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Blockchain and Digital Technologies in th Telecommunications Industry

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Charles Okeyia
Instituto Superior Tecnico (IST),
University of Lisboa, Lisbon, Portugal
E-mail: charles.okeyia@tecnico.ulisboa.pt

Nuno Marques de Almeida
Instituto Superior Tecnico (IST),
University of Lisboa, Lisbon, Portugal
E-mail: nunomarquesalmeida@tecnico.ulisboa.pt

Joe Amad-Echendu
Graduate School of Technology Management,
University of Pretoria, South Africa
E-mail: joe.amadi-echendu@up.ac.za

Simplice A. Asongu
(Corresponding author)
School of Economics, University of Johannesburg,
Johannesburg, South Africa
E-mails: asongusimplice@yahoo.com / asongus@afridev.org

Abstract

This article examines how fourth industrial revolution (4IR) technologies, specifically blockchain and digital twin technologies, can be utilised to address the energy supply challenge and enhance the management of distributed telecom infrastructure assets in a research context. The emphasis is on how blockchain and digital twin technologies can be applied to improve asset maintenance activities.

Following a systematic review of the existing literature and the development of a model, the research methodology involves the use of structured questionnaires and semi-structured interviews – a mixed-methods approach based on operational data on the asset's functionality. The findings from the asset data suggest that the adoption of blockchain and digital twin technologies substantially enhances the effective functionality of assets installed in telecoms-based stations. However, the intricacy of integrating these 4IR technologies with conventional assets, as well as evidence from questionnaires and interviews, further suggests that they provide a foundation for the digitalisation of maintenance methods, resulting in substantial improvements in operational and maintenance effectiveness and efficiency. The blockchain and digital twin technologies accelerate a predictive maintenance method by proactively identifying unexpected asset failures, thereby lowering mean-time-to-repair and operating expenditures.

Keywords: Asset Management, Blockchain Technology, Digital Twins, Digitalised Predictive Maintenance, Telecoms Infrastructure.

1. Introduction

Telecom asset management in developing countries such as Nigeria, Ghana, Rwanda, Morocco, South Africa, Kenya, and Uganda is also characterised by network availability, quality of service that triggers subscriber growth, internet penetration, and data utilisation. Network degradation and increased intermittent asset outages are associated with infrastructure deficiencies (Opara et al., 2022). For instance, telecom asset maintenance management in Ghana has implemented remote sensing and GIS technologies to automate the landline network mapping process and change detection (Klugman et al., 2021) for a specified period, ensuring the essential res activities are carried out as needed. Gaining control of these distributed assets and maintenance activities creates benefits, such as reducing wastage and overspending on operating costs.

For Nigeria, Ghana, Rwanda, Morocco, and South Africa, asset management practices vary as examples of developing countries, depending on the various opportunities and challenges they face. However, Nigeria's telecom industry has undergone significant expansion and revolution within the year. Nigeria's population is large and rapidly increasing, with over 200 million people (NCC, 2022), making Nigeria's telecom industry a leading operation and market. The key telecom organisations and tower companies are Mobile Telephone Network (MTN), Airtel, Globacom, 9mobile, IHS Towers, American Towers Nigeria, and Pan African Towers Limited, which offer a variety of services such as internet, voice, and data services.

Nigeria's telecom operations have benefited from the government's liberalisation policies, which have promoted private participation, competition, and investment (Alemu, 2018). The liberalisation has also resulted in improved accessibility to the internet and mobile services at affordable prices, notably in urban areas and for customers with limited disposable incomes. However, the limited availability of public (grid) electricity, inadequate infrastructure development in rural areas, and high data costs and services for many customers have been persistent challenges.

Additionally, Ghana's telecom industry is characterised by a vigorous and sizable infrastructure that includes satellite, a network of towers, and fibre optic cables, offering network connectivity and coverage across Ghana's operations (Osei-Owusu 2015). This infrastructure has facilitated Ghana's rapid digital transformation, enhancing access to communication services, including data, internet, and voice calls. From a competitive perspective, Ghana's telecom market is highly competitive, with numerous telecom organisations and managed services providers, including MTN, AirtelTigo, Vodafone, American Tower, and IHS Towers. Each organisation provides communication services and supports its asset-managed services. However, the telecom industry in Ghana is regulated by a well-established regulatory framework overseen by the National Communications Authority (NCA). The regulatory body is responsible for licensing approval, managing frequencies and spectrum, and ensuring compliance with all guidelines, principles, specifications, and consumer protection regulations (NCA, 2022).

