is capable of providing programmable transactions (Brito el at, 2015, p. 206), called smart contracts, which execute processes automatically on behalf of a person when some predetermined criteria is met. Therefore, not only does blockchain persist the transaction but it also provides the mechanisms for transaction servicing (Peters et al, 2015). It is in the setting of post-trade infrastructure that smart contracts may prove valuable to insurers to homologate insurance agreements and provide the mechanism to automate routine policy maintenance.

A significant attribute of innovating digital technologies is the inclusion of digital capabilities into objects that previously had only physical materiality (Yoo et al, 2012). Physical materiality refers to an object's tangibility, its ability to be seen and touched. Yoo et al (2012) elaborated on materiality to define digital materiality which in turn refers to how the software code embedded into the digital artefact will alter the digital representations of the artefact. Digital materiality therefore extends physical materiality. Whereas a life insurance policy is traditionally perceived as a tangible object in the form of a paper-based copy of the policy wording, annexures and endorsements, pervasive technologies such as smart contracts adds digital materiality to the product.

Yoo et al (2012) stated that the fundamental benefits of digital technology include reprogrammable functionality and data homogeneity. These benefits equate to the technology affordances of convergence and generativity. The phrase generative technologies was defined by Zittrain (2006) as the following:

> Generativity is a function of a technology's capacity for leverage across a range of tasks, adaptability to a range of different tasks, ease of mastery, and accessibility. (p. 1981).

The generativity of a technology affords users the opportunity to devise valuable new uses or applications for the technology that are easy to diffuse among adopters and may in turn be used for future innovation (Zittrain, 2006). By virtue of offering reprogrammable functionality, digital technologies exhibit a reluctant binding of function and form (Zittrain, 2006) implying that artefact can be enhanced by new functionality and capability added after it has been produced. In contrast, traditional or tangible artefacts often requires redesign in order for it to incorporate new capabilities. Yoo (2012) used the example of smartphones with apps and demonstrates the generativity of the technology through the use of the operating system as a platform for apps. Apps provide extensibility for the smartphone by diversifying its hardware into a proliferation of uses. The reprogrammable nature of smart contracts on blockchain demonstrates the generativity of it as a pervasive technology. The role of the blockchain platform with its affordances of convergence and generativity allows organisations to tailor strategic IT investments aimed at the platform rather than the product. It becomes imperative for organisations to sustain these platforms and enhance platform capabilities to serve a greater subset of organisational activities (Yoo, 2012). Where blockchain is the platform, smart contract technology is a manifestation of its generativity and a demonstration of its reprogrammability.

The innate attributes of digital artefacts were further explored in a study by Kallinikos, Aaltonen & Marton (2013) when they theorised that digital artefacts are by implication incomplete and constantly evolving. The attributes exhibited by digital technologies present opportunities and challenges, with opportunities stemming from alternative uses of the technology. Kallinikos et al (2013) claimed that digital artefacts have an ambivalent ontology, a reference to the constant change it undergoes. Digital artefacts of this kind violates Leibnitz's law of identity of indiscernibles and the indiscernibility of identicals (Kallinikos et al, 2013; Ekbia, 2009) and may be described as quasi-objects due to its lack of the adequacy characteristic found in tangible objects. Relentless evolution of digital technologies offer organisations the opportunity for continual business model innovation through investment is technology. Zittrain (2006) described digital artefacts as intentionally incomplete technologies containing residual potential for innovation. This statement seems to support the findings of Mithas et al (2016) that showed higher sales growth for organisations with proportionally higher IT investment as compared to advertising and research & development. The potential for innovation embedded in pervasive digital technologies materialises in the form of digital traces as by-products (Yoo, 2012) which may lead to new innovations when applied to new use cases.

Digital artefacts are transient assemblies of data and functions (Kallinikos et al, 2013) propagated over the internet and the platforms it is hosted on. This transferability, an attribute of digital technology that underpins generativity (Zittrain, 2006), enables a high degree of distributedness for digital artefacts. Where physical objects are constrained by geographical limits and jurisdictions, those of a digital constitution are borderless (Kallinikos et al, 2013; Ekbia, 2009). For digital ledger technology it implies borderless or multi-jurisdictional trust which emphasises the notion of blockchain's equality (Swan, 2015b) characteristic. The digital artefact functions referred to by Kallinikos et al (2013) mirrors the algorithmic capability of smart contracts on blockchain which, at least in principle, are editable.

A digital artefact is assessed for usefulness in at least two ways by the relevant community of users (Ekbia, 2009, p. 2564); justification and qualification. Justification includes the merits and values of the digital artefact as deliberated on by its community of users (Ekbia, 2009). Once consensus is achieved on the virtue of the qualified quasi-object is made stable by incorporating it into the environment. The roles of trust in technology, usefulness and fit for purpose are apparent even for quasi-objects. Trust in the smart contract technology is directly related to trust of cryptocurrencies and Rosenfeld's (2014) mathematical algorithms for addressing the double-spending problem has been used to develop numerous secure and trusted blockchain platforms (Sompolinsky & Zohar, 2015). The technological developments of cryptocurrency & blockchain security are likely to tempt insurers to introduce blockchain as a broadly-used technology within their companies. In order to understand the parameters of adoption our research questions relate to the aspects of trust, purpose and adoption of smart contracts on blockchain.

2.2 Technology Acceptance Models

Technology acceptance models have achieved widespread use to estimate the probability of technology adoption at individual and organisational levels (Ramdani, Kawalek & Lorenzo, 2009). Gangwar, Date & Raoot (2014) identified six prevalent technology adoption theories. One such model was the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh, Morris, Davis & Davis, 2003) which had evolved from earlier models and into a number of variants. The UTAUT2 model, for instance, featured refined context effects in the form of antecedent factors influencing technology adoption. These were specifically designed for end-consumer adoption and had been broadly applied as a baseline model for end-consumer research for technology (Venkatesh, Thong & Xu, 2016). Similarly, UTAUT has been used to research a variety of contexts including the adoption of speech recognition system by physicians (Alapetite, Andersen & Hertzum, 2009) to biometrics (Miltgen, Popovic & Oliveira, 2013). The

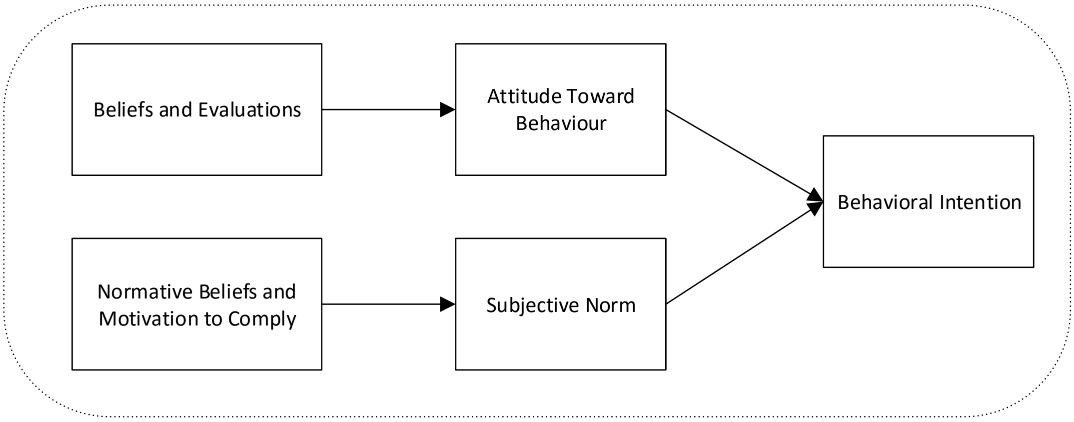
UTAUT model has become a popular theoretical lens used for predicting technology adoption and diffusion within organisations (Williams, Rana & Dwivedi, 2015) and has been applied to broad range technologies, from web sites & mobile technology to management information systems. Purposively selected sets of variables, or antecedent factors, had been developed in an attempt to predict human behaviour when faced with usage and adoption decisions for digital technologies (Venkatesh et al, 2016).

The UTAUT model is an evolution of the technology acceptance model, or TAM (Davis, Bagozzi & Warshaw, 1989), which had been employed to predict the acceptance and adoption of technological innovations among individuals in a firm. TAM put forth two beliefs, perceived ease of use and perceived usefulness (Davis et al, 1989) as important factors influencing a person's intention to use a new technology and ultimately the transformation into actual utilisation of the technology. Davis et al (1989) purported that a person's technology use could be predicted reasonably well from his or hers intention to use it. This assertion had been collaborated by a number of recent studies (Williams et al, 2015; Martins, Oliveira & Popovič, 2014; Gangwar et al, 2014) which explained between 40% and 69% of the intention to use variance in research models using UTAUT.

In early computer adoption research Swanson (1988), as cited in Davis et al (1989), attributed the failure of management information system (MIS) implementations to a lack of management involvement and appreciation. The constructs of perceived ease of use and perceived usefulness (Davis et al, 1989) were not considered in Swanson's model but recognised the need to extend it to include additional co-producers of management involvement. Davis et al (1989) consequently theorised TAM as a foundational theory for establishing an adequate theoretical framework and provided psychometric justification to the technology adoption research stream. With TAM the authors were able to integrate various theories and models from prior studies which in turn explored a wide range of behavioural factors such as belief, attitude and satisfaction in technology adoption (Davis et al, 1989, p. 983).

These factors or 'co-producers' were derived from social psychology models which had laid the foundations for technology acceptance models (Davis et al, 1989). TAM was theorised from the perspective of the Theory of Reasoned Action (Fishbein & Ajzen, 1977, as cited by Davis et al, 1989), an intention model for predicting human behaviour (Venkatesh & Davis, 2000). Since the Theory of Reasoned Action (TRA) had been constructed as a very general intention model, Davis et al (1989) considered it to be appropriate for studying generalised computer technology adoption behaviour. These theories have received widespread validation in the technology adoption field of study (Williams et al, 2015; Venkatesh et al, 2003, p. 436; Gallivan, 2001).

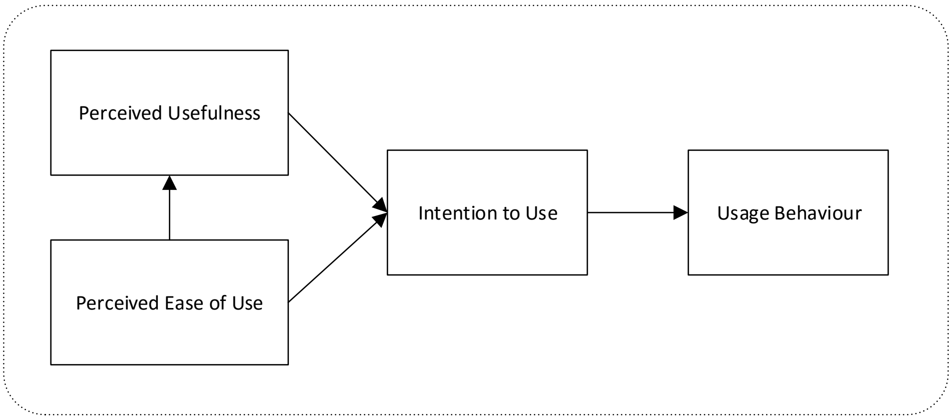
Figure 2: Theory of Reasoned Action (Fishbein & Ajzen, 1977)



In addition to TRA, the Theory of Planned Behaviour (TPB) (Ajzen, 1991), promoted cognitive self-regulation as a factor for predicting human behaviour. It incorporated the belief constructs of attitude towards the behaviour, subjective norms and perceived behavioural control (Venkatesh et al, 2003, p. 434). In other words; attitudinal, normative and control beliefs (Taylor & Todd, 1995). Taylor et al (1995) continued to formulate the decomposed theory of planned behaviour to help predict technology use by synthesising TAM and the theory of planned behaviour, and subjecting a range of antecedent factors for normative and control beliefs to empirical research.

The TAM model established the theoretical link between usage intention and actual behaviour (Venkatesh et al, 2000). Venkatesh et al (2000) suggested approximately 40% accuracy when using TAM to predict actual use from usage intention. Subsequent research continued to add antecedent factors to the technology adoption models resulting in TAM2 (Venkatesh et al, 2000) and UTAUT (Venkatesh et al, 2003). In doing so, the UTAUT model improved the variance between usage intention and actual use to 69% (Williams et al, 2015). By way of illustration, a study conducted by Martins et al (2014) applied the UTAUT model to attempt to quantify internet banking adoption among existing banking customers. Among the antecedent factors measured were the contextual influencers of performance expectancy, effort expectancy and social influence, thus extending the base UTAUT contexts. However, in this particular study, all three of these factors were found to be insignificant in influencing behavioural intention in the adoption decision (Martins et al, 2014).

Figure 3: Technology acceptance model (Davis, 1989)



There was, however, a need to further refine the contextual influence on technology use. Venkatesh et al (2000) articulated this need in their study of antecedents of perceived ease of use in TAM:

> However, in order to design effective training interventions to improve user acceptance, it is necessary to better understand the antecedents and determinants of key acceptance constructs. (p. 451).

For future research directions the authors of the UTAUT theory suggested the testing of new contextual effects in order to conceptualise technology use at a feature level and correlate the outcomes to the UTAUT framework (Venkatesh et al, 2016). Henfridsson, Mathiassen & Svahn (2014) proposed future research to include the sociomaterial elements of designing digital products for business environments which are traditionally categorised by the extensive use of tangible artefacts and paper-based documentation. Henfridsson et al (2014) also suggested to explore how digitisation may enhance cross-industry collaboration of organisations from previously unrelated industries. Decentralised blockchains have the ability to track and report on digital activity (Swan, 2015a) among large sets of stakeholders.

Williams et al (2015, p. 461) described some of the UTAUT framework limitations, citing the fact that studies focussed on single subjects at static points in time, consequently viewed as impeding the generalisation of research findings. In addition to the aforementioned concerns, the fact that UTAUT constructs are generally measured using self-reported usage is considered a weakness. The exclusion of exogenous factors from the TAM and UTAUT models contributed to the vulnerability of research results (Williams et al, 2015; Gangwar et al, 2014, p. 491), even resulting in conflicting findings amongst various studies in technology adoption. As a result Gangwar et al (2014) warned against generalising the TAM model and emphasised the fact that TAM is used to measure perceived adoption and self-reported usage as opposed measuring actual behaviour. The rigidity of the TAM model's constructs are blamed for this weakness. Gangwar et al (2014) called for a diversification of theoretical models in technology adoption research due to the perception that information system innovation is becoming more homogenous.

2.3 Consumer Technology Adoption Models

The unified theory of acceptance and use of technology (UTAUT) professed to integrate a variety of divergent views on technology acceptance by users (Venkatesh, Thong & Xu, 2012; Williams et al, 2015). Venkatesh et al (2003) theorised that the direct determinants of behavioural intention are the four core constructs of the UTAUT model namely social influence, facilitating conditions, performance expectancy and effort expectancy. The UTAUT model were extended by moderators for gender, voluntariness of use, experience and age (Venkatesh et al, 2003). Since then, UTUAT had been applied in wide variety of technology acceptance studies, many of which incorporated new moderators in the correlations among the four core constructs and the behavioural intention construct (Williams et al, 2015). These studies applied the model using moderators and constructs applicable to organisational contexts such as new user populations, the cultural milieu of users and the price sensitivity of consumers (Venkatesh et al, 2012).

Through the extension on the UTAUT model the UTAUT2 version of the model was theorised by Venkatesh et al (2012) to research consumer acceptance and adoption, in the form of eventual use, of technology. The four basic constructs of the framework were extended to include hedonic motivation, price value and habit. The predictors and moderators in the UTAUT2 model were selected intentionally to research consumer adoption and use of technology independent to the organisational context (Venkatesh et al, 2016; Williams et al, 2015). The predictors used in the UTAUT2 model became the exogenous constructs omitted from the TAM model and critiqued by Gangwar et al (2014). As per example, the UTAUT2 research conducted by Venkatesh et al (2012, p. 172) found that the age and gender moderators influence behavioural intention but acknowledged that such significance may relate intrinsically to the context of the study. More important to our research, though, is that Venkatesh et al (2012) found the four core UTAUT constructs to yield the expected significance in a consumer context.

