INTERNATIONAL JOURNAL OF MANAGEMENT PERSPECTIVES

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Management of a Supply Chain Systems Security Framework, using Blockchain Technology in South Africa's Health Sector

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ABSTRACT

In recent years, blockchain technology has shown potential in addressing the vulnerabilities of healthcare supply chains. This study explored the adoption of elements, including knowledge, familiarity, and intention to use, in leveraging blockchain to manage supply chain system security in healthcare. This study aimed to determine how much the healthcare management sector could use blockchain technology to improve supply chain systems in the South African healthcare sector by adopting this new technology. Theories such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) underpinned the study. The study applied a cross-sectional, quantitative methodology, analysing survey data through structural equation modelling (SEM). The findings indicated a significant and positive relationship between blockchain knowledge and intention to use blockchain technology; blockchain familiarity and trust in blockchain technology; trust in blockchain technology and intention to use blockchain technology; intention to use the blockchain technology and the adoption of blockchain technology and adoption of blockchain technology and the security of the healthcare sector supply chain management system in South Africa. Negative results were also found in the analysis; this was in relation to blockchain knowledge and trust in blockchain technology, familiarity and intention to use blockchain technology, and trust in blockchain technology and the adoption of blockchain technology. This study offers new insights into how blockchain knowledge and familiarity shape trust and adoption in South Africa's healthcare sector, aligning with previous research on blockchain technology.

Keywords: Blockchain Knowledge; Adoption; Familiarity; Trust; Intention to Use; South African Healthcare; Supply Chain Management.

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Introduction

Quality management is essential for supply chain security in South Africa's healthcare sector, where challenges such as inefficiencies and corruption undermine operational effectiveness. Blockchain technology is proposed as a solution, offering transparency, accountability, and traceability to improve supply chain security and integrity (Nguyen et al., 2021). Integrating blockchain into healthcare supply chain systems could enhance data security, fraud prevention, interoperability, and regulatory compliance. By implementing blockchain, stakeholders can improve patient safety and the overall quality of care.

A case study by Ngwenya and Shango (2020) highlights blockchain's potential in reducing fraud and corruption in healthcare supply chains. Blockchain technology's role in promoting accountability and efficiency positions it as a valuable tool in combating challenges in South Africa's healthcare context, where corruption is prevalent. With blockchain, healthcare organizations can secure processes and data, establishing a transparent, trust-driven framework that deters fraudulent activities and increases operational transparency. As blockchain adoption progresses, further research is needed to refine its applications and ensure comprehensive security improvements within the sector.

Key factors influencing successful blockchain adoption in healthcare supply chains include stakeholders' knowledge, familiarity, trust, intention to use, and actual adoption of the technology. Knowledge relates to understanding blockchain's applications; familiarity involves stakeholder awareness of the technology. Trust reflects confidence in blockchain's reliability, and adoption signifies its integration into healthcare operations (Smith et al., 2020; Brown et al., 2019, Lee et al., 2021, Garcia et al., 2018, Martinez et al., 2020, Bhatt & Agrawal, 2021). These factors significantly influence stakeholder attitudes and are supported by literature as essential for effective blockchain implementation in healthcare supply chain security systems, contributing to a more secure and reliable healthcare environment.

Literature Review on Blockchain Technology Adoption in Healthcare Supply Chain Systems

Blockchain technology, initially developed to support cryptocurrency transactions, has gained recognition for its potential across various industries, including healthcare (Shrier, 2020). It provides a decentralized, secure, and transparent framework for managing data, making it especially valuable for addressing the challenges of healthcare supply chains, including inefficiencies, corruption, and lack of transparency, particularly in the South African healthcare sector. The integration of blockchain in supply chain management has been widely studied, offering solutions to mitigate inefficiencies and security vulnerabilities associated with traditional systems. Blockchain enhances transparency, traceability, and security (Azaria et al., 2016), with its immutable, time-stamped records ensuring the authenticity and integrity of transactions (Chen et al., 2019). In South Africa, where fraud and corruption are prevalent, blockchain's secure, decentralized ledger can significantly reduce these risks (Nkosi & Hechter, 2017). The South African healthcare supply chain, plagued by inefficiencies and corruption, particularly in procurement and distribution, has suffered from resource shortages and inflated costs (Gresse & Linde, 2020). Blockchain can address these issues by providing a transparent, immutable ledger, ensuring real-time visibility of goods and reducing opportunities for corruption (Shrier, 2020; Van den Heever, 2020). However, the adoption of blockchain in healthcare faces several challenges, including a lack of familiarity among healthcare professionals and policymakers (Ndayizigamiye & Dube, 2019). Educational initiatives and demonstrations of blockchain's effectiveness in enhancing transparency and accountability are essential to overcome scepticism and facilitate its implementation, especially given concerns about the plans to implement a National Health Insurance (NHI) system in South Africa in the face of widespread corruption (Liang et al., 2017; Girdhari & Ndayizigamiye, 2022).