Furthermore, the telecom industry in Rwanda has changed due to the sector's technological evolution and industry liberalisation (Kirabo et al., 2020). However, before the telecom industry was liberalised, Rwanda's government owned the country's national telecom organisation and barred competition in the country's telecom market. Internet services and broadband usage remain a critical policy agenda in Rwanda (Mann et al., 2014; Fox and Signe, 2021), as congestion is a significant issue due to the dependence of Rwanda's internet and external Internet bandwidth on the Intelsat satellite and transit route through the stressed SEACOM optics fibre link (Msangawale et al., 2011), combined with the concentration of internet service providers (ISPs) on the SEACOM optics fibre transit link.

The Moroccan telecom industry was significantly driven by growth factors that have impacted Africa's all-access products and markets (El Aynaoui et al., 2022). This growth in Morocco's telecom industry is due to the spirit of innovation it has demonstrated (Achy, 2005; Doorsamy et al., 2021). For instance, the introduction of voice over internet protocol (VoIP), wireless networks (Fox and Signe, 2021), and third- and fourth-generation (3G and 4G) connectivity has revolutionised the industry ecology in Morocco.

Similarly, the South African telecom industry is crucial to the country's economic infrastructure, providing vital communication services to individuals, corporations, and government agencies. Key telecom organisations in South Africa's telecom industry include MTN, Cell C, and Vodafone, which collectively account for the majority of their market share (Sutherland, 2015). However, the country's telecom industry has experienced considerable expansion in recent years, driven by the increasing adoption of mobile technologies, the deployment of high-speed broadband networks, and a growing demand for internet connectivity and data services. The South African industry is undergoing a transformative phase with the advent of 4IR technologies, including the Internet of Things (IoT) and 5th generation (5G), which are likely to have a significant influence on the approach to providing and delivering telecom services.

1.1 Problem statement

In developing countries, telecoms infrastructure asset problems, including passive assets such as direct and alternative current generators, cooling systems, and diesel management systems, pose key challenges. Within the research context, these passive assets contribute to most performance issues due to deficiencies in real-time monitoring, transparency, and the integrity of maintenance activities. Furthermore, the research context's operating environment presents challenges that affect asset maintenance management practices.

These identified issues are linked to Maletic et al. (2023) 's assertion on barriers to digital transformation in asset management, including inadequate asset management systems, a lack of employee skills and knowledge, an existing mindset and culture, a lack of clear vision and strategy, and a lack of awareness of digital trends.

1.2 Theoretical foundations

This article explains that the telecoms environment is multifaceted, with complex distributed infrastructure assets spanning various operating regions. These assets comprise physical components, including generators, towers, cables, cooling system units, power cabinets, and diesel tanks. Therefore, efficient asset maintenance management is crucial for network availability, reliability, and sustainability. This assertion highlights the critical nature of managing distributed telecoms infrastructure assets as a strategic discipline that encompasses the entire asset degradation process, from deployment and maintenance practices to network sustainability.

Consequently, the comprehensive approach to asset maintenance management enables telecom organisations to optimise maintenance activities, improve performance, and enhance the operating cost-effectiveness and resilience of their infrastructure assets. These actions and assertions are achieved through the findings from Singh et al. (2023) and van Dinter et al. (2023) studies, which adopt and implement digitalised and robust asset identification, condition-based monitoring and tracking, predictive-based maintenance, and data-driven decision-making processes. Telecoms organisations can extend the assets' life cycle and value, minimise operating costs, and optimise performance to deliver uninterrupted network availability and services to their customers.

1.2.1 A Case study on telecoms organisation piloting blockchain and digital twin technologies

Given the existing literature and reports, blockchain technology decentralised planning provides the telecom industry with innovative solutions for persistent problems in asset maintenance management practices. Through secure distributed networks and virtual representations, blockchain technology and digital twins create opportunities for predictive-based maintenance monitoring of asset functionalities and reduced network degradation (Haun and Zukarnain, 2024; Ressi et al., 2024), thus addressing challenges of transparency, traceability, security, and operational efficiency across the asset maintenance management ecosystem.