2.4 Diffusion of Innovations

The generativity of digital technology (Zittrain, 2006) affords an organisation distinctly new types of innovation processes (Henfridsson et al, 2014). The inter-organisational adoption of blockchain by the insurance industry may provide additional and unexpected opportunities (Zittrain, 2006) in terms of new products and services (Nylén & Holmström, 2015; Yoo et al, 2012). The complexity of digital innovation requires a rethink of organisation processes for the diffusion and adoption of digital innovations (Nylén et al, 2015, p. 59) and the effects often include fully digitised products and processes.

Krackhardt (1997) put forth a definition for diffusion of innovation (DOI) as the process of strengthening people's belief and trust in a new innovation. His research theorised three generalised types of innovations; firstly, an innovation which is valued by all parties and is adopted rapidly based on intrinsic value. Secondly, an innovation which is inferior in value to the status quo which is quickly discarded and never diffuses. In these two categories the decision for adoption is a rational process based on the innovation's perceived value proposition (Rogers, 1995).

In the third category of innovations (Krackhardt, 1997) the value of the innovation is not easily determined and involves an irrational decision process. This category of innovation will be central to our research since adoption behaviour is irrational and potential adopters may be converted by non-adopters to retain the status quo. Rogers (1995) noted that for most members of a social system the innovation decision is largely dependent on the innovation-decisions of other members in the social system.

Rogers (1995) defined the diffusion as the process of communicating an innovation through channels and networks within the organisation. More specifically, diffusion of innovation is the rate of spread of new technologies and ideas through cultures. Rogers (1983) identified five general attributes that consistently influence adoption (Moore & Benbasat, 1991):

Table 1: Attributes of Innovation (Rogers, 1983)

Attributes of Innovation (Rogers, 1983)	
Relative advantage	A metric indicative of the added value of the innovation when adopted.
Compatibility	An indication of the innovation's consistency with values and morals of the organisation or target user group.
Complexity	The measure of the innovation's perceived ease of understanding and use.
Observability	This attribute is indicative of the measurability of the innovation's outcomes and results.
Trialability	The degree of experimentation afforded to the user for familiarisation purposes.

The five attributes of innovation diffusion were expanded by Tornatzky and Klein (1982) to ten characteristics frequently referenced in innovation diffusion studies; cost, communicability, divisibility, profitability and social approval. Moore & Benbasat (1991) argued that the additional five characteristics theorised by Tornatzky et al (1982) either exhibited redundancy with Rogers' five attributes or were considered inappropriate for individual level adoption research within organisations. For this reason Rogers' basic five attributes will be central to our research as we measure the diffusion of blockchain technology in organisations.

Also in line with our research objectives is Krackhardt's research pertaining to the diffusion of innovation within organisations. Krackhardt & Stern (1988), in their organisational design paper concerning the diffusion of innovation argued that the structure of organisations may aid or deter the adoption of new innovations. This argument gave rise to the theory of organisational viscosity (Wunderlich, Größler, Zimmermann & Vennix, 2014, p. 171; Krackhardt, 1997) which hypothesised that, since people are usually locally contained in their interactions with others in an organisation, structural differentiation may have bearing on diffusion processes. The principal of optimal viscosity (Krackhardt, 1997) was consequently formulated and theorised that there exists an initial period of time during which a minority group of adopters will succeed to retain the innovation despite a non-adopter majority (Wunderlich et al, 2014). Wait too long and the non-adopter majority will dominate the diffusion network and defeat the adopters (McGrath & Krackhardt, 2003).

The second of Krackhardt's principals of innovation is the principle of peripheral dominance which states the likelihood of successful diffusion of an innovation throughout the organisation is increased if the source of the diffusion is located at the periphery of the organisation (Wunderlich et al, 2014, p. 178; Krackhardt, 1997). McGrath et al (2003) refers to this peripheral location in the organisation as a secluded cluster. The advantage of the secluded cluster is to initiate the diffusion process in isolation thus avoiding disruptive behaviour from non-adopters (McGrath et al, 2003). It allows the innovation to become established in the adopters' environment before exposing it to the non-adopters. Thirdly, the principle of irreversibility argues that once an innovation has successfully diffused throughout an organisation it becomes virtually impossible for non-adopters to reverse it (McGrath et al, 2003; Krackhardt, 1997).

The theory of diffusion of innovation (DOI), although not applied directly in our research model, features dominantly in technology adoption research. Conrad (2013, p. 103) equated the DOI construct of relative advantage to the TAM antecedent factor of perceived usefulness. Similarly, DOI's complexity construct mirrored perceived ease of use in TAM. Both theories formulated research models designed for predicting behavioural intent in adopting new technologies (Conrad, 2013; Davis et al, 1989). In DOI this dependent variable was labelled the willingness to use and described by Rogers (2003) as the measurement of the rate of adoption. Having established the theoretical link between DOI and TAM (Wunderlich et al, 2014; Miltgen et al, 2013), subsequent sections in this chapter will demonstrate the intuitive similarities between DOI and trust in technology, the latter of which forms an integral element of our research model.

2.5 Trust in Technology

This study hypothesises that trust in technology would be an important influencer in the adoption of the potentially disruptive blockchain technology by life insurance policyholders. TAM, derived from the theory of reasoned action (TRA) (Venkatesh et al, 2000), did not include explicit constructs for trust and as a result dealt little with antecedent factors where trust is the underlying behavioural construct. Davis et al (1989) elaborated:

> TAM does not include TRA's subjective norm (SN) as a determinant of behavioural intention. As Fishbein and Ajzen acknowledge (1975, p. 304), this is one of least understood aspects of TRA. (p. 5)

This implied that much of the potential adopter's belief & trust framework was neglected by TAM. As a result our research model includes theoretical models pertaining to trust in technology. McKnight & Chervany (2006) set out to endorse the relationship between IT-related beliefs and human behaviour in the context of technology acceptance. McKnight et al (2006) defined trust in technology to "refer to individuals depending on, or being willing to depend on technology to accomplish a specific task". Clegg, Unsworth, Epitropaki & Parker (2002), however, pointed out that there is no generally accepted operationalisation of trust and argued that, for a problem-centric approach, the components of trust are specific to the context (Bigley & Pearce, 1998).

Pivotal to the study of trust in technology had been the understanding of trust in people. It appears to be easier to have trust in a person than to trust a technology (McKnight, Carter, Thatcher & Clay, 2011). The basic premise is that trust reflects dependency on another person due to characteristics of the other (Rousseau, Sitkin, Burt, and Camerer, 1998 as cited by McKnight et al, 2011). Similarly, trust in technology refers to an individual's willingness to depend on a given technology to successfully complete a particular task (McKnight et al, 2011). McKnight et al (2011) humanised trust in technology by stating that trust in people as well as trust in technology feature perceived risk. The authors argued that trust in the attributes of a technology, which in turn moderates behavioural intentions, are better predictors for technology adoption.

McKnight et al (2011) proceeded to map aspects of the two concepts as depicted in Table 2. The authors hypothesised that although the concepts of trust in people and trust in technology are similar, the context and nature of the technology influences salient beliefs of trust in technology.

Table 2: Conceptual comparison of trust in people versus trust in technology (McKnight et al, 2011; Lankton et al, 2015)

	Trust in People	Trust in Technology
Nature of expectations	Do things for you reliably and competently, representing the ability construct by Mayer et al (1995).	The technology's ability to complete the required task satisfactorily.
	Consideration and willingness to be helpful, representing the benevolence construct by Mayer et al (1995).	The technology's ability to provide assistance when required.

	Predictability (McKnight et al, 1998), the need to be consistent.	The technology's ability to perform consistently and reliably.

Not all researchers had been keen to match human attributes with technology in order to study the trust in technology construct. "People trust people, not technology" stated Friedman, Kahn & Howe (2000, p. 36) as cited by McKnight et al (2011). Lankton, McKnight & Tripp (2015) criticized the approach of conceptualising trust in technology as if it possesses human attributes and endorsed the constructs put forward by McKnight et al (2011). The authors claimed that empirical studies incorporating the system-like trust constructs reliability, helpfulness and functionality have validated this view (Lankton et al, 2015). However, Lankton et al (2015) also emphasized that the choice of human-like versus system-like constructs is contextual to the technology under study. Chatbots and robo-advisor technology which display human characteristics in their interaction with users are appropriate to consider as exhibiting human-like trust constructs. Lankton et al (2015) hypothesised that human-technology relationship development is in some way linked to the humanness of the technology which in turn influences its use. There is therefore a need to be able to conceptualise measurements for technology humanness, an aspect of trust research which Lankton et al (2015) acknowledged to require further research.

Research into the willingness to use new computer technologies (Conrad, 2013) regularly invoked the five characteristics of innovation (Rogers, 2003) to link diffusion of innovation theories to technology adoption models (Miltgen et al, 2013). Gallivan (2001) incorporated the constructs of diffusion of innovation models into technology acceptance theory built on Ajzen's (1991) theory of planned behaviour which, as demonstrated in preceding sections, is a foundational theory for the technology acceptance model (TAM). Both studies used the five characteristics of innovation by Rogers (2003) to measure a person's willingness to adopt a new technological innovation.

Trust in technology encourages a potential user to use a technology when apprehensive to do so (Miltgen et al, 2013; Zhou, 2011, p. 528; Clegg et al, 2002). In their study in the field of biometrics adoption, Miltgen et al (2013) confirmed a positive correlation between trust in technology and the user's intention to use a new technology. This research acknowledged that customer acceptance of new technology is driven predominantly by the consumer's behavioural intent towards adoption and the study concluded that trust in technology reduces the perceived risk of adoption (Miltgen et al, 2013).

The concepts of information quality, system quality, structural assurance and trust propensity were tested as antecedent factors for initial trust by Zhou (2011). This quantitative study sought to explain adoption behaviour among mobile banking users in China and blended technology acceptance constructs from TAM and UTAUT with the initial trust model theorised by McKnight et al (2002) to measure perceived usefulness. Using a research conclusion by Mayer, Davis & Schoorman (1995) postulating that trust is reflective of the willingness to be liable to another party's behaviour given the expectations of a positive outcome, Zhou (2011) hypothesised that the initial trust model affects perceived usefulness. It was found that structural assurance and information quality affected initial trust more relative to the other variables tested.

The research of Clegg et al (2002) neatly synthesised innovation diffusion and trust in technology into the innovation trust construct; 'trust that heard' and 'trust that benefit'. However, since their research focussed on the innovation process it falls outside of the scope of the work to be done in this study. Of keen interest are the moderating effects of perceived risk, trialability and observability (Rogers, 2003) on technology adoption within an organisation. These are similar to the system-like trust concepts such as reliability, functionality and helpfulness (Lankton et al, 2015). If the new technology is low in humanness then system-like trust constructs have the stronger influence on behavioural intention (Lankton et al, 2015). The aforementioned study theorised that researchers are able to measure trust in non-human-like technologies without having to apply human attributes to the technology.

Considering that smart contracts running on blockchain technology is very much an agent for disintermediation of the insurance industry, it infers that system-like trust constructs should be tested as part of our research. The nature of expectations described in trust literature is integral to this research insofar it is represented as the performance expectancy construct in the research model. Trust plays a central role in technology adoption since it is an effective way of reducing uncertainty (Miltgen et al, 2013; Zhou, 2011). Trust creates a sense of security for consumers by reducing perceived risks and in the adoption of blockchain, a technology low in humanness, trust will be a fundamental influencer of its adoption.

2.6 Institution-based Trust in Technology

Oliveira, Faria, Thomas & Popovič (2014) defined institution-based trust as the beliefs pertaining to the context in which a technology is deployed for use. The institution-based trust factors that influence consumer perceptions are reputation, capability, integrity, market role and benevolence (Oliveira et al, 2014). Institution-based trust is therefore influenced by environmental forces (McKnight et al, 2002) consisting of situational normality and structural assurances, with situational normality describing the belief that by using a particular technology the user can be successful (McKnight et al, 2011). This belief infers that the user perceives the environment to be ordered and with an adequately sense of normality for trusting the use of a new technology.

Structural assurances have been defined as one of the environmental factors influencing the perceived trustworthiness of a technology (McKnight et al, 2002). This includes the information technology platforms and infrastructure (Oliveira et al, 2014) used as a host environment for the technology. Not restricted to the physical context, structural assurances also pertain to the legality of a technology, contractual warranties guaranteeing the quality of the technology, and information security, all of which coalesce to form the structural assurance belief construct in trust (McKnight et al, 2011). Zhou, Lu & Wang (2010) concluded their study of trust in mobile banking technology by stating that information quality and structural assurances were found to be the key influencers of initial trust. Both factors in turn have a significant effect on the TAM construct of perceived usefulness (Zhou et al, 2010).

Institution-based trust and its components of structural assurances and situational normality are important antecedent factors of trust in technology. These are represented by the ITM construct of structural assurances and is tested alongside personal propensity to trust in our research model.

2.7 The TOE Framework

In order to study technology adoption at an organisational level many researchers have turned to the technology-organizational-environmental (TOE) framework. The authors of TOE, Tornatzky & Fleischer (1990), envisaged a framework for examining information technology and services adoption within firms (Tornatzky et al, 1990 as cited by Gangwar, Date & Ramaswamy, 2015) and incorporated concepts of value creation in their model. Using the TOE model to study the adoption of cloud-based services in organisations, Gangwar et al (2015) stated that TOE is industry agnostic and is not prone to firm size limitations. It is widely regarded as a generic model for technology adoption in organisations.

The TOE model is able to provide a holistic view of enterprise system adoption in organisations, the impact of the new technology on existing processes, the challenges and advantages, and diffusion of the technology throughout the firm (Gangwar et al, 2015). The TOE model combined determinants from three contexts in order to predict enterprise system adoption within organisations namely technological, organisational and environmental (Ramdani et al, 2009). The technological context in TOE comprised entirely of the five attributes of innovations as theorised by Rogers' (1995) diffusion of innovation theory (Ramdani et al, 2009) as discussed in preceding sections of this chapter.

Ramdani et al (2009) applied a pure TOE framework to the study of enterprise system adoption in firms and concluded that the model's environmental context is irrelevant in predicting system adoption among employees. In contrast, the antecedent factor top management endorsement and encouragement in the organisational context measured as the strongest influencer in user adoption (Ramdani et al, 2009). The innovation attribute relative advantage measured as the second-strongest influencer which implied that it's a significant variable in user adoption of enterprise systems in firms.

Despite widespread application in technology adoption literature, Gangwar et al (2015) pronounced TOE to incorporate ambivalent constructs and therefore considered TOE to be too generic. Gangwar et al (2015) and had found it necessary to design hybrid research models incorporating TAM in order to measure perceived usefulness and perceived ease of use as theorised by TAM. TOE is also not considered an end-consumer technology adoption tool. It implies that studying smart contract adoption from the end-consumer perspective, thus an extra-organisational perspective, will not be best served by the TOE model.