Problem Statement and Research Hypothesis

South Africa's healthcare supply chain faces significant challenges such as corruption, fraud, and inefficiencies, which undermine the secure distribution of medical resources. This study proposed a blockchain-based security framework to improve transparency and security using Web 3 technologies. It examines factors influencing blockchain adoption, testing hypotheses on how knowledge, familiarity, trust, and adoption intentions impact the healthcare supply chain. Blockchain knowledge is expected to enhance trust (H1) and adoption intention (H2), while familiarity is anticipated to strengthen trust (H3) and intention (H4). Trust is also hypothesized to influence intention (H5) and adoption (H6), with adoption positively impacting supply chain security (H8). This research contributes to technology adoption theory and provides stakeholders with a practical tool for evaluating blockchain's potential to improve security and efficiency in South Africa's healthcare sector (Liang et al., 2017).

3.1 Significance of the study

Recent research shows growing global interest in blockchain technology, particularly in Europe, the USA, and Asia (Hughes, Park, Kietzmann, & Brown, 2019; Irresberger, John, Mueller & Saleh, 2021). However, a notable gap exists in studies from developing African countries, particularly South Africa. The literature highlights inefficiencies and corruption in South Africa's healthcare supply chain that blockchain could address (Ngwenya & Shango, 2020; Passchier, 2017). Most research focuses on sectors like finance and logistics, with limited empirical evidence on blockchain's role in healthcare supply chains (Gresse & Linde, 2020; Mafolo, 2020). This study filled that gap, as it aimed to both theoretically and practically enhance understanding of blockchain adoption in South African healthcare, thereby offering insights to policymakers and Information and Communication Technology (ICT) administrators to improve supply chain security.

Conceptual framework

4.1 Theories on Adoption of Technology

The Technology Acceptance Model (TAM), developed by Davis (1985), explains users' acceptance of technology based on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (see Figure 1). PU assesses how technology enhances job performance, while PEOU evaluates its ease of use (Davis et al., 1989). TAM has evolved to incorporate models like the Technology Readiness Index (TRI) and Diffusion of Innovation Theory (DIT) to explain technologies such as blockchain (Lou & Li, 2017). Researchers have further adapted TAM by including variables like pain and insecurity (Kamble, 2021) and compatibility and complexity (Lou & Li, 2017) to better understand blockchain adoption. TAM's predictive power remains valuable in studying user intentions to adopt new systems like blockchain (Szajna, 1996; Verma & Sinha, 2018).

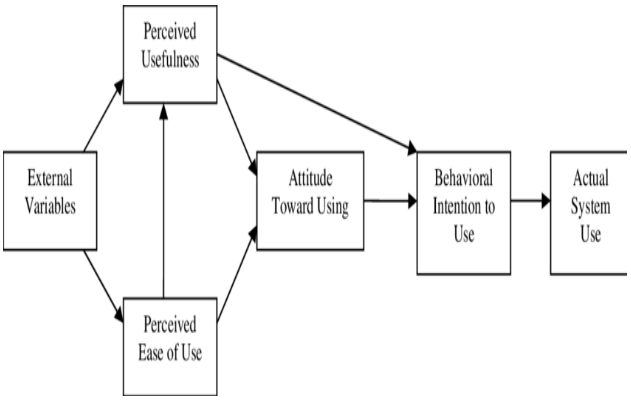


Figure 1: TAM framework

TAM is complemented by the Technology Readiness Index (TRI), which assesses individuals' readiness for new technologies through four dimensions: optimism, innovativeness, discomfort, and insecurity (Parasuraman & Colby, 2000). Optimism and innovativeness drive adoption, while discomfort and insecurity hinder it (Parasuraman & Colby, 2015). The TRI is useful in evaluating blockchain adoption, especially in healthcare systems (Martens et al., 2017). The Diffusion of Innovation Theory (DIT) by Rogers (1995) further explores adoption factors like relative advantage, compatibility, complexity, observability, and trialability, with complexity posing a challenge for blockchain in healthcare systems (Lou & Li, 2017). The Unified Theory of Acceptance and Use of Technology (UTAUT) integrates these frameworks, adding performance expectancy, effort expectancy, social influence, and facilitating conditions to explain adoption (Venkatesh et al., 2003). UTAUT can help understand blockchain's adoption in healthcare, influenced by peer pressure and available support (Wong et al., 2020). Together, these frameworks offer insights into blockchain adoption, emphasizing factors like usefulness, readiness, and social influence (Lou & Li, 2017; Wong et al., 2020).

4.2 Blockchain knowledge

Knowledge influences the ability to differentiate products or services by their attributes and emotional connections (Kotler & Keller, 2009; Sherry, 2005). It includes both descriptive and evaluative information, with blockchain knowledge covering awareness, benefits, and personal experiences (Chiang et al., 2017). Knowledge can be explicit, objective, and accessible, or implicit, subjective, and experiential (Kamath, 2018), both of which are essential for understanding blockchain adoption. In contrast, familiarity is an automatic, emotional memory response, triggered by sensory and perceptual experiences (Mandler, 1980; Mandler, 1991), and is crucial in the perceptual integration of blockchain technology.