A case of transforming infrastructure by a managed service organisation in Nigeria, whereby they leveraged blockchain technology for detailed infrastructure and asset maintenance activities, ensuring traceability, transparency, and streamlined asset auditing. For instance, real-time visibility of infrastructure and asset elements and components enhances maintenance scheduling and reduces the likelihood of outages or failures.

Blockchain technology's immutability characteristics enable the recording of maintenance activities and eliminate discrepancies in spare replacement and management. The outcome of this pilot includes a 70% improvement in operations and maintenance scheduling, as well as increased transparency across various distributed assets. Thus, offers a blueprint for telecom managed service organisations seeking to leverage these technologies in asset maintenance management.

1.2.2 Existing Market Statistics on Blockchain and Digital Twin Technologies

The adoption of blockchain and digital twin technologies in the telecom industry is accelerating swiftly, driven by the 5th generation (5G) network development and the explosion of the internet of things (IoT), with (Haun and Zukarnain, 2024; Onopa and Kotulski, 2024) signifying these technologies as the most promising systems. For instance, the advantages of improved security based on decentralised, tamper-proof ledgers that protect against manipulation of asset maintenance activities and services, spare replacement, and records. This action enhances transparency by fostering trust among teams through verifiable records, automating maintenance activities, and minimising manual interventions.

Additionally, Table 1 illustrates the application of blockchain technology that aligns with the benefits of integrating legacy infrastructure and assets, ensuring scalability in connecting other distributed assets and complying with re-equipment requirements.

Table 1 Blockchain-based telecom application

Application	Description	Benefits	Practicability
Activity Management	Tamper-proof digital and record-keeping	Improved security reduces the manipulation of data and activities	Telecom organisations providing infrastructure services reduce inefficient asset management practices
IoT asset management	Decentralised ledger for IoT device authentication and update	Enhanced automation, trust and security	Managing base stations through various distributed assets for power availability
Network Availability performance	Remote and automated monitoring of asset functionality and activities	Real-time escalation, accuracy, transparency, traceability, security and cost saving	IHS Towers ServiceNow app for verifying site activities.

Consequently, implementing blockchain and digital twin technologies in the telecom sector delivers improved operational efficiency, increases trust through transparent activities, and streamlines regulatory compliance, as demonstrated in these telecom applications.

1.3. Gaps in the reviewed extant studies

Despite the evolution of blockchain and digital twin technologies, significant research gaps remain in adopting these technologies within asset maintenance management in the telecom industry. Although the existing literature lacks detailed studies on interoperability, and in addition to the lack of a framework that addresses scalability, real-time implementation, and security, this characterises a critical knowledge gap, thereby demonstrating a cost challenge for implementation.

Accordingly, the reviewed literature provides direct insight into sensor devices and data streaming, enabling the accomplishment of asset maintenance management activities such as real-time escalation, virtual replication of physical asset functions, simulation, and resolution. However, other research does not specify how devices and data are accessed to provide maintenance activities, as they focus on individual asset activities, which might permit a direct real-time visibility that aligns with the research gaps; limited inclusive studies on blockchain technology and digital twin implementation in telecoms that addresses interoperability, scalability, confidentiality in evolving 5th generation (5G) networks—inadequate study of blockchain technology and the digital twin role in improving telecom digital asset maintenance management practices.

These concerns also include customer complaints about the quality of services, intermittent asset outages, high operating costs, and security and theft of assets and service spares, all of which have direct and indirect impacts on asset performance. This insight aligns with Carvalho and Chauhan's (2022) propositions, which acknowledge that scholars of network theories and concepts recognise that, due to the complexity of network maintenance operations, such as the research context's operating environment, deep levels of ambiguity are inevitable in planning, managing, and generating solutions for complex network operations.

2. Asset maintenance management

Asset maintenance management remains an issue as organisations face pressure to reduce operating costs and improve performance. Algabroun et al. (2022) described asset management as the merging of technical and non-technical activities and management measures during the operational stage of asset degradation to maintain and sustain asset functionality. This position demonstrates that AMM is a framework for implementing maintenance tasks. Naji et al. (2019) noted that AMM is a significant characteristic of asset management in most organisations, due to its complexity, requirements, and widespread application in all infrastructure engaged in achieving performance outcomes.