2.8 Task-technology Fit

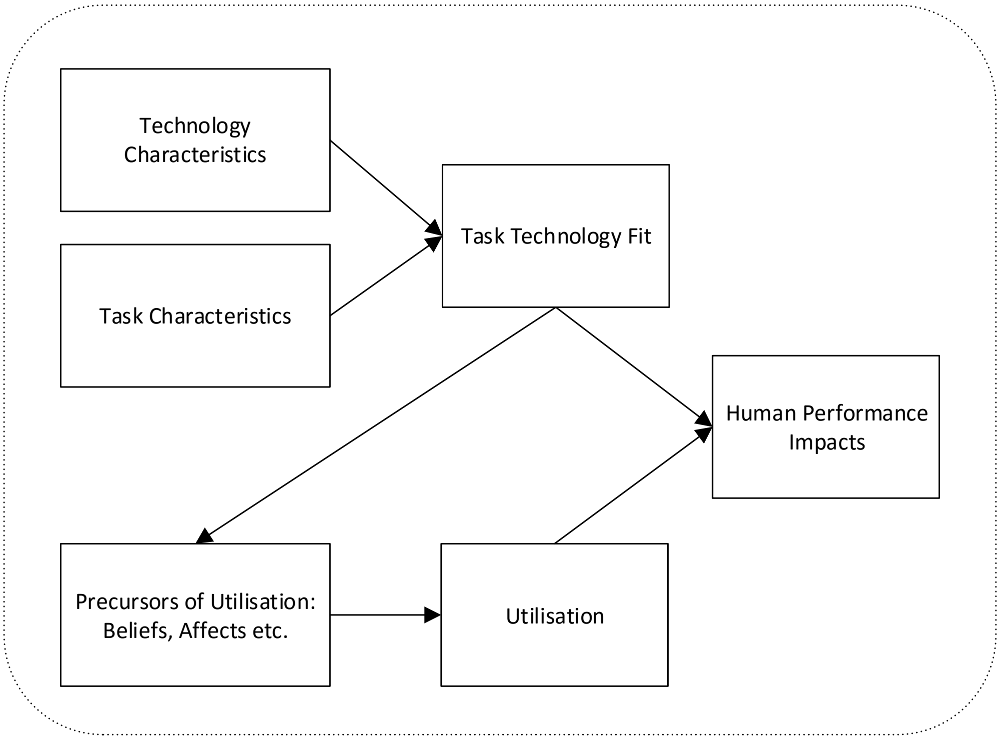
The task-technology fit (TTF) adoption model (Goodhue & Thompson, 1995) argued that users are likely to adopt a new information technology if considered good enough for efficient execution of the routine tasks it was meant to perform. The authors defined task-technology fit as the measure by which a technology enables individual users to perform their tasks. From a quantitative perspective the task-technology fit model correlated task requirements, individual user abilities and the value-adding capability of the technology (Goodhue et al, 1995). TTF can be summarised as the rational perspective of how a new technology can optimise a task (Oliveira et al, 2014).

The TTF model encompasses the four constructs of task characteristics, technology characteristics, task technology fit and ultimately, utilisation (Goodhue et al, 1995). The model assesses the nature of the task and the usefulness of the technology to complete a task (Oliveira et al, 2014). The four constructs were synthesised into the technology-to-performance chain (TPC) by Goodhue (1992), as cited by Goodhue et al (1995), and incorporated into the task technology fit model in 1995. The purpose of the task technology fit model was to establish the theoretical link between information technology and human performance. Goodhue et al (1995) found TTF to have a significant impact on human performance when using technology to perform tasks. The study also found empirical evidence that for TTF to achieve positive impact for human performance the utilisation construct must be included in the model. The utilisation construct in TTF provides a placeholder for a technology adoption framework for predicting user adoption.

The antecedents of the utilisation construct includes normative beliefs, habit, facilitating conditions, affect towards using the technology and expected consequences of utilisation (Oliveira et al, 2014). The theory of reasoned action (TRA) (Fishbein et al, 1975, as cited by Davis et al, 1989), one of the foundational theories for TAM, theorised that a person's subjective norm can be modelled as a function of his or her normative beliefs (Davis et al, 1989). Included in the normative beliefs construct in the TAM model are the person's perceived expectations of specific groups and sometimes referent individuals as well as the person's motivation to comply with such expectations. Included in the latter are the influencing factors of social norms. Davis et al (1989) conceded that from a technology adoption perspective the TRA was particularly weak at measuring the influence of social norms in behavioural intention, a weakness that transferred into TAM. A research model for the measurement of the effect of social norms on technology adoption was theorised by Venkatesh et al (2003) in the UTAUT framework which defined social norms as the extent to which referent individuals or groups believe they should use a particular technology.

The research model of this study transposes the utilisation construct of the TTF model with the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al, 2003). The UTAUT model in turn borrows behavioural constructs selectively from the technology adoption theory (TAM) namely performance expectancy, effort expectancy and social influence (Oliveira et al, 2014; Venkatesh et al, 2012). Experience and voluntariness of technology use have a moderating influence on the relationship between social influence and behavioural intention (Oliveira et al, 2014).

Figure 4: Fit focus constructs in the TTF model (Goodhue et al, 1995)



Hybrid task technology fit (TTF) models have been used in several studies. Zhou et al (2010) augmented the TTF model with UTAUT (Venkatesh et al, 2003) in order to measure mobile banking adoption among consumers. Zhou et al (2010) constructed their research model in such a way to measure technology adoption from the perspectives of user perceptions, namely perceived usefulness and perceived ease of use, and the appropriateness of the technology for completing the user's task. If end-users perceive a technology as being advanced they may not adopt it if they perceive it as unfit for their tasks. The study condensed constructs from both theories into two overarching constructs: Technology perception and task technology fit. In conclusion the study found that user behaviour in the technology adoption process is significantly influenced by both the user's perception of technology as well as the task technology fit (Zhou et al, 2010). The model replaced TTF's utilisation construct with UTAUT antecedent factors including social influence.

The study of mobile banking adoption by Zhou et al (2010) compared the explained variances of the individual models, namely TTF and UTAUT, with that of the hybrid research model. The explained variances for the distinct TTF and UTAUT models were 43.3% and 45.7% respectively. The integrated research model measured explained variances at 57.5%, higher than the individual models which demonstrated its explanatory advantage over the individual models (Zhou et al, 2010).

2.9 Synthesised Research Model

Regarding the use of a synthesised research model, the adoption of complex new technology at individual level warrants the combination of two or more theoretical models but require further research (Gangwar et al, 2014, p. 497). In their study of cloud computing adoption Gangwar et al (2015) described such complexity by contrasting the technological benefits of adoption with the risks and challenges thereof. It is likely that the adoption decisions faced by firms in the context of blockchain and smart contracts will be equally complex.

Venkatesh et al (2016) acknowledged the use of composite models to study technology adoption in the organisational setting. The practise of synthesising Rogers' diffusion of innovation (DOI) theory with technology acceptance models such as UTAUT has increased in popularity. Conrad (2013) applied a hybrid model to the study of adoption of performance management systems. The study correlated perceived usefulness (TAM) with relative advantage (Rogers), and perceived ease of use (TAM) with complexity (Rogers), thus demonstrating the relatedness of the TAM and DOI constructs.

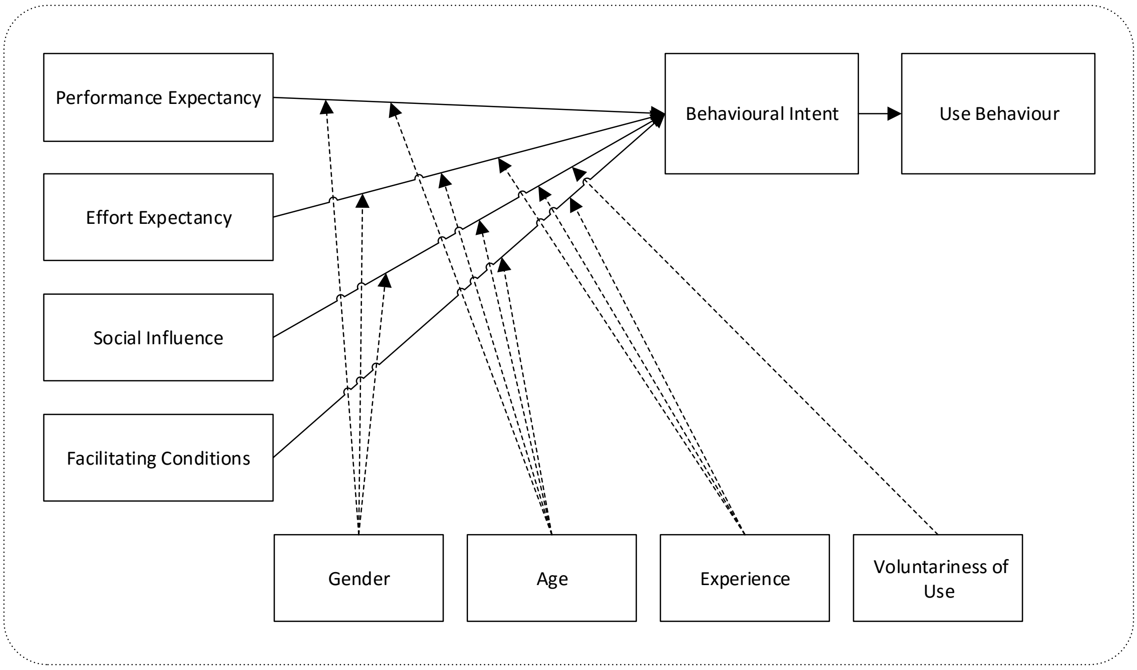
Another comparative study was done by Miltgen et al (2013) in the end-user acceptance of biometrics which synthesised the TAM, DOI and UTAUT models. The study discussed a common attribute of these technology adoption theories namely that behaviour is perceived as an outcome of a set of beliefs about the technology including associated responses to the behaviour (Miltgen et al, 2013). The relevance of Miltgen et al (2013) to our research was partly due to the manner in which trust in technology was incorporated as a determinant for perceived usefulness, perceived ease of use, perceived risks and behavioural intention to accept the technology. As demonstrated earlier these trust constructs originated from the DOI theory (Rogers, 1983).

Using neither DOI nor ITM, Martins et al (2014) applied the perceived risk framework (Featherman & Pavlou, 2003 as cited by Martins et al, 2014) to study trust in technology adoption. In this literature the perceived risk model is described as the potential loss for a consumer in pursuit of a desired outcome. The perceived risk model is an extensive model featuring seven types of risk namely performance risk, financial risk, time risk, psychological risk, social risk, privacy risk and overall risk (Featherman et al, 2003 as cited by Martins et al, 2014). These risk constructs form the antecedent factors for perceived risk which in turn influences perceived usefulness and adoption intention (Featherman et al, 2003 as cited by Martins et al, 2014). The model does not, however, provide sufficiently for the structural assurances and situational normality concepts incorporated in the initial trust model (McKnight et al, 2006). Since these constructs comprise the definition of institution-based trust in technology they are better suited to our research and we did not consider the perceived risk model.

Chapter 2.3 discussed the contextual moderators of the UTAUT framework for purposes of improving the accuracy of the framework in focussed studies. Research applying the UTAUT framework use these moderators to introduce a variety of context-specific control variables (Williams et al, 2015, p. 444). Oliveira et al (2014, p. 694), however, chose to disregard the effects of age and gender moderators in their study of mobile banking adoption, citing these moderators as statistically insignificant in their research model. Our research model likewise does not feature UTAUT moderators but rather existing constructs from the TTF, ITM and UTAUT models. Venkatesh et al (2016) acknowledged that the use of UTAUT extensions such as the inclusion of control variables and moderators have been inadequate in explaining relationship between feature-level adoption of technology and individual outcomes. While the UTAUT and UTAUT2 models would continue to serve as the baseline model for future research, Venkatesh et al (2016, p. 348) called for redefinition of existing UTAUT moderators and empirical evidence of influences on feature-level use.

Figure 5 illustrates the basic UTAUT framework (Venkatesh et al, 2003) with age, gender, voluntary use and experience moderators.

Figure 5: UTAUT framework and moderators, reproduced from Venkatesh et al (2003).



The vulnerabilities of UTAUT (Gangwar et al, 2014) described in chapter 2.2 supported the development of integrated research models in technology adoption. In their literature review of UTAUT research Williams et al (2015, p. 469) considered 102 quantitative studies and identified 32 studies which incorporated multiple technology adoption models. Consequently our research model represents a confluence of theoretical models adapted from smart contracts in life insurance from Oliveira et al (2014) and discussed in detail in chapter 3.

3. Research Model and Hypotheses

The preceding chapter discussed the theories and frameworks applicable to trust in technology, user adoption of technology, diffusion of innovation and task-technology fit. After briefly exploring the TOE framework as an alternative adoption model we argued for the use of a synthesised research model consisting of proven theories in order to measure policyholder perceptions pertaining to blockchain technologies in life insurance. We discussed prior application of such composite research models in extant technology adoption and trust research, and argued for the omission of certain framework elements that were deemed not applicable to our topic of research.

In this chapter we proceed with a concise definition for our research model as adapted from Oliveira et al (2014) and mould the hypotheses of our study.

3.1 Research Model

Our quantitative research will be descriptive in design and will measure the antecedent factors in the initial trust model (ITM) (McKnight & Chervany, 2006), task technology fit (TTF) (Goodhue & Thompson, 1995) and constructs from UTAUT (Venkatesh & Davis, 2000) used for predicting technology adoption.

The research model for this study was adapted from Oliveira et al (2014) which was used to predict mobile banking adoption among end-consumers using a hybrid research model consisting of ITM, TTF and UTAUT. It was designed to measure the influence of selected constructs in behavioural intention and ultimately adoption intention.

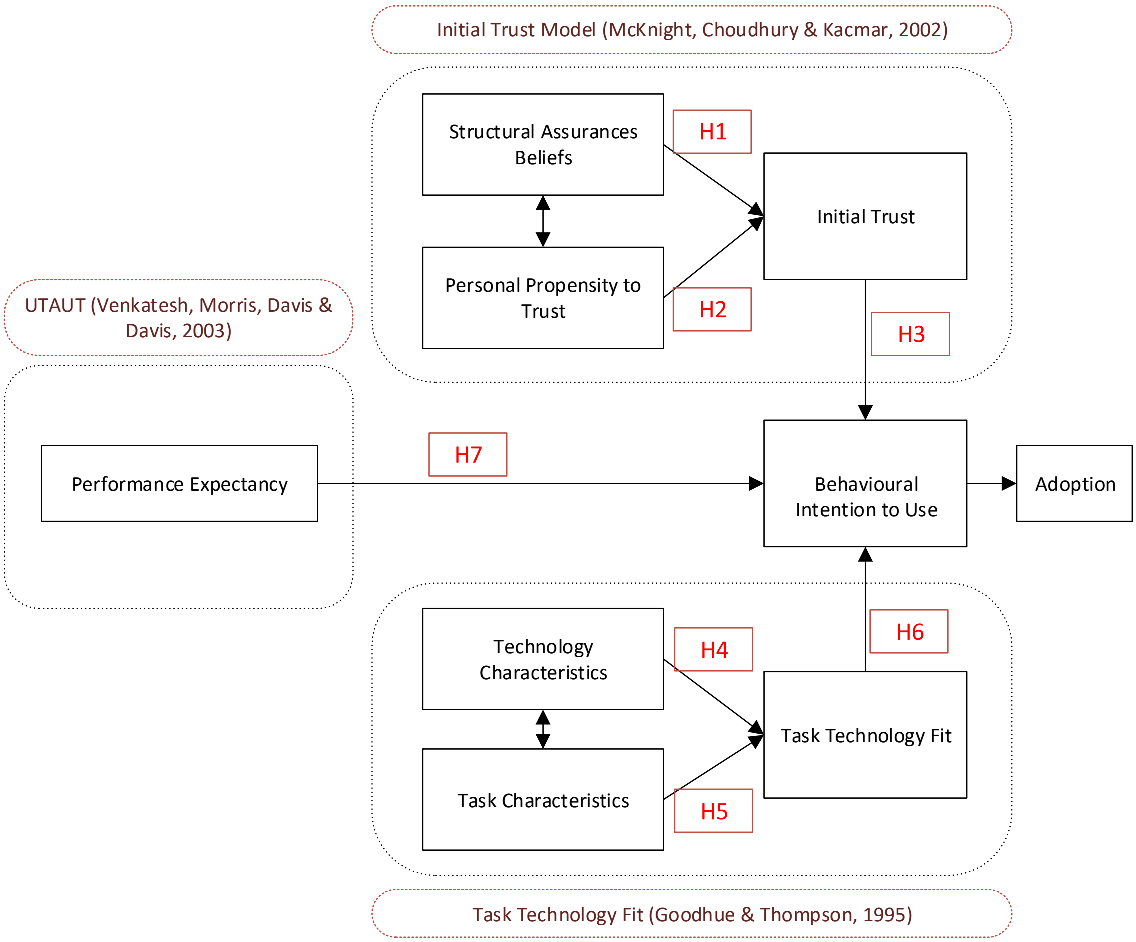
As is the nature of new technologies, blockchain and smart contracts technologies are emerging as value-creating platforms for banks and insurance companies (Mithas et al, 2012, p. 219). Our holistic research model and survey tool was designed to provide empirical measurements of the relationships among the constructs of ITM, TTF and UTAUT. Since blockchain would be the technology responsible for securing the premium and claim transactional data, and smart contracts used to represent the insurance contract and its events, we believe that consumer trust in blockchain technology is an essential factor in its adoption in the insurance industry. For that purpose our research model includes the task technology fit (TTF) model and the initial trust model (ITM).