4.3 Trust in blockchain technology

Blockchain technology is often labelled as trustless because it removes the need for a trusted authority, relying instead on publicly verifiable proofs (Baiyere et al., 2020). However, this characterization overlooks the multiple layers of trust in blockchain governance and the complex power dynamics within blockchain systems (Chiang et al., 2018; Laurence, 2017). Blockchain should be seen as a confidence machine, increasing confidence in a system and indirectly reducing the need for trust. This enhanced confidence reduces perceived risks, facilitating transactions. In this study, confidence refers to reliability, a key aspect of trust (Laurence, 2017; Chiang et al., 2018).

4.4 Intention to use blockchain technology

Intention to use refers to an individual's readiness and willingness to adopt and engage with a specific technology or service, influenced by their perceived needs, motivations, and the potential benefits of its use (Lu, Chang, and Chang, 2014). It is shaped by factors such as perceived

usefulness, ease of use, and trust in the technology, which collectively drive an individual's decision to utilize it (Anderson et al., 2014; Ko and Megehee, 2012). Users' interest and confidence in the technology are integral to intention to use, as these factors promote positive attitudes and acceptance (Gao et al., 2010). This study aligns with Gao et al.'s (2010) framework by emphasizing that intention to adopt blockchain technology signifies a proactive interest and readiness among users to integrate the innovation into their activities, reflecting its perceived value and relevance.

4.5 Adoption of blockchain technology

Blockchain adoption follows Rogers' (2003) Innovation Adoption Model, which categorizes adopters into five stages: knowledge, persuasion, decision, implementation, and confirmation (Goldsmith & Reinecke, 1992; Rogers, 2005). The process starts with awareness-building through research on blockchain's benefits, followed by assessment of advantages like data integrity (Swan, 2015; Janssen, 2017), decision-making based on compatibility (Zheng et al., 2017; Shin et al., 2018), and implementation of solutions (Lee et al., 2018; Liu et al., 2020). The final

confirmation stage validates decisions through observed benefits (Champier et al., 2020; Yli-Huumo et al., 2016). Over the past decade, blockchain adoption has surged in the USA (Han et al., 2020), and Asia (Zhou et al., 2021), but Africa, especially South Africa and Nigeria, has seen slower progress due to infrastructure and technical challenges (Ndayizigamiye & Dube, 2019). Rogers' model helps explain these regional differences and adoption trends.

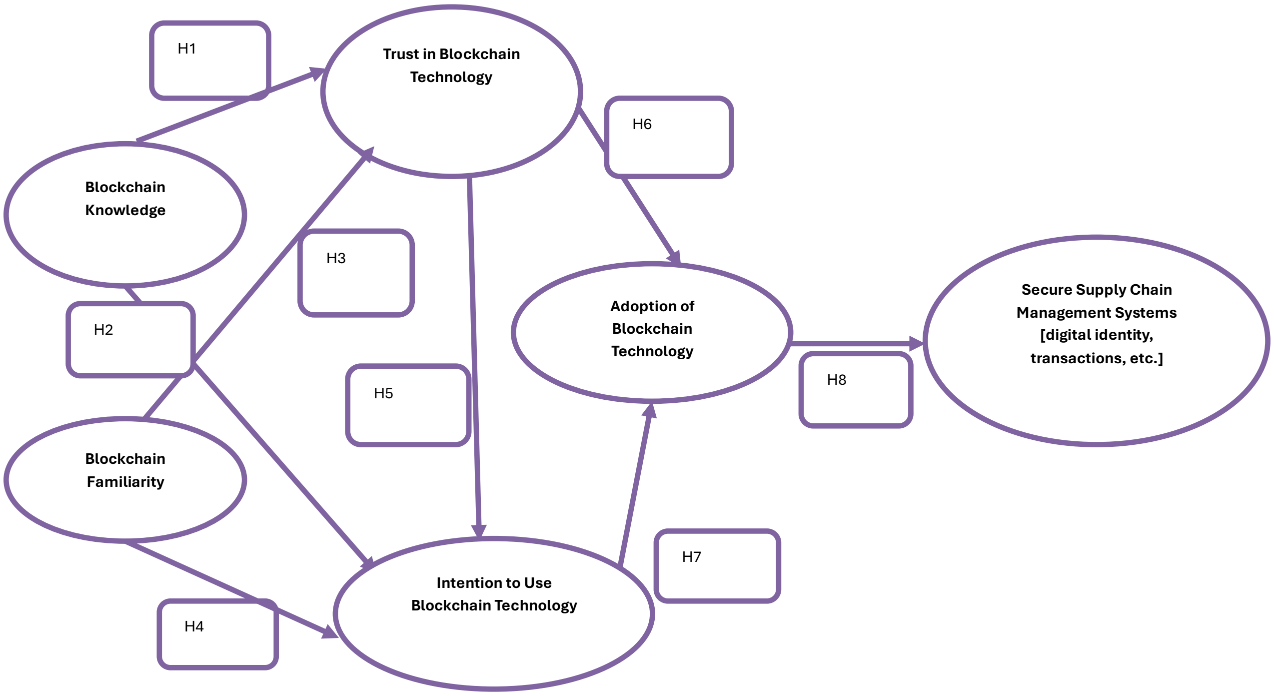
4.5 The Secure Supply Chain Management Systems

A secure healthcare supply chain ensures the consistent availability of medical resources while prioritizing data security, given the high risk of cybercrime targeting healthcare information (Xiao et al., 2021; Yaqoob et al., 2019). Blockchain technology offers a solution by securing sensitive data through traceability and encryption, preventing unauthorized access (Beaulieu & Bentahar, 2021; Reda et al., 2020). Its decentralized structure reduces risks from system failures and unauthorized changes, fostering consumer trust, which is crucial for adoption (Jayaraman et al., 2019). Additionally, blockchain enables controlled data sharing, improving patient privacy and supporting accurate diagnoses (Yaqoob, 2019). Its robust encryption processes meet the increasing need for secure data exchange in healthcare (Khalilzadeh et al., 2017; Flavian & Guinallu, 2006).

Hypothesis

The conceptual research framework (Figure 2) is based on reviewed literature and illustrates relationships between constructs, specifically how predictor variables—blockchain knowledge and familiarity—influence mediating factors such as trust, intention to adopt, and actual adoption of blockchain technology. These mediating variables collectively impact the primary outcome: secure supply chain management systems within South Africa's healthcare sector, including aspects like digital identity and transactions.

Figure 2: Conceptual Framework



5.1 Blockchain Knowledge and Trust in Blockchain Technology

This research explored how individuals' understanding of blockchain influences their trust and inclination to adopt blockchain technology. Downey, Bauchot, and Roling (2018) suggest that familiarity with a system can predict trust, as knowledge reduces uncertainty, which fosters trust. However, empirical findings vary on the relationship between knowledge and trust. While Downey et al. (2018) found that knowledge decreases uncertainty and builds trust, Hoffman et al. (2023) observed a negative correlation between the two (Raimundo and Rosário, 2021). Koehn (2019) argues that trust based on knowledge exists mainly among users who are already familiar with each other. Genfen et al. (2005) also noted that while knowledge indirectly influences trust through perceived ease of use, its direct effect on trust was not statistically significant. Despite these inconsistencies, an understanding of blockchain should boost confidence in its use (Nyame et al., 2020). This study proposed:

Null (H0): Trust in blockchain technology does not significantly positively impact the intention to use it.

H1: There is a positive relationship between blockchain knowledge and trust in blockchain technology in South Africa's healthcare sector supply chain management system.

5.2 Blockchain Knowledge and Intention to Use Blockchain Technology

Knowledge competence in Information Technology (IT) services refers to an individual's understanding and proficiency in using information technology (Chang et al., 2020). This study explored the relationship between individuals' blockchain knowledge and their familiarity with blockchain services. According to Essam and Salama (2017), the extent of one's understanding of data protection impacts their intention to comply with regulations, emphasizing the importance of information security education. Knowledge in IT is often acquired through experiential learning (Lim, 2016), and this knowledge is essential for adopting IT services, including blockchain in healthcare. The connection between knowledge and behavioural intentions plays a key role in users continued or discontinued use of these services, shaped by changing attitudes. Thus, the study hypothesized that:

Null (H0): There is no significant relationship between blockchain knowledge and intention to use blockchain technology in South Africa's healthcare sector supply chain management system.

H2: There is a positive relationship between blockchain knowledge and the intention to use blockchain technology in South Africa's healthcare supply chain management system.

5.3 Blockchain Familiarity and Trust in Blockchain Technology

Familiarity helps individuals reduce uncertainty and simplify their interactions. It is based on past experiences and knowledge of others' actions and behaviours (Dann et al., 2020). While familiarity involves understanding present behaviours, trust concerns beliefs about future actions (Garaus and Treiblmaier, 2021). Both familiarity and trust work together to reduce complexity—familiarity provides a framework for decreasing uncertainty (Hawlitschek, 2019), while trust offers reliable expectations about future positive actions (Mathiyazhagan and Rana, 2020). Luhmann (2018) notes that trust is focused on uncertain future actions, which involve complexity and risk. Research shows that familiarity with the institutions behind IT systems enhances trust in those technologies (Zavolokina, Zani and Schwabe, 2020). Accordingly, this study hypothesized:

Null (H0): There is no significant relationship between blockchain familiarity and trust in blockchain technology in South Africa's healthcare sector supply chain management system.

H3: There is a positive relationship between blockchain familiarity and trust in blockchain technology in South Africa's healthcare sector supply chain management system.

5.4 Blockchain Familiarity and Intention to use Blockchain Technology

Familiarity with blockchain is crucial for understanding its business applications. Mathiyazhagan and Rana (2020) found that many firms avoid adopting blockchain due to a lack of awareness about its benefits. They identified business unfamiliarity with blockchain as a major barrier to adoption and usage in supply chains. Abu-Shanab (2017) also noted that familiarity with blockchain often leads to a positive impression of its efficiency, increasing the intention to reuse the platform. Selim (2003) suggested that an individual's perception of a technology's characteristics influences their intention to use it. Similarly, Komiak and Benbasat (2006) found that familiarity indirectly boosts the intention to use recommended technologies. Based on this evidence, the study proposed:

Null (H0): There is no significant relationship between blockchain familiarity and intention to use blockchain technology in South Africa's healthcare sector supply chain management system.