The UTAUT framework plays a diminished role in our research model due to the perceived nature of blockchain technology. Neither blockchain nor its offspring technology, smart contracts, have seen any significant adoption in the insurance industry

(IAIS, 2017) to serve as reference points. As a consequence, it would be premature to measure the adoption construct in the UTAUT model. Behavioural intent, the antecedent factor for the adoption construct, was chosen as our dependent variable.

Of the four core UTAUT constructs (Venkatesh et al, 2003, p. 447) only one, namely performance expectancy, was selected for hypothesis testing. Effort expectancy and social influence was considered problematic to test due to the lack of consumer exposure the technology under study. The facilitating conditions construct was considered to influence the adoption construct directly (Venkatesh et al, 2003) and not via behavioural intent, and consequently was not included in our research model.

Figure 6: Research model adapted from Oliveira et al (2014).



The table below summarises the independent variables of our research model with behavioural intention as the dependent variable.

Table 3: List of independent variables.

Independent variable	Model
Task characteristics	TTF
Technology characteristics	TTF
Task technology fit	TTF
Structural assurances	ITM
Personal propensity to trust	ITM
Initial trust	ITM
Performance expectancy	UTUAT

Our research model was purposively constructed to be measured using structural equation modelling (SEM) techniques. Variance-based SEM methods such as partial least squares (PLS) has become a quasi-standard in recent technology adoption research (Williams et al, 2015, p. 450). Chapter 4.5 discusses our chosen analytical technique in greater detail.

Structural equation models consist of measurement models and a structural model (Henseler, Hubona & Ray, 2016). Measurement models are theory-based (Henseler et al, 2016) and are built from constructs in the underlying literature (Hair, Sarstedt, Ringle & Mena, 2012). The three measurement models represented in our research model are TTF, ITM and UTAUT. We have chosen composite measurement models (Henseler et al, 2016) for all three underlying theories in order measure covariance amongst their latent variables. The structural model contains the key constructs of the research model, in our case behavioural intention to use, initial trust, task technology fit and performance expectancy.

3.2 Research Hypotheses

Hypothesis 1 (H1):

Life insurance policyholders are concerned with privacy and the protection of personal information as entrusted with the insurer. Structural assurances (McKnight et al, 2002) measure the degree of trust policyholders attribute to blockchain security and the extent to which the insurer is perceived to be accountable for security breaches. The results will allow us to judge the privacy reputation (Miltgen et al, 2013) of blockchain as perceived by end-consumers in the context of personal insurance. Hypothesis 1 expects to find that structural assurances, as one of the components of the initial trust model, exhibits a positive effect on initial trust.

$H1_o$: Structural assurances (SA) beliefs in blockchain has a positive effect on initial trust (IT).

Hypothesis 2 (H2):

The personal propensity to trust construct in the initial trust model is comprised of two aspects; the person's general attitude towards technology use and his or hers faith in general technology (Oliveira et al, 2014). An individual's propensity to trust is influenced by pre-existing beliefs and experiences (Bigley et al, 1998) which has been theorised to remain consistent across different technologies and situations (McKnight et al, 2011). As a consequence of PPT's demonstrated predictability, hypothesis 2 posits that the consumer's propensity to trust blockchain in life insurance will have a positive influence on initial trust.

$H2_o$: The policyholder's personal propensity to trust (PPT) technology positively influences initial trust (IT).

Hypothesis 3 (H3):

Hypothesis 3 posits that we will find a positive relationship between initial trust and behavioural intention. Initial trust (IT) represents measurements for technology reliability and dependability (McKnight et al, 2006) and within the context of our study it measures the consumer perceptions of blockchain technology trustworthiness (McKnight et al, 2011). We theorise that a moderate to strong effect on behavioural intention by initial trust is likely to correspond with actual adoption of blockchain and smart contracts (Venkatesh et al, 2003).

$H3_o$: Initial trust (IT) positively influences the consumer's intention to adopt (BI) blockchain technology in life insurance.

Hypothesis 4 (H4):

Our study is concerned, in part, with the policyholder's perception of blockchain applicability to the life insurance context and its usefulness in policy administration. We hypothesise that the influence of blockchain's technological characteristics such as reliability and responsiveness will have a positive effect on the overall task-technology fit (Goodhue et al, 1995). Reliability is one of Rogers' (1983) attributes of innovation and an important driver for technology adoption both inside an organisation (Wunderlich et al, 2014) and outside.

$H4_o$: The technology characteristics (TeC) of blockchain has a positive effect on task technology fit (TTF).

Hypothesis 5 (H5):

The task-technology fit model describes the fit-for-purpose aspects of blockchain as perceived by life insurance policyholders. Task characteristics is a proxy concept for the diffusion of innovation attributes (Rogers, 1983) of complexity, observability and trialability. Each of these is a determinant in the user's perception on the technology's usefulness and influences his or hers adoption intention (Zhou et al, 2010; Goodhue et al, 1995). As one of the antecedent factors in the TTF model, the user's perception of the technology's usefulness influences his or hers individual performance (Zhou et al, 2010).

$H5_o$: Task characteristics (TaC) of blockchain and smart contracts positively influences task technology fit (TTF).

Hypothesis 6 (H6):

The generative nature of blockchain technology (Yoo et al, 2012) affords insurers an opportunity to redesign distribution channels and policy administration functions for improved customer experiences. Consumers will respond positively to the new features, security and performance offered by blockchain, as well as the capability derived from smart contracts. Consumers will consider the use of public blockchain platforms as an appropriate technology for storing policy master data. These salient attitudes are measured holistically by the task-technology construct which in turn is influenced by task and technology characteristics (Goodhue et al, 1995).

$H6_o$: Task-technology fit (TTF) positively influences the consumer's intention to adopt (BI) blockchain technology in life insurance.

Hypothesis 7 (H7):

The performance expectancy of a technology impacts the user's adoption intention (Martins et al, 2014; Venkatesh et al, 2016). Performance expectancy in the UTAUT framework measures the individual's belief regarding the usefulness of a technology and the benefits it will bring the user (Venkatesh et al, 2003). Oliveira et al (2014) likened performance expectancy in UTAUT to perceived usefulness in TAM and described it as an essential part of the technology's value proposition to the potential adopter. Public blockchain platforms and self-executing smart contracts for policy administration will be deemed as beneficial by policyholders and this will have a positive influence on their intention to adopt the technology.

$H7_o$: Performance expectancy (PE) has a positive influence on the consumer's behavioural intention (BI) to adopt blockchain and smart contracts in life insurance.

4. Research Methodology

4.1 Population

Our research instrument collected responses from life insurance policyholders between the ages of twenty-five and sixty-five. Where possible we tried to ensure that survey respondents had a material interest in the storage and preservation of digital artefacts related to their life insurance policies. The policyholder represents the end-consumer in the life insurance value chain.

The population for our study was selected based on the understanding that the trustworthiness of information systems used to store policyholder information is important to the individual. The survey respondent is thus regarded to have a vested interest in a life insurance policy to the extent that trust in digital versions of his or hers policy requires trust in the underlying information technology. It is assumed that the respondents in this study understands that a technological failure involving blockchain smart contracts may incur significant financial loss for them either immediately or at some point in the future.

Digital materiality extends physical materiality, according to Yoo et al (2012). It implies a transformation from physical materiality into digital representations. The digital artefact is required to encapsulate its physical counterpart's capabilities accurately in order for it to attract a similar level of user trust, in other words it is required to exhibit a commensurate level of reliability as perceived by the consumer. We perceive the selected population as being representative of life insurance policyholder opinions relating to blockchain digital representations of information, and their adoption thereof, as influenced by personal propensity to trust the technology.

The study was contained to a single population consisting of South African life insurance policyholders. In order to generalise the finding of our research, factors such as the monetary value of insurance and chosen insurance firm of the policyholder were not considered material to this study.

4.2 Sampling

Our research aimed at collecting a sample of two hundred survey responses from life insurance policyholders. The purposive sampling technique was used to collect responses from the population of the study and participation in the survey was voluntary. An online survey company based in South Africa assisted in collecting responses.

The research model for our study was adapted from an academic paper by Oliveira, Faria, Thomas and Popovič (2014) studying mobile banking adoption among banking customers. The sample size for their research was 194 respondents (Oliveira et al, 2014). Since we were able to simplify our research model by omitting some UTAUT constructs as well as all of the moderators, a sample size of around 200 responses was deemed adequate.

In choosing a sample size for our study we also consulted the UTAUT literature review by Williams et al (2015). The use of general technology users as the population for technology adoption research is a popular approach. Williams et al (2015, p. 456) lists general users as having been using in 63 studies that featured the UTAUT model. The table below is an excerpt from a list of technology adoption studies compiled by Williams et al (2015) which applied the UTAUT and UTAUT & TAM theories. The research studies listed below concentrated on the digitisation of financial records and we regarded these as closely aligned with our study of technology adoption in the insurance industry.

Table 4: UTAUT studies and sample sizes (Williams et al, 2015)

Study	Application type	Sample size	Models / theories
Luo et al. (2010)	Mobile Banking	122	UTAUT
Mayer et al. (2011)	Smart Products	166	UTAUT
Shin (2009)	Mobile Wallet	296	UTAUT and TAM
YenYuen and Yeow (2009)	Internet Banking	280	UTAUT
Yeow et al. (2008)	Online Banking Service	190	UTAUT

Furthermore, for the statistical analysis tools we intended to use, namely structured equation modelling, certain sample size requirements needed to be adhered to. Henseler et al (2016, p. 8) stated that the sample must be large enough so that the PLS algorithm's regressions do not evoke singularities. Iacobucci (2010, p. 92) prescribed a sample size of at least 100 observations per construct variable in order to achieve convergence. Having at most two endogenous factors per measurement model construct confirmed our target sample size at 200.

4.3 Unit of Analysis

The unit of analysis of a research study identifies the person or object to provide the data at the expected level of aggregation (Zikmund, Babin, Carr & Griffin, 2013, p. 118). Units of analysis include individuals, households, organisations and physical objects (Zikmund et al, 2013).

The unit of analysis of our research is the policyholder's opinion of the blockchain and smart contract use by the life insurer. This opinion manifests as the behavioural intention construct in our research model. Since blockchain and smart contracts remain in an experimental setting, and lack broad adoption by life insurers for use in policy issuing and servicing, we are unable to measure actual use as envisaged by the technology adoption models discussed in chapter 2. Instead, our research measures behavioural intent instead. Extant research on TAM and UTAUT confirmed a positive correlation between behavioural intent and actual use (Alapetite et al, 2009, p. 38; Venkatesh et al, 2000, p. 186; Davis et al, 1989b, p. 997).

4.4 Research Instrument

A standardised, self-administered questionnaire was developed and deployed as a survey to respondents for the collection of primary data. It was adapted from extant literature and designed to capture the attitudes and beliefs of the respondents of this study.

Williams et al (2015, p. 468) identified a dominant cross-sectional and survey approach to research conducted using the UTAUT model. Their findings were based on an examination of 102 quantitative research studies applying the UTAUT model in technology user adoption (Williams et al, 2015, p. 456). The survey method was by far the most frequently used tool for data collection, representing 87% of studies considered in their literature review.

The survey questionnaire for our research used constructs and questions from Oliveira et al (2014). A five-point Likert scale was used to measure the independent variables of the structural model. Each independent variable in the study represented a construct which were measured with four to five questions in the survey questionnaire. Oliveira et al (2014) used a two-step method to test the reliability and validity of the instrument followed by an analysis of the structural model (Anderson & Gebring, 1988 as cited by Oliveira et al, 2014).

The question counts and Cronbach alpha per construct are listed in the table below. The full survey questionnaire is attached as Appendix B: *Survey questionnaire*.

Table 5: Referent research model constructs and Cronbach alphas

Construct	Number of items	Cronbach Alpha from Oliveira et al (2014)
Task characteristics From Zhou et al (2010)	4	0.91
Technology characteristics From Zhou et al (2010)	4	0.89
Task technology fit From Zhou et al (2010)	4	0.94
Structural assurances From Kim et al (2009) as cited by Oliveira et al (2014).	4	0.85
Personal propensity to trust From Kim et al (2009) as cited by Oliveira et al (2014).	4	0.83
Initial trust From Kim et al (2009) as cited by Oliveira et al (2014).	4	0.91
Performance expectancy From Zhou et al (2010)	4	0.92
Behavioural intention From Kim et al (2009) as cited by Oliveira et al (2014).	5	0.93

The survey instrument contained a total of thirty three questions measuring eight constructs. In an attempt to contextualise the survey questionnaire for the respondent, the instrument was designed to offer an explanation of blockchain and smart contract technologies. A short description of the technologies introduced the survey questionnaire to the respondent. It included a description of feature-level blockchain use in life insurance and how they, the respondent, could potentially be affected. The full respondent orientation text is attached as Appendix A: *Survey respondent orientation*.

Certain questions in the questionnaire were optional. The compulsoriness of questions was chosen based on the construct within the research model. For reasons of consistency entire constructs were made optional in the questionnaire, rather than subsets of questions within a particular construct. Finally, optional questions were only allowed in endogenous variables representing the antecedent factors for TTF and UTUAT. The optional question therefore derived from the task characteristics, technology characteristics and performance expectancy constructs.

4.5 Analysis Approach

The survey instrument collected cross-sectional data for statistical analysis. The UTAUT literature review by Williams et al (2015) listed the analysis methods of 102 quantitative research studies and ranked structural equation modelling (SEM) as having been used 45 times. Second in the ranking was regression analysis at 42 studies (Williams et al, 2015, p. 455) but it was noted that there had been a gradual evolution of methodology away from regression analysis in favour of SEM.

The analytical method used by Oliveira et al (2014), whose research model was adapted for our research context, was the partial least squares (PLS) method. PLS is member of the variance-based family of structural equation modelling methods (Henseler et al, 2016). The PLS method is a combination of path models and constructs (Iacobucci, 2010, p. 94). A structural model contains both exogenous and endogenous constructs, and simultaneously defines the relationships among these constructs. The exogenous constructs obtain their values from the research instrument and are not explained by related constructs. Endogenous constructs, on the other hand, are partially explained by related constructs in the model (Henseler et al, 2016). The paths in the measurement and structural models are representative of directional linear relationships among the constructs (Hair, Ringle & Sarstedt, 2011, p. 141). These path relationships may only occur in a single direction and are assumed to be linear (Henseler et al, 2012). The independent variables inform the endogenous constructs in the measurement models which in turn influences the constructs in the structural model (Henseler et al, 2016).

Hair et al (2011) compared the PLS-SEM method with the covariance-based alternative (CB-SEM) and noted that the former provides more accurate structural model estimations more frequently. PLS-SEM is based on total variance whereas CB-SEM interprets common variance in order to measure path coefficients (Hair, Hollingsworth, Randolph & Chong, 2017). The PLS-SEM method has subsequently become a popular analytical tool in marketing and business research (Hair et al, 2017a, p. 444; Henseler et al, 2016; Hair et al, 2012; Hair et al, 2011, p. 140) where the objective of the research is theory development or prediction. The PLS-SEM method is cited as being particular effective in the measurement of complex structural models and where assumptions about the data are less restrictive (Hair et al, 2011). Popularised by its use in marketing research, the PLS-SEM method has consequently been widely used in information system research (Hair et al, 2017a, p. 442; Henseler et al, 2016). A possible reason for this is the belief that the PLS-SEM method has very few limiting assumptions in terms of model specification (Hair et al, 2011, p. 148).