H4: There is a positive relationship between blockchain familiarity and the intention to use blockchain in South Africa's healthcare supply chain management.

5.5 Trust in Blockchain Technology and Intention to use Blockchain Technology

The fifth hypothesis posits a positive link between trust and individuals' intent to adopt blockchain technology. Blockchain's consensus mechanism supports trust by securely verifying transactions, an essential aspect for its adoption. Gefen et al. (2003) underscore trust's role in e-commerce adoption, strengthened by safety mechanisms that users perceive. Trust is especially crucial in sectors like healthcare, where the secure handling of sensitive patient data is a primary concern (Saberi et al., 2019). Studies confirm that trust significantly influences behavioural intention toward adopting emerging technologies, including blockchain (Francisco et al., 2015; Gao and Waechter, 2017; Fernández-Caramés et al., 2019). Therefore, the hypothesis is:

Null (H0): There is no significant relationship between trust in blockchain technology and intention to use blockchain technology in South Africa's healthcare sector supply chain management system.

H5: There is a positive relationship between trust in blockchain technology and intention to use blockchain technology in South Africa's healthcare sector supply chain management system.

5.6 Trust in Blockchain Technology and the Adoption of Blockchain Technology

As more user information is collected online, concerns about information privacy increase (Janic, Wijbenga, & Veugen, 2013). Trust is defined as users' confidence that a system, like blockchain, will consistently deliver on its key attributes. Trust has been shown to positively influence behavioural intention (Shaw, 2014; Slade et al., 2015) and is a belief that the trusted party will meet expectations (Lu et al., 2011). Trust plays a crucial role in technology adoption, as it reduces perceived risk and increases users' willingness to invest in new technologies. This study suggests that lack of trust is a significant barrier to blockchain adoption. If individuals believe blockchain will improve their work, they are more likely to adopt it. Therefore, the following hypothesis is proposed:

Null (H0): There is no significant relationship between trust in blockchain technology and its adoption in South Africa's healthcare sector supply chain management system.

H6: There is a positive relationship between trust in blockchain technology and its adoption in South Africa's healthcare sector supply chain management system.

5.7 Intention to use the Blockchain Technology and the Adoption of Blockchain Technology

There is a growing tendency to integrate new IT into information systems, supported by various empirical and theoretical studies. Gao et al. (2010) suggest that consumer intention to use a service reflects their interest and willingness to adopt it. According to Venkatesh et al. (2003), behavioural intention is a key predictor of actual behaviour in technology adoption. While empirical research has explored blockchain adoption in Western countries, literature on blockchain adoption in South Africa remains limited. Specifically, studies on the intention to use blockchain in South Africa's healthcare supply chain management system (SA HC SCM) are scarce. The intention to use blockchain technology is proposed as a mediator in the adoption of blockchain within the SA Healthcare Supply Chain Management, with a positive relationship hypothesized between intention and adoption.

Null (H0): There is no significant relationship between the intention to use blockchain technology and its adoption in South Africa's healthcare sector supply chain management system.

H7: There is a positive relationship between the intention to use blockchain technology and its adoption in South Africa's healthcare sector supply chain management system.

5.8 Adoption of Blockchain Technology and the Security of Healthcare Sector Supply Chain Management System

Blockchain technology provides a robust solution for data privacy and security issues by utilizing a decentralized ledger system, initially conceptualized by Nakamoto in 2008). This technology ensures enhanced system resilience against failures and unauthorized access through cryptography and consensus mechanisms, making it a secure, distributed database crucial in tracking pharmaceuticals within healthcare supply chains. Its security foundation lies in the proof-of-work mechanism, which validates transactions through computational effort (Tob-Ogu et al., 2018). User trust in blockchain adoption is positively influenced by perceived security and control, leading to increased confidence in the technology (Bhattacherjee, 2001; Hur and Lim, 2017). Consequently, strong platform and network security within blockchain systems are expected to support broader acceptance and usage.

Null (H0): There is no significant relationship between adopting blockchain technology and the security of the healthcare sector supply chain management system in South Africa.

H8: There is a positive relationship between adoption of blockchain technology and the security of healthcare sector supply chain management system in South Africa.

Research Methods and Design

This study employed a quantitative research approach, utilizing a structured questionnaire to collect numerical data on the conceptual model variables from respondents within the target sample (Bryman et al., 2017). A deductive methodology was adopted, enabling the empirical assessment of hypothesized intervariable relationships (Snyder, 2019). This approach involved testing theoretical hypotheses using empirical data to evaluate their validity (Chevalier & Buckles, 2019). The sample size was determined using the Raosoft online sample size calculator, applying a 95% confidence level, a 3% margin of error, and a response distribution of 50%. To ensure the reliability of the measurement instruments, the Cronbach's Alpha coefficient was employed, while convergent validity was assessed using the Average Variance Extracted (AVE) metric.

6.1 Settings

This study focuses on professionals within South Africa’s healthcare sector, targeting individuals involved in areas such as medical practices, pharmaceutical distribution, hospitals, clinics, medical aid administration, and healthcare consumer services.

6.2 Study population and sampling strategy

Using random probability sampling, the sample included healthcare professionals involved in supply chain systems, specifically registered professionals and Med Pages members. Of the 367 questionnaires distributed, 146 were usable for analysis. To control for response biases, respondents were asked to indicate their healthcare sector and years of experience, ensuring the inclusion of those most likely engaged with hospital supply chains. They were also asked about their knowledge, familiarity, and trust in blockchain technology.

6.3 Measurement Instrument and Questionnaire Design

The measurement scales from previous studies were modified to align with the current research constructs. Blockchain knowledge and familiarity were measured using four-item scales adapted from Lombart and Louis (2016) and Islam et al. (2020), respectively. Trust in blockchain technology was assessed with a five-item scale adapted from Woods et al. (2016), while intention to use blockchain technology was measured using a six-item scale adapted from Salinas and Pérez. A five-point Likert scale (1 =

strongly disagree, 5 = strongly agree) was used. Table 1 below shows the research constructs and adapted measurement scales, with individual items listed in the Appendix.

Data Analysis

The acquired data in this research study was analysed using structural equation modelling (SEM). This is a method employed by researchers to statistically generate hypothetical constructs and verify the proposed cause-and-effect connections by utilizing two or more structural equations (Brewer, 2015; Byrne, 2016; Hair et al., 2017; Avkiran, 2018). SmartPLS, a component-based approach to structural equation modeling, was used in this study to test the research model using SEM. The study followed a two-stage procedure for hypothesis testing recommended by Anderson and Gerbing (1988), first examining the convergent and discriminant validity of items and constructs in the measurement model, followed by an examination of path coefficients between constructs in the structural model.

7.1 Ethical Considerations

The research was reviewed and approved by the South African Medical Association Research Ethics Committee, with study approval number 1 (280808016/032/2023). Written consent was obtained from all human participants involved in the study. To ensure confidentiality, the survey is designed to be confidential and anonymous, as participants are not required to enter their names on the questionnaire. Participants are solely involved in answering the questionnaire, and their participation poses no risks or loss of benefits, regardless of their decision to participate or not. The research does not involve any payment under any circumstances. Furthermore, participation is completely voluntary; participants may choose not to engage in the study, skip any questions, or withdraw at any time without facing any penalties.

Results

8.1 Respondent Profile

The participant profile reveals that 43.8% of respondents were aged 51 and older, followed by 26.7% in the 29–39 age group and 25.3% in the 40–50 group, with only 4.1% aged 18–28. Most participants were healthcare practitioners (70.5%), followed by top management (15.8%), middle management (8.9%), and officers (4.2%). Regarding education, 66.4% held postgraduate degrees, 18.5% had undergraduate degrees, and 8.9% held diplomas. Professionally, 30.1% were specialized doctors in private hospitals, 26.7% were general practitioners, and 19.2% were clinicians, nurses, or pharmacists. The remaining 13.7% worked in hospital management, and 10.3% were service providers in the healthcare sector.

8.2. Measurement Model Assessment

To establish convergent validity, item loadings should exceed 0.6 for their respective constructs, while discriminant validity requires no significant cross-loadings. The results in the table show item-to-total correlations below the threshold of 0.5, indicating acceptable values. Factor loadings for retained items exceed the 0.5 threshold, indicating successful convergence and accounting for at least 50% of the intended constructs. Additionally, Cronbach's alpha coefficients for all variables surpass 0.5, supporting reliability, and composite reliability values exceeding 0.6 confirm the instruments' dependability for measuring research variables (refer Table 1).

Table 1: Measurement Model Assessment Results

Research construct		Cronbach's Alpha	CR	AVE	Factor Loadings
BCK	BCK1	**0.908**	**0.920**	**0.784**	0.910
	BCK2				0.863
	BCK3				0.834
	BCK4				0.933
BCF	BEWP 1	**0.949**	**0.951**	**0.867**	0.921
	BEWP 2				0.929
	BEWP 3				0.953
	BEWP 4				0.920
TBCT	TBCT1	**0.951**	**0.957**	**0.837**	0.807
	TBCT2				0.932
	TBCT3				0.933
	TBCT4				0.952
	TBCT5				0.943
IUBCT	IUBCT 1	**0.962**	**0.965**	**0.842**	0.866
	IUBCT 2				0.933
	IUBCT 3				0.926
	IUBCT 4				0.946
	IUBCT 5				0.932
	IUBCT 6				0.902
ABCT	ABCT1	**0.908**	**0.917**	**0.783**	0.885
	ABCT2				0.921
	ABCT3				0.873
	ABCT4				0.858
SGS	SGS1	**0.914**	**0.935**	**0.792**	0.880
	SGS2				0.915
	SGS3				0.911
	SGS4				0.854