The use of PLS-SEM extended into trust in technology research and was used by Lankton et al (2015) in a complex model testing technology humanness. The authors cited one of the reasons for choosing PLS-SEM as the violation of normality of their data and PLS-SEM's ability to accommodate that (Lankton et al, 2015, p. 894). Similarly, McKnight et al (2011) theorised constructs for propensity to trust and institution-based trust using a structural models and path analysis. Structural equation modelling was also used by Gangwar et al (2014) in evaluating their TAM-TOE composite model. Interpretation of the results was performed using regression weight outputs of the structural model. Using SEM they constructed a measurement model using TOE antecedent factors and a structural model for the TAM constructs (Gangwar et al, 2014, p. 118).

Since we are, in part, evaluating alternative theories (TTF, ITM and UTAUT) with a common dependent variable in behavioural intention, the ML-SEM method was the appropriate choice for our research (Hair et al, 2011, p. 144). Maximum likelihood SEM (ML-SEM) is the default method for the SPSS AMOS tool due to its robust handling of violations of multivariate normality (Iacobucci, 2010, p. 95). Our research model is non-recursive and hence does not require PLS-SEM which would normally be used for complex models featuring large numbers of constructs (Hair et al, 2011). In this regard our measurement models have been simplified by the omission of UTUAT moderators. Finally, having obtained a sample set of 199 observations which Iocobucci (2010) deemed satisfactory, maximum likelihood SEM (ML-SEM) became the de facto method of analysis for our research.

The significance and size of the path relationships (Henseler et al, 2016) between constructs in our model formed the basis of our interpretations of statistical results. The coefficient of determination (R^2) criteria was used to ascertain the predictive capacity of the structural model whereas the path coefficients provided the magnitude of direct and indirect effects among variables (Henseler et al, 2016). In order to generalise this predictive capacity from our sample to the population we evaluated the model path coefficients for significance (Henseler et al, 2016) at a target confidence level of 95%. The resultant beta (β) or path coefficients, essentially standardised regression coefficients, were used to adjudicate the research hypotheses for our measurement models. Henseler et al (2016, p. 12) cited Cohen (1988) to quantify the path coefficient (β) values for assessing effect sizes with measurement models.

Table 6: Path coefficient interpretation (Henseler et al, 2016)

β-value	Interpretation
$0.02 < \beta \leq 0.15$	Weak
$0.15 < \beta \leq 0.35$	Moderate
$0.35 < \beta$	Strong

The sign and absolute value of the R^2 values for the structural model constructs is indicative of significance (Hair et al, 2011, p. 147). Hair et al (2011, p. 145) prescribed the following guidelines for evaluating endogenous latent variables in the structural model using the resultant absolute R^2 values:

Table 7: SEM structural model evaluation (Hair et al, 2011)

$\lvert R^2 \rvert$ value	Interpretation
≤ 0.25	Weak
$0.25 < R^2 \leq 0.5$	Moderate
$0.5 < R^2 \leq 0.75$	Substantial

Lastly, our model performed correlation analysis for indicator variables in the TTF and ITM measurement models. The SEM path modelling algorithm used for calculating path coefficients differ to that used for finding empirical linear correlations between indicator variables (Henseler et al, 2016). Henseler et al (2016, p. 5) stated that in terms of discrepancies between the empirical and model-implied correlation matrix, maximum likelihood SEM is more efficient at minimising those discrepancies than PLS-SEM. We interpreted linear correlations between variables in the measurement models as part of the discussion of results in chapter 6.

4.6 Limitations of the Research Method

PLS path modelling may utilise two different methods for measuring constructs: factor models or composite models (Henseler et al, 2016, p. 4). The research model used by our research utilised composite-based structural equation modelling. Composite models relax the covariance restrictions among the indicator variables of the construct (Henseler et al, 2016). The understanding of SEM measurement models' actual performance is still limited and Hair, Hult, Ringle, Sarstedt & Thiele (2017b) urged researchers to understand the underlying mechanism of these methods in order to estimate their relative performance.

PLS path modelling, of which our chosen method maximum likelihood SEM is a variant, generalises the model in order to predict sample data (Hair et al, 2017b). For the PLS path modelling method there is ambiguity among current literature regarding goodness-of-fit indices and the use of those indices to determine the fit of the model (Hair et al, 2017b). It is argued that these goodness-of-fit indices are by-products of the PLS algorithm rather than indices that are explicitly minimised (Hair et al, 2017b).

Each construct in the measurement models should have at least three indicator variables according to Iocobucci (2009). The ITM and TTF models feature only two indicators in the respective measurement models. Furthermore, the only UTAUT indicator variable we chose to include was performance expectancy. Our research model therefore violated this model specification recommendation.

5. Results

5.1 Pilot Study

A pilot study was conducted using nineteen (n = 19) life insurance policyholder responses collected by a market research company. The five-point Likert scale was converted to numerical representations using Table 8.

Table 8: Likert scale numerical values

Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly agree	5

The questionnaire scales were tested for reliability and validity using the IBM SPSS software. Cronbach's Alpha values were calculated in order to measure the internal consistency of our model constructs (Zikmund et al, 2013, p. 302). The coefficient alphas of these tests indicate whether the items of a construct converge and a value below 0.6 is indicative of a scale with poor reliability (Zikmund et al, 2013, p. 302).

The resulting Cronbach alphas for the pilot study as attached as Appendix C: *Pilot study reliability tests*. The Cronbach alphas calculated using the pilot study data confirmed the internal consistency of the scales with all values above 0.852 and therefor deemed acceptable (Hair, Sarstedt, Ringle & Mena, 2012, p. 424).

Similarly to Oliveira et al (2014) our pilot study indicated that item PPT4, question 4 of the personal propensity to trust constructs, was not significant. Item PPT4 was not removed from the questionnaire for final data collection.

5.2 Reliability and Validity Testing

The nineteen responses that compromised the pilot study were removed from the final dataset. In total one hundred ninety-nine (N = 199) survey responses were collected as the sample by an online market research company.

We started our analysis of the survey data by testing the measurement model for reliability and validity (Anderson & Gebring, 1988 as cited by Oliveira et al, 2014) using the IBM SPSS software. In order to confirm internal consistency and reliability we calculated Cronbach's Alpha values (Zikmund et al, 2013; Hair et al, 2012) for our final survey dataset. Table 8 was used to convert the questionnaire's five-point Likert scale into numerical representations.

The Cronbach alpha for personal propensity to trust (PPT) was calculated at 0.664 as was deemed to be marginally unacceptable (Bagozzi & Yi, 1988 as cited by Oliveira et al, 2014). The reliability statistics for this construct indicated that the removal of item PPT4 would result in Cronbach alpha of 0.843 and it was consequently removed followed by a re-execution of the reliability statistics. A Cronbach alpha of 0.843 was subsequently confirmed for construct personal propensity to trust. Appendix D: *Reliability statistics for construct PPT* attaches the statistical output of this factor adjustment.

The reliability statistics were followed by confirmatory factor analysis (CFA) using the principal component analysis (PCA) method. CFA tests the validity of a construct in the research model insofar how accurately it reflects a singular concept (Zikmund et al, 2013). The Kaiser-Meyer-Olkin measures of sampling adequacy returned values greater than 0.500 and indicated good sampling adequacy (Bagozzi & Yi, 1988, p. 81 as cited by Oliveira et al, 2014).

Table 9: Reliability and validity statistics

Construct	Number of items	Original Cronbach Alpha	Cronbach Alpha **less PPT4**	KMO measure	Bartlett's Test (sig.)
Task characteristics	4 TaC1 – 4	0.831	-	0.801	0.000
Technology characteristics	4 TeC1 – 4	0.785	-	0.775	0.000
Task technology fit	4 TTF1 – 4	0.780	-	0.767	0.000
Structural assurances	4 SA1 – 4	0.682	-	0.565	0.000
Personal propensity to trust	4 PPT1 – PPT4	**0.664**	0.843	0.664	0.000
Initial trust	4 IT1 – 4	0.882	-	0.820	0.000
Performance expectancy	4 PE1 – 4	0.874	-	0.825	0.000
Behavioural intention	5 BI1 – 5	0.865	-	0.833	0.000

Subsequently we analysed the structural model in order to test the research hypotheses. We calculated means per construct for the structural model analysis by creating new variables as depicted in Table 10 below.

Table 10: Mean variables per model construct

Construct	Items	Mean Variable
Task characteristics	TaC1 – 4	TaC-AVG
Technology characteristics	TeC1 – 4	TeC-AVG
Task technology fit	TTF1 – 4	TTF-AVG
Structural assurances	SA1 – 4	SA-AVG
Personal propensity to trust	PPT1 – 4	PPT-AVG
Initial trust	IT1 – 4	IT-AVG
Performance expectancy	PE1 – 4	PE-AVG
Behavioural intention	BI1 – 5	BI-AVG

5.3 Descriptive Statistics

Descriptive and distribution of sample statistics are tabled below.

Table 11: Descriptive statistics

Mean Variable	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Task characteristics (TaC-AVG)	4.1344	0.7259	0.527	-1.104	2.367
Technology characteristics (TeC-AVG)	3.8329	0.5763	0.332	-0.457	1.593
Task technology fit (TTF-AVG)	3.8568	0.6084	0.370	-0.269	1.010
Structural assurances (SA-AVG)	3.4108	0.6769	0.458	0.106	0.124
Personal propensity to trust (PPT-AVG)	4.0653	0.8962	0.803	-1.244	1.724

Initial trust (IT-AVG)	3.7676	0.6925	0.479	-0.646	1.674
Performance expectancy (PE-AVG)	3.9749	0.6600	0.436	-0.627	1.557
Behavioural intention (BI-AVG)	3.9005	0.6810	0.464	-0.586	0.633

The descriptive statistics indicated that not all of our mean variables are normally distributed. Appendix E*: Tests for Normality* lists the Kolmogorov-Smirnov test results for our study's mean variables with no p-value greater than 0.05 as required for normality (Hair et al, 2012). The fact that our mean variables were not normally distributed justified the use of ML-SEM which is less restrictive on data distribution requirements (Hair et al, 2011, p. 144).

5.4 Model Fit Analysis

The model was run in SPSS AMOS using 4,999 bootstrap samples as recommended by Henseler et al (2016, p. 11). Statistical analysis using a 95% confidence interval started with calculated averages for responses received for each construct or independent variable.

In assessing the model fit we evaluated the estimates produced by the AMOS software. Both the comparative fit index (CFI) and Chi-square (χ^2) measurements were indicative of a less-than-ideal model fit. CFI is a goodness-of-fit index and deemed an appropriate model fit metric by Iocobucci (2010) in structural equation modelling. CFI reflects the model's incremental fit (Iocobucci, 2010, p. 96), also explained as the comparative fit among various measurement models. This fit metric ranges from 0 to 1 and increases when the data exhibits greater explanatory power. AMOS measured CFI for our model and data at 0.474 which indicated a low amount of variance in our data (Iocobucci, 2010, p. 97).

Chi-square (χ^2) is regarded as an absolute model fit indicator. The chi-square value of a model is large when model fit is worse (Iocobucci, 2010). AMOS calculated χ^2 = 370.3 and degrees of freedom (DF) = 19, producing a measurement (CMIN/DF) of 19.5 which is significantly higher than the upper threshold of 5 (McDonald & Ho, 2002).

When considering RMSEA as the fit index, McDonald et al (2002) is quoted saying 0.05 to correspond to a good model fit. Our SMSEA measurement was 0.306 and once again indicated low levels of model fit.

Our model fit indices are attached as appendix F and summarised in the table below.

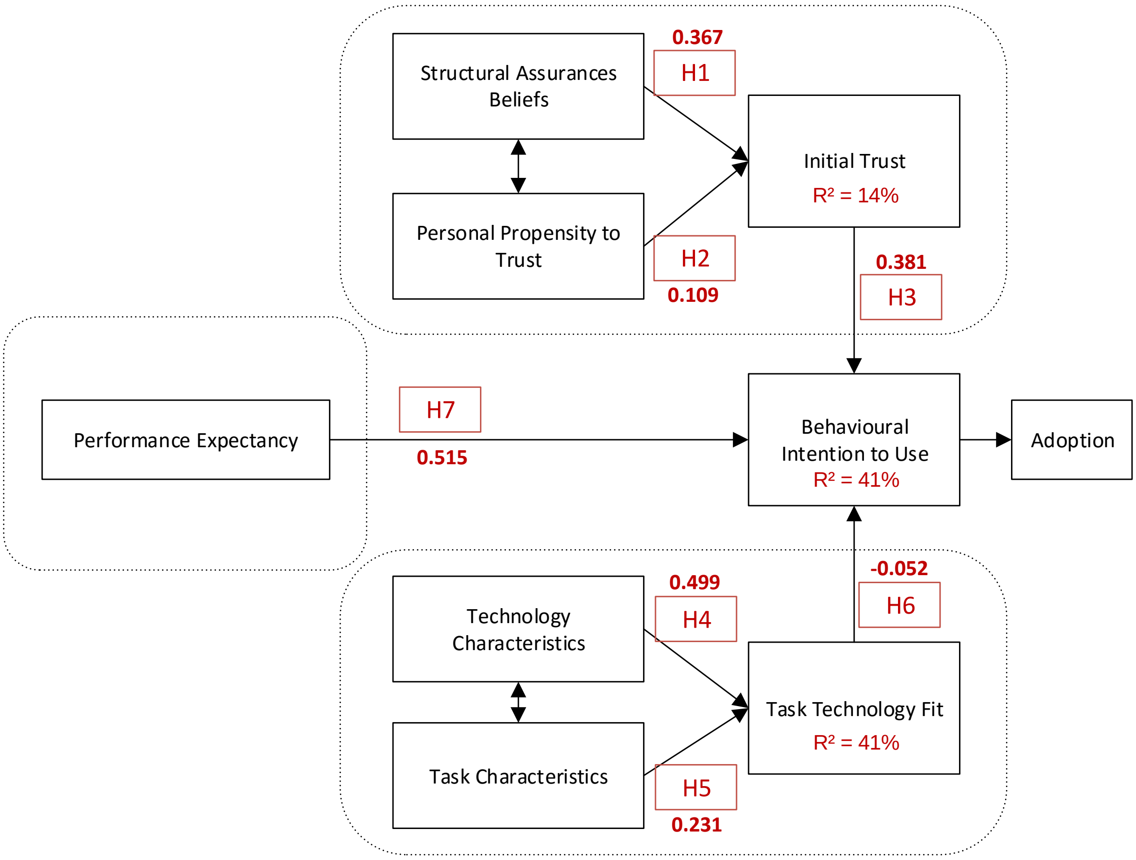
Table 12: Summary of model fit indices

Fit index	AMOS measurement
(χ^2 / df)	19.487
CFI	0.474
RMSEA	0.306

5.5 Model Analysis Results

Using AMOS at a 95% confidence interval, the model produced the path coefficients and squared multiple correlations indicated in the diagram below.

Figure 7: Model analysis results



1. Hypothesis 1 (H1): Structural assurances positively influences initial trust

$H1_0$: Structural assurances beliefs in blockchain has a positive effect on initial trust.

The path coefficient for variables structural assurances (SA) and initial trust (IT) indicate a statistically significant relationship (β = 0.367, ρ-value < 0.01). The standardised regression coefficient (β = 0.367) for this path in the structural model is interpreted as being moderate to strong.

We fail to reject the null hypothesis.

2. Hypothesis 2 (H2): Personal propensity to trust positively influences initial trust

$H2_o$: The policyholder's personal propensity to trust technology positively influences initial trust.