8.3 Global Fit Index

The coefficient of determination (R^2) indicates that the model explains over 49% of the variance in the dependent variable. The global goodness-of-fit (GoF) statistic of 0.38, exceeding the 0.36 threshold (Kuo et al., 2020), confirms a satisfactory model fit and strong relationships among latent variables (Li, 2022). The equation presented by Han and Johnson (2019) was utilised to generate the study model's global goodness-of-fit (GoF) statistic:

$$\text{GoF} = \sqrt{\overline{\text{AVE}} * \overline{R^2}}$$

8.4 Smart PLS Model Fit Indices

The model fit was assessed using the Chi-square (χ^2/df) and Normed Fit Index (NFI). While both met the minimum thresholds, the results were only marginally acceptable. The NFI score of 0.802 indicates an adequate fit, though a score above 0.9 would be ideal. Additionally, the SRMR value of 0.117 suggests a poor fit, but overall, the model shows reasonable alignment (refer Table 2).

Table 2: Model Fit Indices (own source)

	Saturated model	Estimated model
SRMR	0.062	0.117
d_ULS	1.432	5.199
d_G	1.193	1.249
Chi-square	925.817	955.217
NFI	0.808	0.802

8.5 Structural Model

The study utilized a structural path model to assess how blockchain knowledge and familiarity influence trust, intention to use, and adoption of blockchain technology, as well as how trust and intention impact adoption. A non-parametric bootstrap technique provided estimates for standard errors, t-values, and p-values, with critical t-values of 1.65, 1.96, and 2.57 representing significance levels of 10%, 5%, and 1%, respectively (Hair et al., 2014b, 2017). Using the Bias-Corrected and Accelerated (BCa) bootstrap method, the study calculated 95% confidence intervals, deeming path coefficients significant if zero was not within the interval. This robust methodology supports the reliability of coefficient estimates. Figure 2 illustrates the model, showing the influence of blockchain knowledge and familiarity on trust and intention to use, as well as the mediating role of blockchain adoption in secure supply chain management systems (Hair et al., 2017).

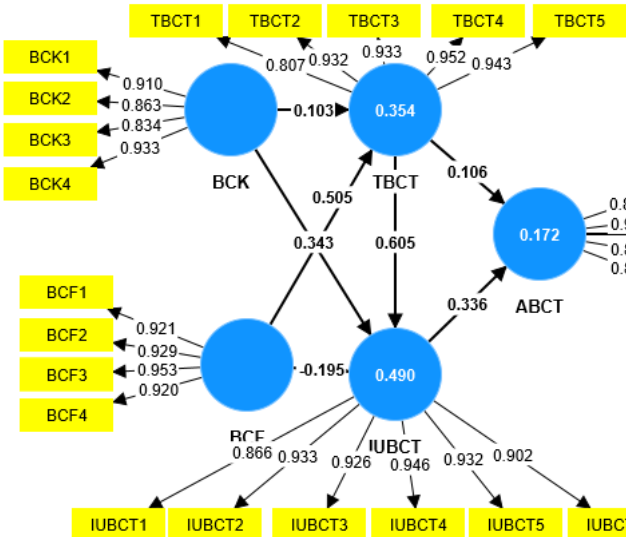


Figure 2. Results of Structural Path Model Estimation (n = 146)

Discussion

9.1 Hypothesis Results

Eight hypotheses were tested, and their corresponding path coefficients, t-statistics, and p-values were analysed to determine statistical significance. Hypotheses were considered significant if they met a 95% significance threshold ($p \leq 0.05$), with a t-statistic value exceeding 1.96, as recommended by previous studies (Grilo et al., 2019; Hayat et al., 2020). The path coefficients indicated the strength of relationships between dependent and independent variables (Collier, 2020). Of the eight hypotheses, five were supported by the findings, while hypotheses H1, H4, and H6 did not align with the expected outcomes.

The final decisions on hypothesis acceptance or rejection were based on these statistical results (refer Table 3).

Table 3: Path Analysis Results

Hypothesis		Path Coefficient	T statistics (|O/STDEV|)	P values	Outcome
BCK -> TBCT	H1	0.103	0.913	0.362	Supported but insignificant
BCK -> IUBCT	H2	0.343	2.581	0.010	Significant and supported
BCF -> TBCT	H3	0.505	4.434	0.000	Significant and supported
BCF -> IUBCT	H4	-0.195	1.420	0.156	Not supported and but insignificant
TBCT -> IUBCT	H5	0.605	7.784	0.000	Significant and supported
TBCT -> ABCT	H6	0.106	1.001	0.317	Supported but insignificant
IUBCT -> ABCT	H7	0.336	3.493	0.000	Significant and supported
ABCT -> SGS	H8	0.463	7.413	0.000	Significant and supported

The researcher performed structural equation modelling using the intelligent PLS 4 programme. The potential benefits of driving factors, specifically BCK, BCF, TBCT, IUBCT, and ABCT, on SGS were examined in this study. For H1, H2, H3, H4, H5, H6, H7, and H8, the corresponding individual route coefficients are 0.103, 0.343, 0.505, -0.195, 0.605, 0.106, 0.336, and 0.463. Overall, the results of this investigation indicate that five of the eight proposed correlations are supported.

9.2 Results after testing hypothesis 1 to hypothesis 8.

The findings from the hypothesis tests provide a comprehensive understanding of the relationships between blockchain knowledge, familiarity, trust, intention to use, adoption, and their impact on the healthcare sector supply chain. Hypothesis 1 (H1) revealed a weak correlation between blockchain knowledge (BCK) and trust in blockchain technology (TBCT), with a path coefficient of 0.103, indicating minimal impact (t=0.913, p=0.362). In contrast, Hypothesis 2 (H2) demonstrated a significant positive correlation between blockchain knowledge (BCK) and intention to use blockchain technology (IUBCT), with a path coefficient of 0.343 (t=2.581, p=0.010). Similarly, Hypothesis 3 (H3) confirmed that blockchain familiarity (BCF) positively impacts trust in blockchain technology

(TBCT), with a strong correlation observed (path coefficient = 0.505, t=4.434, p=0.000). However, Hypothesis 4 (H4) indicated an insignificant and slightly negative association between blockchain familiarity (BCF) and intention to use blockchain technology (IUBCT), with a path coefficient of -0.195 (t=1.420, p=0.156).

Hypothesis 5 (H5) established the strongest relationship in the study, highlighting a substantial positive correlation between trust in blockchain technology (TBCT) and intention to use blockchain technology (IUBCT), with a path coefficient of 0.605 (t=7.784, p=0.000). In contrast, Hypothesis 6 (H6) revealed an insignificant and weak negative correlation between trust in blockchain technology (TBCT) and the adoption of blockchain technology (ABCT), with a path coefficient of 0.106 (t=1.001, p=0.317). Hypothesis 7 (H7) confirmed a positive impact of intention to use blockchain technology (IUBCT) on the adoption of blockchain technology (ABCT), with a path coefficient of 0.336 (t=3.493, p=0.000). Finally, Hypothesis 8 (H8) demonstrated a strong positive correlation between the adoption of blockchain technology (ABCT) and the security of the healthcare sector supply chain management system (SGS), with a path coefficient of 0.463 (t=7.413, p=0.000). These results collectively underline the interconnected roles of blockchain knowledge, familiarity, trust, and adoption in enhancing healthcare supply chain security.

Limitations

The scope of the study is limited to South Africa’s healthcare sector supply chain security systems environment. The choice of the scope was made for several reasons. Most previous studies on blockchain focused on the private sector environment and the healthcare sector supply chain systems environment are challenging to come by. The system's inefficiencies also contribute to the poor state of the public healthcare system.

Implication of the Results for Research

The study identifies two key research implications for blockchain technology in South Africa's healthcare supply chain. First, it introduces a conceptual model assessing the relationships among blockchain knowledge, familiarity, trust, intention to use, and adoption, offering insights into how these factors influence supply chain security (Mavilia & Pisani, 2022; Dowelani et al., 2022). Second, the findings reveal that blockchain knowledge does not significantly impact trust among healthcare practitioners, challenging prior research (Garaus & Treiblmaier, 2022). This highlights the need to explore alternative factors affecting trust in blockchain to address knowledge gaps in healthcare supply chain practices (Shin & Bianco, 2020). For managers, the study clarifies blockchain's potential benefits and challenges, providing a strategic framework for its adoption.

Conclusion

This study explored the underrepresented area of blockchain adoption in healthcare supply chain systems, focusing on South Africa as a developing country. While previous research primarily addresses Western and Asian contexts (Kshetri & Loukoianova, 2019; Al-Farsi et al., 2021), the African healthcare sector lacks sufficient empirical studies on secure supply chain systems (Azzi et al., 2019; Chen et al., 2017). By introducing and validating a conceptual model grounded in frameworks like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), this study provides a framework for hospital managers, policymakers, and IT researchers to improve blockchain implementation. Findings reveal that blockchain knowledge does not necessarily build trust among healthcare professionals, though it strongly correlates with the intention to adopt. This highlights the need for governance frameworks to ensure ethical adoption and address concerns around data ownership and security.

From a practical perspective, the study offers managers actionable insights on critical constructs like knowledge, familiarity, and trust, which influence adoption behaviours. The findings demonstrate that while intention to use blockchain does not directly guarantee adoption, adoption serves as a mediator for achieving secure supply chain systems, validating calls for empirical testing of blockchain's role in healthcare (Khalil et al., 2021). By addressing these gaps, the study makes a significant contribution to understanding blockchain's determinants and outcomes in healthcare, particularly in the African context, and highlights its potential to enhance supply chain security.

Acknowledgments

I acknowledge the invaluable insights and expertise in blockchain technology to Dan Doney (Chief Technology Officer of Digital Assets for DTCC). His guidance has

significantly shaped my doctoral thesis concept, illuminating pathways for industry adoption and fostering a deeper understanding of this transformative technology.

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