The regression coefficient for constructs personal propensity to trust (PPT) and initial trust (IT) indicates a small β and statistical insignificant result (β = 0.109, ρ-value > 0.01).

We reject the null hypothesis.

3. Hypothesis 3 (H3): Initial trust positively influences behavioural intention

$H1_o$: Initial trust positively influences the consumer's intention to adopt blockchain technology in life insurance.

The standardised regression coefficient of the two variables initial trust (IT) and behavioural intent (BI) was statistical significant (ρ-value < 0.01). The regression coefficient (β = 0.381) is indicative of a moderate to strong effect between these two constructs.

We fail to reject the null hypothesis.

4. Hypothesis 4 (H4): Technology characteristics positively influences task technology fit

$H4_o$: The technology characteristics of blockchain has a positive effect on task technology fit.

The technology characteristics (TeC) variable demonstrates a strong, positive and statistically significant relationship with task technology fit (TTF). The standardised regression coefficient (β) is 0.499 (ρ-value < 0.01).

We fail to reject the null hypothesis.

5. Hypothesis 5 (H5): Task characteristics positively influences task technology fit

$H5_o$: Task characteristics of blockchain and smart contracts positively influences task technology fit.

Although the relationship between task characteristics (TaC) and task technology fit (TTF) is measured as statistically significant (ρ-value < 0.01), the standardised regression coefficient is considered to be moderate to weak (β = 0.231).

We reject the null hypothesis.

6. Hypothesis 6 (H6): Task technology fit positively influences behavioural intention

$H6_o$: Task technology fit positively influences the consumer's intention to adopt blockchain technology in life insurance.

The results indicate that the relationship between task technology fit (TTF) and behavioural intent (BI) is not statistically significant (β = -0.052, ρ-value > 0.01). The ρ-value for this regression is 0.335 and indicates statistical insignificance.

We reject the null hypothesis.

7. Hypothesis 7 (H7): Performance expectancy positively influences behavioural intent

$H7_o$: Performance expectancy has a positive influence on the consumer's behavioural intention to adopt blockchain and smart contracts in life insurance.

The path coefficient for the performance expectancy (PE) and behavioural intent (BI) constructs are indicated as statistically significant (ρ < 0.01). The standardised regression coefficient of β = 0.515 shows a strong relationship between these two constructs.

We fail to reject the null hypothesis.

8. Summary of Hypothesis Outcomes

This section summarises our hypothesis findings alongside statistical evidence.

Table 13: Summary of hypothesis outcomes

Hypothesis		Accept	β	P-value
$H1_o$	Structural assurances → Initial trust	✓	0.367	$\rho < 0.01$
$H2_o$	Personal propensity to trust → Initial trust	X	0.109	$\rho = 0.1$
$H3_o$	Initial trust → Behavioural intent	✓	0.381	$\rho < 0.01$
$H4_o$	Technology characteristics → Task technology fit	✓	0.499	$\rho < 0.01$
$H5_o$	Task characteristics → Task technology fit	X	0.231	$\rho < 0.01$
$H6_o$	Task technology fit → Behavioural intent	X	-0.052	$\rho = 0.335$
$H7_o$	Performance expectancy → Behavioural intent	✓	0.515	$\rho < 0.01$

9. Squared Multiple Correlations

The predictive capacity of our research model is represented by the R^2 values of the intercept constructs. Table 14 contains a summary of the statistical results.

Table 14: Squared multiple correlations

Measurement Model	R^2
Initial trust	0.140
Task-technology fit	0.413
Behavioural intent	0.413

10.Composite Measurement Model Correlations

We measured latent variable correlations as part of our structural equation model. These correlations were intended to provide insights into the consistency and strength of the measurement models namely initial trust and task-technology fit. Our use of composite measurement models (Henseler et al, 2016, p. 4) for these two theories allowed us measure the linear correlations among their latent variables. The results are tabled below.

Table 15: Composite Measurement Model Correlations

Measurement model correlations	r
Initial trust Structural assurances ←→ Personal propensity to trust	-0.083
Task-technology fit Technology characteristics ←→ Task characteristics	0.481

6. Discussion of Results

6.1 Hypothesis 1_o: Structural assurances influences initial trust

The structural assurances (SA) construct is a predictor variable in the initial trust model (ITM) (McKnight et al, 2002) alongside personal propensity to trust. Structural assurances encompass the environmental factors that influence the perceived trustworthiness of a technology (McKnight et al, 2002). Such factors include information technology platforms and infrastructure, information quality and the warranties offered by the providers of the digital service to the user.

The results indicate a statistically significant relationship between structural assurances (SA) and initial trust (IT) ($\beta = 0.367$, ρ-value < 0.01). Furthermore, the structural assurances construct is considered to have a moderate to strong effect on initial trust and is therefore a significant influencer.

Zhou (2011) hypothesised that the initial trust model affects perceived usefulness. In their study it was found that structural assurance and information quality affected initial trust more relative to the other variables tested. Our analysis indicate a similar finding, with structural assurances exhibiting stronger influence on initial trust than the user's personal propensity to trust.

Our research instrument posed questions related to blockchain and smart contract security, more specifically to personal information risk and the insurer's liability in such an event of loss of personal information. We measured the mean response for structural assurances at 3.41 ($s^2 = 0.458$) which we interpret as a "Neutral" on the Likert scale. This outcome is less than similar measurements in comparative studies of financial technology adoption by end-consumers (Oliveira et al, 2014; Zhou, 2011).

Ever-increasing privacy concerns such as the vulnerability of personal data are important to consumers (Miltgen et al, 2013). These perceived risks relate to the privacy reputation of the technology (Miltgen et al, 2013). A heightened perception of risk on the part of the consumer lowers their tolerance levels for the technology. In contrast, consumer trust in the technology is strengthened by structural assurance beliefs (McKnight et al, 2002).

We find that our sample of life insurance policyholders are ambivalent about the security offered by blockchain platforms. This may be due to the lack of a privacy reputation since the majority of hypothesised blockchain solutions remain theoretical (Collomb et al, 2016). A privacy reputation is cognitively constructed by consumers as they use a technology and these perceptions are propagated throughout the user base by means of user feedback. Established technologies have privacy reputations assimilated over time which may either contribute or detract from the successful adoption of a technology. The principle of peripheral dominance (Krackhardt, 1997) encapsulates this user behaviour. A secluded cluster of adopters will drive adoption of technologies at the periphery of the industry at a faster pace and lower cost (Wunderlich et al, 2014). The structural assurances provided by the technology are therefore vital to its successful diffusion among end-consumers.

6.2 Hypothesis 2_o: Personal propensity to trust influences initial trust

McKnight et al (2011) strengthened the conceptual relatedness of trust in people to trust in technology. Subsequent research by Lankton et al (2015) reaffirmed these associations and the resulting humanisation of trust in technology. This avenue of technology trust research argued that the attributes of technology has a moderating effect on behavioural intentions (McKnight et al, 2011). In the initial trust model trusting intention is measured by the initial trust construct.

The user's disposition to trust (Bigley et al, 1998) is one of the perspectives to evaluate when measuring initial trust. An individual's propensity to trust is influenced by pre-existing beliefs and experiences (Bigley et al, 1998) which tend not to vary across different technologies and situations (McKnight et al, 2009). Propensity to trust technology compromises of two dimensions; the person's general attitude towards technology and his or hers faith in general technology (McKnight et al, 2009).

In the context of our study, we measured propensity to trust along these two dimensions: General propensity to use technology and the respondent's faith in blockchain technology. Our result show that personal propensity to trust (PPT) is statistically insignificant in influencing initial trust (IT) ($\beta = 0.109$, ρ-value > 0.01).

The mean response for personal propensity to trust was 4, interpreted as "Agree" using the five-point Likert scale. Variance (s^2) for PPT is high at 0.8 and is the construct in our research model with the highest degree of variance. Notwithstanding, the sample respondents demonstrated a fair degree of personal propensity to trust technology, even though we found a weak relationship with initial trust in the context of our study.

We theorise that this may be due to the digital materiality (Yoo et al, 2012) associated with insurance policies persisted on blockchain. It represents a digital artefact from something that before exhibited only physical materiality. Yoo et al (2012) posits that the "crashability", or the perceived innate unreliability of digital technologies by a user, leads to unintended consequences and uncertainty. Such beliefs are powerful determinants in an individual's propensity to trust a technology.

The lack of relatedness of personal propensity to trust to initial trust demonstrates a misalignment between the two concepts within the context of blockchain and smart contracts. Whereas our study's respondents demonstrated a fair degree of personal trust in technology, this did not translate into trust in blockchain in insurance. We discuss this finding further in the next section where we interrogate findings from ITM measurement model holistically.

6.3 Hypothesis 3_o: Initial trust influences behavioural intention

The concept of initial trust signifies an individual's beliefs and assumptions (McKnight et al, 2002) regarding the properties of a specific technology. The formation of trust has been theorised as a process consisting of emotional and calculative processes (Bigley et al, 1998) and to some extent trust is a product of the individual's emotional mindset. Extant literature shows initial trust to be a moderate influencer on the individual's intention to adopt the technology (Oliveira et al, 2014, p. 697; Zhou, 2011, p. 534; McKnight et al, 2002). Our research seems to endorse these findings and indicates a moderate to strong relationship between initial trust (IT) and behavioural intention (BI) ($\beta = 0.381$, $\rho\text{-value} < 0.01$).

Lankton et al (2015) explored the impact of human-like and system-like characteristics of technologies trust outcomes. Blockchain demonstrates a distinct inhumanness as a technology, akin a database management system and almost entirely obscured from the end-user. The system-like characteristics of blockchain implies that potentially it has greater bearing on the trust outcomes of usefulness, enjoyment, continuance intention and importantly, trusting intention (Lankton et al, 2015, p. 899) than technologies exhibiting more human traits.

Bigley et al (1998) reminded us that trust is contextual. The context for initial trust's relatedness to user intentions in our research consists partly of trust in digital artefacts. It is representative of the policyholder's willingness to depend (McKnight et al, 2006) on blockchain to persist his or her life insurance information and to execute administrative processes as smart contracts. For ease of reference, the questions posed to survey respondent for measuring the initial trust construct are listed below.

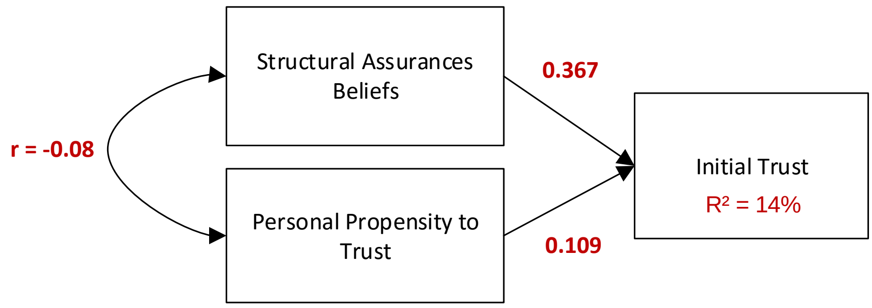
1. Blockchain smart contracts seems <u>dependable</u>.
2. Blockchain smart contracts seems <u>secure</u>.

3. Blockchain smart contracts seems reliable.
4. Blockchain smart contracts was created to help the policyholder.

The mean response on these questions was 3.8 on our five-point Likert scale, closer to "Agree" than "Neutral", with variance (s^2) of 0.48 and a median value of 4. We interpret this measurement as being positive for the perception of blockchain technologies in general. Blockchain's impersonal or system-like attributes may have contributed to this general opinion with Lankton et al (2015) having shown that users potentially exhibit greater trust towards technologies with system-like properties, as opposed to those with human-like properties. It would seem to us that the calculative process in evaluating blockchain for trustworthiness assumed precedence over the emotional process by the respondents in our sample. It is affirmation that they perceive blockchain to be a trustworthy technology in general which would perform consistently and reliably (McKnight et al, 2011).

On examination of the coefficient of determination (R^2) for the initial trust construct, we find weak predictive capacity (R^2 = 14%). This result implies that only 14% of initial trust is explained by its antecedent factors namely structural assurances and personal propensity to trust. Inspecting the linear correlation between structural assurances and personal propensity to trust we found a weak relationship between the two constructs ($r = -0.08$). In the context of our study initial trust's indicator variables are neither well correlated nor is initial trust well explained by them.

Figure 8: ITM measurement model results



The lack of predictive capacity in the ITM measurement model (R^2 = 14%) may partly be explained by the disconnect between the personal propensity to trust and initial trust constructs. Our results have shown that personal propensity to trust neither correlates ($r = -0.08$) with structural assurances nor have a relationship with initial trust ($\beta = 0.109$, ρ-value > 0.01). This result stands in contrast to structural assurances for which demonstrated a statistically significant relationship with initial trust (β = 0.367, ρ-value < 0.01). This is not to say that personal propensity to trust technology was low in our sample since the mean PPT response was 4, "agree". It is indicative of the fact that blockchain is an underlying platform that enables feature-level applications such as cryptocurrencies. We theorise that the user's own beliefs and experiences about general technology has no bearing on his or hers intention to accept blockchain and smart contracts as a technology used by the long-term insurance industry.

Our results show implicit trust in blockchain through the initial trust construct and a moderately strong relationship to adoption intention. In addition, we have seen that structural assurance concepts are strong drivers for initial trust.

6.4 Hypothesis 4_o: Technology characteristics influences task-technology fit

Good task-technology fit is achieved when a technology possesses features that fit the task requirements well (Goodhue et al, 1995). The fit of the technology to the task subsequently affects the performance of the technology as applied to the task by the user. In our research model we supplanted TTF's utilisation construct with TAM's behavioural intention in order to measure its influence on adoption intention. We hypothesised that a strong cognitive fit of task to technology would imply strong behavioural intention to adopt the technology (Oliveira et al, 2014).

The technology characteristics construct in our research model entails the performance attributes of blockchain and smart contracts. The survey questionnaire collected responses relating to the perceived availability and responsiveness of a hypothesised blockchain platform. We found a strong, positive and statistically significant relationship with task-technology fit (β = 0.499, ρ-value < 0.01).

The mean for the technology characteristics construct measured at 3.8 (s^2 = 0.332) which is indicative of survey answers grouping close to "Agree". Considering that our survey questions pertaining to technology characteristics included one about the pervasiveness of blockchain, we are led to theorise that blockchain's relatedness to cryptocurrencies are influenced in this response. It is unlikely that any of our respondents has knowingly interacted with software utilising smart contracts, therefore a general understanding of blockchain's role in cryptocurrencies (Swan, 2015a) is perhaps bolstering its reputation as a reliable technology. Our finding in this regard seems to underscore the implicit trust in blockchain deduced from our initial trust model analysis.

Our results indicate that our sample of respondents perceive blockchain and smart contracts to be secure, fast and reliable. This finding corroborates our initial trust measurement in the initial trust model where respondents confirmed their faith in blockchain's security and reliability. Rogers (1995) defined relative advantage as an attribute of innovation to construe the added value of the innovation when adopted. Consequently we theorise that the respondents in our study perceive significant relative advantage in the use of blockchain in insurance systems.

6.5 Hypothesis 5_o: Task characteristics influences task-technology fit

A complex task will reduce a technology's task-technology fit (Goodhue et al, 1995). Task complexity in the context of our research describes the ease of understanding and use (Rogers, 1995) of blockchain-based software. As an attribute of innovation, the complexity of a technology influences the degree and speed of its diffusion (Taylor et al, 1995) among a population of potential users.

Although the relationship between task characteristics (TaC) and task technology fit (TTF) is measured as statistically significant (ρ-value < 0.01), the standardised regression coefficient is considered moderate to weak ($\beta = 0.231$).

With the task characteristics construct we attempted to quantify the policyholder's technology needs. Questions pertaining to this construct included accessibility, availability and administrative functionality for policyholders. We deduce a positive response from our sample survey with the mean response at 4.1 on the five-point Likert scale. We interpret the moderately weak relationship with the task-technology fit construct as the respondents' disagreement with the use of blockchain and smart contracts in providing the aforementioned administrative capability.

Our survey instrument's task characteristics questions omitted questions concerning digital artefacts. Digital artefacts are distributed (Kallinikos et al, 2013, p. 316) by virtue of being interoperable and are transient containers for data and functions (Ekbia, 2009). Blockchain and smart contracts serve exactly this purpose and constitute both the persistence of data as well as the algorithms. It is possible that our survey instrument's task characteristics questions should have steered away from pure functional aspects and focussed rather on the digital materiality (Yoo et al, 2012) of blockchain artefacts.

The weak statistical relationship between task characteristics and task-technology fit is perhaps indicative of the end-consumer's understanding that blockchain is intended as a platform technology and not a policy servicing system. Such consumer insight is surprising since blockchain suffers from a lack of observability and trialability (Rogers, 1995). As with our findings pertaining to technology characteristics, we are led to theorise that such consumer beliefs are determined by the popularity of cryptocurrencies as a topic in mainstream media and the information discerned from such media.

6.6 Hypothesis 6_o: Task technology fit influences behavioural intention

The task-technology fit model was designed to establish the theoretical link between information technology and human performance (Goodhue et al, 1995). The model assesses the nature of the task and the usefulness of the technology to complete a task (Oliveira et al, 2014). The mean response for the task-technology fit construct was positive as indicated by a calculated mean of 3.9 on our Likert scale. The task-technology fit construct featured these questions:

1. Smart contracts in life insurance services are appropriate.
2. Smart contracts performing policy processing services are appropriate.
3. Real-time policy processing services are appropriate.
4. In general, blockchain smart contract services are enough.

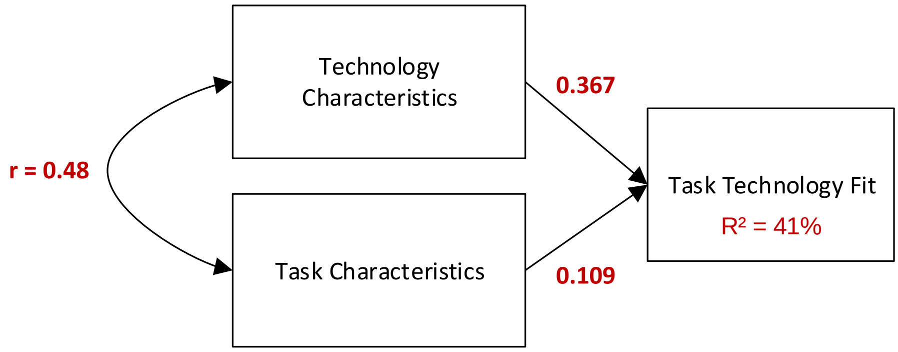
Behavioural intent is the end-consumer's expression of interest in the technology and his or hers intention to use it. Both the behavioural intent and task-technology fit constructs reported mean positive survey responses roughly equating to "Agree". Despite this, our research model did not find a statistical significant relationship with behavioural intent ($\beta = -0.052$, ρ-value = 0.335).

As posited by Bigley et al (1998), a person's propensity to trust is influenced by pre-existing beliefs and experiences. In turn, these are moderated by the technology's trialability (Rogers, 1995) which is construed as an attribute of innovation. An innovation's trialability is the degree of experimentation afforded to the user for familiarisation purposes (Rogers, 1995). Whereas the lack of task-technology fit's effect on behavioural intent cannot be explained, we theorise that blockchain's lack of trialability has a deprecating effect on this empirical relationship. A lack of use experience on behalf of policyholders is likely causing a misalignment between fit-for-purpose perceptions and the end-consumer's technology needs.

In the context of our study we found technology characteristics a prominent factor in explaining overall task-technology fit. Technology characteristics, in its relationship with the task-technology fit construct, exhibits a more significant path coefficient than task characteristics ($\beta = 0.5$ versus $\beta = 0.23$). The result is indicative of consumer perceptions more accepting of the technology attributes of blockchain than its functional purpose. It is a direct measurement of perceived usefulness of these technologies in the context of life insurance.

Our analysis demonstrates moderate contextual predictive capacity for the TTF model with a squared multiple correlation of 41% in our structural model. This result implies the TTF model is able to explain 41% of variance in our data. The dominant latent variable in this measurement model was technology characteristics.

Figure 9: TTF measurement model results



Our SEM research model also measured the correlation of task characteristics and technology characteristics. The result (r = 0.48) indicated a moderately positive linear association between the two constructs. This result is surprising as it seems to disprove the moderately strong relationship between technology characteristics and task-technology fit.

Whereas the TTF model tested strongly in our study, it does not translate into adoption intention by policyholders. Task characteristics, although it expresses a clear need for policy administration functionality, was not measured as significant in the model. However, our respondents agreed and confirmed their belief in blockchain as a reliable technology through the technology characteristics construct.

6.7 Hypothesis 7_o: Performance expectancy influences behavioural intent

Performance expectancy in the UTAUT framework measures the individual's belief regarding the usefulness of a technology and its benefits to the user (Venkatesh et al, 2003). Oliveira et al (2014) likened performance expectancy in UTAUT to perceived usefulness in TAM and described it as an essential part of the technology's value proposition to the potential adopter. Our research measured performance expectancy perceptions of policyholders for public blockchain platforms and the use of self-executing smart contracts used for routine administrative functions.

The questions we posed relating to performance expectancy were:

1. I would save time using smart contracts in life insurance.
2. Smart contracts in life insurance would optimise my financial operations.
3. Smart contracts in life insurance would allow me to maintain policy options and benefits quicker.
4. I would benefit financially from using smart contracts in life insurance.

The mean response for performance expectancy was 4.97, with variance (s^2) of 0.4, which we interpret as "strongly agree". The SEM path coefficient for the performance expectancy (PE) and behavioural intent (BI) constructs showed a strong relationship between the two ($\beta = 0.515$, $\rho < 0.01$).

The consumer's performance expectancy of a technology influences the user's adoption intention (Martins et al, 2014; Venkatesh et al, 2016). Our research results indicate a strongly affirmative response, on average, by policyholders when asked about the direct and measurable benefits of blockchain and smart contracts. In addition to this we found a meaningful relationship between performance expectancy and behavioural intent.

Behavioural intent in our research model measured policyholder responses pertaining to their explicit intention to use the technologies under study. As with the questions pertaining to performance expectancy, behavioural intent also used blockchain and smart contract terminology in the wording of its questions.

1. I have the intention of viewing my policy options and benefits using blockchain smart contracts.
2. I have the intention of making adjustments to my policy options and benefits using blockchain smart contracts.
3. I'm curious about the real-time processing of smart contracts for life insurance.
4. I have the intention of managing my life insurance policy using blockchain smart contracts.
5. I want to know more about blockchain and smart contracts.

The mean response for behavioural intent was 3.9 ($s^2 = 0.5$), interpreted as an "agree" using our five-point Likert scale.

Taking into consideration the R^2 value of behavioural intent as an endogenous variable in our structural model, the result is indicative of moderately strong predictive capacity for behavioural intent ($R^2 = 0.41$). In other words, our research model is able to explain 41% of variance for the behavioural intent construct. Its most significant influencers were performance expectancy and initial trust. It was established that task-technology fit is an insignificant influencer for behavioural intent ($\beta = -0.052$, ρ-value > 0.01).

Behavioural intention (BI) is the dependent variable in the theory of reasoned action (Fishbein et al, 1977), adopted into technology adoption model by Davis et al (1989) and used as an important predictor variable for technology usage (Venkatesh et al, 2003), also expressed as final adoption. The relationship between behavioural intention and usage (U) has been thoroughly researched in a broad variety of contexts. Williams et al (2015) analysed the outcomes of BI-U measurements in 61 distinct studies and found 49 of them to have been statistically significant. The finding also established BI to be a best predictor for usage intention (Williams et al, 2015, p. 460). We therefore conclude that the mean response of 3.9 for behavioural intent in our study will equate to usage intention of a similar magnitude.

7. Conclusion

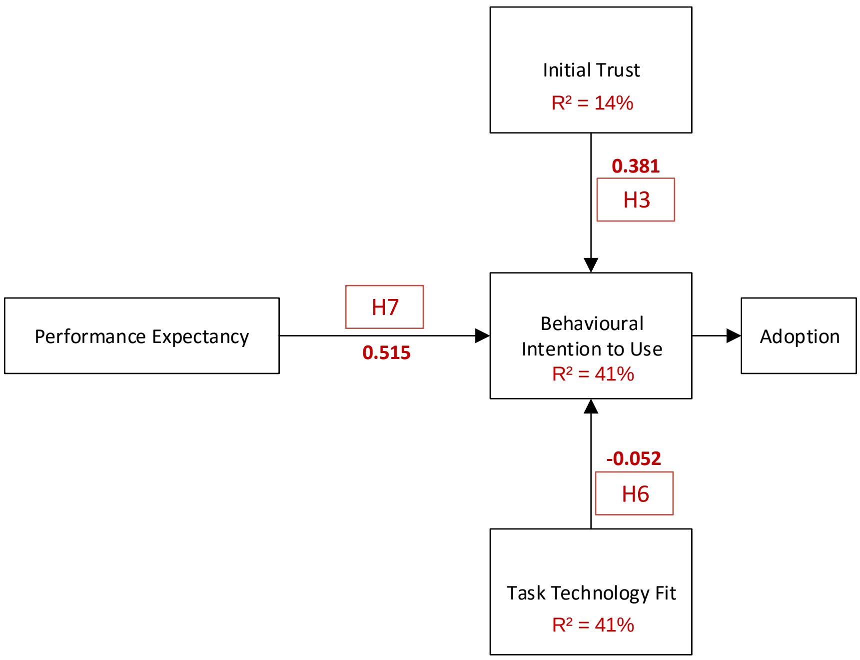
The concepts central to our research into policyholder perceptions of blockchain and smart contracts used in life insurance platforms are trust in technology, task-technology fit and technology adoption. We tested these concepts quantitatively and presented the empirically analysis in the preceding chapter. This chapter summarises our findings, articulates recommendations for management and concludes with research suggestions and limitations.

7.1 Principal Findings

The research model used in our study is a confluence of mainstream technology adoption theories, an approach that has become popular in technology adoption research (Williams et al, 2015). Structural equation modelling provides the analytical tooling for such models and consists of structural and measurement models (Henseler et al, 2016). Structural model path coefficients provide are indicative of the direct effects between constructs.

We observe performance expectancy and initial trust to have the most pronounced effect on behavioural intent. These construct originated in the UTAUT and ITM frameworks, respectively.

Figure 10: Structural model results



Policyholders, through the performance expectancy construct, seem convinced of the benefits and advantages of blockchain-driven insurance solutions. Performance expectancy encapsulates the end-consumer's salient beliefs regarding the usefulness and benefits of a technology and was the only UTAUT antecedent factor we tested in our research model. This finding was corroborated by our initial trust measurement which in turn was shown to be influenced significantly by structural assurances. We deduce that end-consumer faith and trust in blockchain will not be an inhibitor of its deployment in insurance platforms. It implies that blockchain relate to Krackhardt's first category of innovations (Krackhardt, 1997) whereby the intrinsic value of the innovation is understood by all parties and it diffuses rapidly.

Structural assurance beliefs and personal propensity to trust are poorly correlated in our research findings and neither explain the variance of initial trust in our research model very well. Our initial trust measurement show an underlying trust in the technologies under study, partly due to the structural assurances such as security and reliability that they exhibit. We could not, however, find a relationship with personal propensity to trust. Our results indicate that the policyholder's personal trust beliefs concerning technology has little bearing on his or hers adoption intention in the context of our research. The envisaged benefits of blockchain and smart contracts measured stronger than personal misgivings about technology.

End-consumers instinctively trust blockchain and appreciates its benefits as a technology in insurance policy servicing. Based on our measurements for the structural assurances (ITM) and technology characteristics (TTF) constructs, we theorise that cryptocurrencies infer a privacy reputation upon blockchain which is to its benefit.

Our study suggests that structural assurances and initial trust in a technology may be inferred from adjacent or related technologies. We theorise that cryptocurrencies such as the well-known Bitcoin cryptocurrency infer trust beliefs onto blockchain as a platform technology. A by-product of digital artefacts is the volume of digital traces is leaves (Yoo et al, 2012). These digital traces not only afford opportunities for new innovations (Yoo et al, 2012, p. 1400) but also enhances the traceability and auditability of digital artefacts. Both of these aspects enhances the observability (Rogers, 1995) of digital innovations, consequently increasing end-user trust in the technology (Lankton et al, 2015).

Whereas the task-technology fit measurement model in our research model proved structurally significant (R^2 = 41%) it had no meaningful bearing on the policyholder's intention to adopt blockchain technologies. We theorise that the diffusion of innovation attributes (Rogers, 1983) of observability and trialability had a deprecatory effect on user perceptions. The notable lack of demonstrable blockchain applications detract from the technology's observability and trialability, thus confusing the user's ability to associate the technology with its envisaged feature-level use in life insurance. Through this result we gained valuable insight into the end-consumer's understanding of blockchain technology which we found to be aligned with its intended purpose as a transactional platform.

7.2 Implications for Management

The purpose of an industry-wide blockchain platform in long-term life insurance would be to harness digital convergence. Pervasive technologies such as blockchain enable digital convergence (Yoo et al, 2012) and consequently drives digital standardisation which in turn produces technology platforms.

Life insurers must consider that the digital technology deployed throughout their organisations is inherently dynamic and will require a continual redesign of operational processes. Smart contracts in life insurance has the potential to create new processes, new distribution channels, new business models and new organisational forms. Innovative organisations will seize the initiative and explore the digital materiality of new product designs as part of their IT investment strategy.

Insurers should define IT investment strategies to take advantage of the fundamental benefits of digital technology such as programmability and data homogeneity. The latter is construed as an innate capability of blockchain technology. Extant research theorise that organisations for concise IT investment strategies and objectives derive greater returns from such investments (Mithas et al, 2016, p. 224). The findings of our research underscore end-consumer trust in- and understanding of blockchain which should position it firmly as the artefact platform technology of choice. Even with industry platform standardisation, the generativity of smart contracts will offer insurers the opportunity to differentiate and innovate through diverse policy servicing capabilities. Industry-wide participation will enhance platform sustainability and capabilities, allowing insurers to serve a greater subset of organisational activities as the platform evolves (Kallinikos et al, 2013; Yoo et al, 2012).

Since we have shown how the policyholder's general propensity to trust technology is inconsequential to his or hers adoption decision, it affords insurers greater latitude in positioning blockchain as a beneficial and value-adding system. Krackhardt's principles of innovation diffusion includes that of peripheral dominance (Wunderlich et al, 2014) whereby a secluded population of adopters manages to initiate and sustain diffusion of a new technology from the periphery. An industry blockchain platform initiative tailored to this principle may present the insurance industry with an effective strategy to emulate insurtech's innovating distribution channels.

The insurance industry is well-placed to take advantage of the inferred privacy reputation of blockchain and the implied institutional trust beliefs, of which structural assurances is a component. Regulators and financial officers stand to benefit from the traceability and auditability of blockchain-based transactional systems (Collomb et al, 2016). Smart contract technology promises simplification and automation of compliance procedures for insurers (Collomb et al, 2016). The innate generativity of smart contracts offers multiple avenues for innovation in post-trade infrastructure. Premium and commission exchanges among carriers and reinsurers are theoretical examples demonstrating the convergence offered by digital technologies. A standardised blockchain platform for the South African insurance industry have the potential of reducing compliance costs and lowering insurance transaction costs for the policyholders. In competing with vibrant insurtech start-ups such a shared blockchain platform may prove to be the predominant factor for ensuring an established insurer's survival.

7.3 Research Limitations

Blockchain is an emerging technology with very few observable reference implementations and our research have highlighted this fact throughout. As a results we were unable to include the usage behaviour construct in TAM (Davis, 1989) in our research model. Our assumption in terms of policyholder adoption intentions was based on empirical results from prior research. However, the degree of correlation between behavioural intent (BI) and usage behaviour in the existing body of research varied between 40% and 69%.

Table 16: Variance explained by adoption theories

Model / theory	Author	Correlation of BI and usage behaviour
TAM	Davis et al, 1989b	45% - 57%
TAM	Venkatesh et al, 2000	40%
UTAUT	Williams et al, 2015	69%

The appropriateness of retrofitting prior measurements into our assumptions pertaining to eventual adoption would only be endorsed or disproved by research of similar contexts yielding direct measurements of policyholder usage behaviour.

Furthermore, Williams et al (2015, p. 469) highlighted the data collection issues that seem to diminish TAM and UTAUT research outcomes. These concerns pertained to studies focussing on single tasks or single subjects, and being cross-sectional in nature. Self-reported use of technology in TAM and UTAUT research was also raised as a concern (Williams et al, 2015). Consequently, the reported correlations between behavioural intent and usage behaviour may not be as robust as some researchers claimed. Gallivan (2001) observed that technology adoption studies are sensitive to the features of technology under study as well as the context of adoption. Often complex adoption scenarios are unsuitable for traditional technology adoption models (Gallivan, 2001, p. 55).

The social influences are manifested in the subjective norm concept of the theory of reasoned action (TRA) (Fishbein et al, 1977, as cited by Davis et al, 1989). The TAM theory does not feature subjective norms (Davis et al, 1989b) and consequently neither does UTAUT. We augmented our research model by using the initial trust model (ITM) (McKnight et al, 2002) as a measure of social influences, more specifically the personal propensity to trust and structural assurances constructs. Of these two, personal propensity to trust proved an ineffective predictor of initial trust. Thus we observed a weak representation of the effect of social influences on our research objectives. We theorise that the use of the subjective norm construct as defined in TRA would have provided better insights into how social influences moderate behavioural intention.

Propensity to trust is not a fixed personality trait (Mayer, et al, 1995) but rather a dynamic behavioural attribute perceived to be contextual and changeable. In the context of technology adoption it implies universal trust in technology by an individual which may well prove to be a decisive determinant in the acceptance of complex new technologies. Our research topic presented a challenge in that the technology under study is a platform and end-consumers will have no direct interaction with smart contracts but rather the system interfaces that present the policy information to humans. We are left to theorise that ITM's personal propensity to trust construct may not be the ideal social influences concept for technology platform research.

Apart from academic limitations to our research, the data collected by our survey questionnaire was not normally distributed. We selected maximum likelihood SEM (ML-SEM) as an AMOS configuration in order to cope with these violations of multivariate normality (Iacobucci, 2010, p. 95). Had this not been the case, partial least squares SEM (PLS-SEM) would have been ideal as it has become the dominant method of statistical analysis in information systems research (Hair et al, 2017a).

As a further consequence of blockchain's lack of observability and trialability by end-users, we removed many UTAUT antecedent factors from our research model and left only performance expectancy. Henseler et al (2016, p. 7) discourages the use of single-indicator measurements in SEM since it is difficult to determine the random measurement error for the indicator. This limitation, along with violations of multivariate normality in our data, had a detrimental effect on our model fit metrics and consequently on our research model's predictive capacity.

7.4 Suggestions for Future Research

Moore & Benbasat (1991, p. 195) discussed voluntariness of use as a factor in diffusion of innovation alongside Rogers' five attributes. The concept of voluntariness of use has been neglected in subsequent mainstream technology adoption research. Moore et al (1991, p. 196) theorised that an innovation's perceived voluntariness is a stronger influencer for adoption than actual voluntariness in cases where innovations are recommended or discouraged by organisations.

The use of prevailing technology adoption theories at industry level, where transformational technologies such as cryptocurrencies, blockchain and smart contracts exist, may be deprecated in their predictive capability if the concept of voluntariness of use is not considered. Voluntariness of use featured as a moderator in the UTAUT framework (Venkatesh et al, 2003) but not as a fully-fledged research construct. In fact, an argument could be built for including voluntariness of use as a first-order construct in TAM alongside perceive usefulness and ease of use. Gallivan (2001) conceptualised categories for the adoption of new innovations along two axis, one of which was the locus of innovation adoption. The locus of innovation adoption axis split adoption behaviour between the individual and the organisation, the latter of which has an organisational mandate for innovation diffusion (Gallivan, 2001, p. 60). The concept of the organisational mandate was intended to measure voluntariness of use. Their study, however, did not extend beyond organisational boundaries and may be inappropriate for use in technology platform adoption research.

Considering the rapid evolution of technology over the last few decades, and the way that new generations of humanity are born into this period of rapid innovation, it is paramount for technology adoption models to evolve in order to remain relevant. Trust in technology remains an important influencer as recent research have shown, but it would seem that personal propensity to trust is reducing in its significance. Oliveira et al (2014) provided a comparative measurement for the personal propensity to trust and initial trust (PPT-IT) relationship. Their study concerning mobile banking adoption measured the PPT-IT standardised regression weight as statistically insignificant (β = -0.02, ρ-value > 0.01), very similar to our findings. This may indicate that the personal propensity to trust concept in ITM may not be a good fit for contemporary information systems research.

We have suggested that a tailored social influences construct, in the form of TRA's subjective norm (Fishbein et al, 1977, as cited by Davis et al, 1989), could assist to modernise trust in technology models. The way technology news and information is disseminated by technology itself is a sign of a very self-immersive system. Research into the effect of referent power of online media in the trusting beliefs of consumers will add value to future technology adoption literature.

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Appendix A: Survey respondent orientation

This preamble was used to introduce the research topic and its technologies to the survey respondent.

> Blockchain is the database technology underpinning cryptocurrencies such as Bitcoin. One of the most concerning aspects of digitising information is its replicability, in other words how electronic information can be duplicated. Cryptocurrencies faced a similar issue – how to avoid double transacting with digital currencies that are easily duplicated? The answer is blockchain which forms part of a broader technology set called distributed ledger technologies or DLTs. These are distributed, verifiable and non-corruptible ledger of electronic transactions.
>
> The verifiable and non-corruptible aspects of blockchain are very important since it allows blockchains to maintain a single version of the truth in electronic form. Distributed means there are many copies of the data distributed among the nodes of the blockchain. This makes the technology more secure than traditional information systems.
>
> Blockchain has found a number of practical applications. One such use is to store electronic contracts rather than financial transactions on a blockchain, thus offering contract stakeholders trusted access to the information. The 'smart' adjective is used to identify a contract on a blockchain that performs some contract-related processing by itself and at the appropriate times. It is a digital contract on a blockchain that changes state by itself.
>
> This study explores the adoption of smart contracts by life insurance companies. It intends to measure your willingness to trust this technology and to measure how appropriate it would be to use it to store and maintain your life insurance policy.

Appendix B: Survey questionnaire

Construct	Question Number	Question
Introduction	IN1	(*mandatory*) – YES/NO I have read and understood the informed consent letter.
	IN2	(*mandatory*) - YES/NO I have read the preamble to the survey questions regarding the technologies under study.
	IN3	(*mandatory*) - list Select your age group: - 25 to 34 - 35 to 49 - 50 to 65 - 65 or older
	IN4	(*mandatory*) – YES/NO I am a South African citizen.
	IN5	(*mandatory*) – YES/NO I have a life insurance policy
Task characteristics	TaC1	I need to view my life insurance policy at anytime, anywhere.
	TaC2	I need to administrate policy options and benefits anytime, anywhere.
	TaC3	I need to have a real-time control over policy options and benefits.
	TaC4	The policy instructions I give can't wait.
Technology characteristics	TeC1	Blockchain and smart contracts provide ubiquitous or pervasive services.
	TeC2	Blockchain and smart contracts provides a real-time service.
	TeC3	Blockchain and smart contracts would provide secure services.
	TeC4	Blockchain and smart contracts would provide a quick service.
Task technology fit	TTF1	(*mandatory*) Smart contracts in life insurance services are appropriate.
	TTF2	(*mandatory*) Smart contracts performing policy processing services are appropriate.
	TTF3	(*mandatory*) Real-time policy processing services are appropriate.

	TTF4	(*mandatory*) In general, blockchain smart contract services are enough.
Performance expectancy	PE1	I would save time using smart contracts in life insurance.
	PE2	Smart contracts in life insurance would optimise my financial operations.
	PE3	Smart contracts in life insurance would allow me to maintain policy options and benefits quicker.
	PE4	I would benefit financially from using smart contracts in life insurance.
Personal propensity to trust	PPT1	(*mandatory*) I don't use new technologies.
	PPT2	(*mandatory*) I avoid the use of new products like electronic documents.
	PPT3	(*mandatory*) I avoid the use of non-classical means to store important insurance documents.
	PPT4	(*mandatory*) I'm cautious with the personal insurance transactions I execute.
Structural assurances	SA1	(*mandatory*) I do not incur in the risk of financial losses using smart contracts in life insurance policies.
	SA2	(*mandatory*) I do not incur in the risk of personal information theft using smart contracts for life insurance policies.
	SA3	(*mandatory*) My life insurer has a Client Protection Policy.
	SA4	(*mandatory*) My personal information would be secure should I use smart contracts for life insurance policies.
Initial trust	IT1	(*mandatory*) Blockchain smart contracts seems dependable.
	IT2	(*mandatory*) Blockchain smart contracts seems secure.
	IT3	(*mandatory*) Blockchain smart contracts seems reliable.
	IT4	(*mandatory*) Blockchain smart contracts was created to help the policyholder.

Behavioral intention	BI1	(*mandatory*) I have the intention of viewing my policy options and benefits using blockchain smart contracts.
	BI2	(*mandatory*) I have the intention of making adjustments to my policy options and benefits using blockchain smart contracts.
	BI3	(*mandatory*) I'm curious about the real-time processing of smart contracts for life insurance.
	BI4	(*mandatory*) I have the intention of managing my life insurance policy using blockchain smart contracts.
	BI5	(*mandatory*) I want to know more about blockchain and smart contracts.

Appendix C: Pilot study reliability tests

Reliability analysis of the research instrument as conducted as part of the pilot study of 19 respondents:

Construct	Number of items	Cronbach Alpha
Task characteristics	4 TaC1 – 4	0.957
Technology characteristics	4 TeC1 – 4	0.852
Task technology fit	4 TTF1 – 4	0.937
Structural assurances	4 SA1 – 4	0.874
Personal propensity to trust	4 PPT1 – 4	0.869
Initial trust	4 IT1 – 4	0.913
Performance expectancy	4 PE1 – 4	0.929
Behavioural intention	5 BI1 – 5	0.922

Appendix D: Reliability statistics for construct PPT

Below is the original SPSS output of reliability statistics for the construct personal propensity to trust (PPT). Item PPT4 was removed from the construct in order to obtain a satisfactory Cronbach alpha.

PPT4	I'm cautious with the personal insurance transactions I execute.

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PPT1	10.21	5.026	.616	.677	.484
PPT2	10.28	4.870	.662	.699	.451
PPT3	10.70	4.606	.589	.384	.487
PPT4	12.20	7.229	.044	.034	.843

The reliability statistics after the removal of item PPT4:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PPT1	7.94	3.507	.755	.675	.740
PPT2	8.02	3.409	.793	.699	.704
PPT3	8.43	3.479	.598	.364	.900

Appendix E: Tests for Normality

SPSS output for Kolmogorov normality tests for each of our research model constructs.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Task characteristics	.135	199	.000	.897	199	.000
Technology characteristics	.165	199	.000	.939	199	.000
Task-technology fit	.146	199	.000	.958	199	.000
Performance expectancy	.143	199	.000	.938	199	.000
Personal propensity to trust	.159	199	.000	.867	199	.000
Structural assurances	.106	199	.000	.975	199	.001
Initial trust	.168	199	.000	.924	199	.000
Behavioural intent	.186	199	.000	.949	199	.000

a. Lilliefors Significance Correction

Appendix F: AMOS results for model fit indices

SPSS AMOS output: Model fit summary

CMIN

	NPAR	CMIN	DF	P	CMIN/DF
Default model	25.000	370.260	19.000	0.000	19.487
Independence model	16.000	695.967	28.000	0.000	24.856

Baseline Comparisons

	NFI	RFI	IFI	TLI	CFI
Default model	0.468	0.216	0.481	0.225	0.474
Independence model	0.000	0.000	0.000	0.000	0.000

Parsimony-adjusted Measures

	PRATIO	PNFI	PCFI
Default model	0.679	0.318	0.322
Independence model	1.000	0.000	0.000

NCP

	NCP	LO 90	HI 90
Default model	351.260	292.446	417.505
Independence model	667.967	585.727	757.622

FMIN

	FMIN	F0	LO 90	HI 90
Default model	1.870	1.774	1.477	2.109
Independence model	3.515	3.374	2.958	3.826

RMSEA

	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.306	0.279	0.333	0.000
Independence model	0.347	0.325	0.370	0.000

AIC

	AIC	BCC	BIC	CAIC
Default model	420.260	422.641		
Independence model	727.967	729.491		

ECVI

	ECVI	LO 90	HI 90	MECVI
Default model	2.123	1.825	2.457	2.135
Independence model	3.677	3.261	4.129	3.684

Appendix G: SPSS AMOS model results

SPSS AMOS output: Model analysis

Regression Weights

	Estimate	S.E.	C.R.	P
Task characteristics to Task-technology fit TTFAVG <-- TaCAVG	0.194	0.052	3.723	***
Technology characteristics to Task-technology fit TTFAVG <-- TeCAVG	0.527	0.066	8.038	***
Structural assurances to Initial trust ITAVG <-- SAAVG	0.376	0.068	5.554	***
Personal propensity to trust to Initial trust ITAVG <-- PPTAVG	0.084	0.051	1.645	0.100
Performance expectancy to Behavioural intent BIAVG <-- PEAVG	0.491	0.052	9.458	***
Task-technology fit to Behavioural intent BIAVG <-- TTFAVG	-0.054	0.056	-0.964	0.335
Initial trust to Behavioural intent BIAVG <-- ITAVG	0.346	0.049	6.998	***

Standardised Regression Weights

	Estimate
Task characteristics to Task-technology fit TTFAVG <-- TaCAVG	0.231
Technology characteristics to Task-technology fit TTFAVG <-- TeCAVG	0.499
Structural assurances to Initial trust ITAVG <-- SAAVG	0.367
Personal propensity to trust to Initial trust ITAVG <-- PPTAVG	0.109
Performance expectancy to Behavioural intent BIAVG <-- PEAVG	0.515
Task-technology fit to Behavioural intent BIAVG <-- TTFAVG	-0.052
Initial trust to Behavioural intent BIAVG <-- ITAVG	0.381

Intercepts

	Estimate	S.E.	C.R.	P
Task-technology fit (TTFAVG)	1.036	0.242	4.286	***
Initial trust (ITAVG)	2.144	0.326	6.573	***
Behavioural intent (BIAVG)	0.853	0.355	2.406	0.016

Correlations

	Estimate
Task characteristics <--> Technology characteristics	0.481
Personal propensity to trust <--> Structural assurances	-0.083

Variances

	Estimate	S.E.	C.R.	P
Task characteristics (TaCAVG)	0.524	0.053	9.950	***
Technology characteristics (TeCAVG)	0.330	0.033	9.950	***
Personal propensity to trust (PPTAVG)	0.799	0.080	9.950	***
Structural assurances (SAAVG)	0.456	0.046	9.950	***
Task-technology fit (e1 on TTFAVG)	0.216	0.022	9.950	***
Initial trust (e3 on ITAVG)	0.410	0.041	9.950	***
Performance expectancy (PEAVG)	0.433	0.044	9.950	***
Behavioural intent (e2 on BIAVG)	0.231	0.023	9.950	***

Squared Multiple Correlations

	Estimate
Initial trust (ITAVG)	0.140
Task-technology fit (TTFAVG)	0.413
Behavioural intent (BIAVG)	0.413

Appendix H: Ethics clearance letter

Gordon Institute of Business Science
University of Pretoria

24 August 2017

Jan Andries Lombard

Dear Jan Andries,

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

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