This insight suggests that asset and maintenance practitioners require decision-making models and tools to efficiently and effectively organise resources in support of physical asset management and performance. Naji et al. (2019) and Sedghi et al. (2021) argue that planning and scheduling are viewed as integral to the maintenance work management process. However, various scholars have modelled several management maintenance components, focusing on reducing gains in operating costs.

Babaeimorad et al. (2022) also suggested using the shared optimisation approach to model the combined maintenance scheduling investors' strategy modification. From a mathematical perspective, this model determines the inventory level and PPM planning for an individual asset functionality and performance system with intermittent outages or breakdowns (Babaeimorad et al., 2022). This concern is related to the research context, specifically a problem with asset downtime and intermittent outages resulting from ineffective maintenance activities.

BabaeiMorad et al. (2022) also emphasise that asset practitioners can reduce operating costs by adjusting decision variables, including production capacity quantities, maintenance costs, and asset failure distribution. This proposition only addresses the research's cost issues, but does not address the intermittent asset outage caused by ineffective maintenance practices.

In contrast, Ismail (2022) proposed an effective maintenance system that is intelligently oriented to improve and address ineffective maintenance practices. Conventional management maintenance approaches lack defect-predictive and analytical tools, as well as strategic decision-making for data and information analysis, in asset management and maintenance-related project outcomes.

The suggested management maintenance system is designed to reduce the frequency of asset repairs and overhauls, thereby lowering operating costs and enhancing system functionality. Pant et al. (2022) supported this scheme by subjecting the modelled system to random inspections with hidden failures, which underscores the system's accessibility and longrun average cost rate. The optimal inspection period was determined, thereby reducing operating costs.

2.1 Emerging asset maintenance management practices

The adoption and emergence of intelligent and advanced Internet of Things (IoT) technologies enable significant advances in these technologies and platforms (Jabeen and Ishaq 2022). The International Society of Engineering Asset Management (ISEAM) facilitates and promotes global efforts in the engineering asset management discipline through journals and conferences that appeal to academics and practitioners (Hashemina, 2018). These journals and conferences aim to foster a broad conversation and increase knowledge of 4IR technologies and emerging predictive maintenance analytics.

Nevertheless, with high operating cost pressure and environmental issues, network quality service demands, and unsustainable resource approaches, organisations are starting to recognise that they need to change their direction regarding mapping their asset and service delivery. Adopting an asset maintenance management outlook aligned with intelligent and digitalised technologies has advantages such as effective and reliable service delivery and reduced costs. Considering maintenance as part of the overall asset management practice helps organisations improve service delivery and asset performance.

2.2 Asset hierarchy – distributed infrastructure

The critical distributed asset consists of an intricate passive infrastructure, generators, cooling systems, hybrid power systems, a diesel tank, cables and a palisade fence. Maintaining and optimising these distributed assets is a constant challenge for telecom tower organisations, requiring meticulous planning, proactive and predictive maintenance and the strategic deployment of the 4IR technologies (ErKoyuncu et al., 2020; Tran 2021; Amadi-Echendu et al., 2021), understanding the hierarchical contacts between these distributed assets, these telecom organisations can better allocate resources, identify and address challenges, and ensure the resilience and reliability of their functionality and real-time activities.

Furthermore, these distributed assets operate at various levels of the asset hierarchy, from critical generators to multiple ecosystem components. Therefore, it is crucial to maintain these assets and their hierarchical relationships. This insight is key to ensuring effective asset maintenance management practices, scalability, security, and performance that drive continuous asset functionality and management.

Furthermore, the asset hierarchy is instrumental in devising predictive maintenance strategies. The integration of 4IR technologies empowers telecom organisations to enhance the reliability of their infrastructure, thereby fostering continuous improvement in network availability.

2.3. Organisational hierarchy – asset management

The organisational hierarchy, encompassing the top-tier management and leadership teams of telecom tower organisations, is not just responsible for charting the organisation's long-term strategic vision. Their role in defining objectives and goals is pivotal, as it steers the organisation towards its mission, making their contribution crucial (Amadi-Echendu et al., 2021; Kaur and Randhawa, 2021).

By aligning the organisational process, as shown in Figure 1, with the asset hierarchy, telecom tower organisations can ensure the continuous and effective deployment of resources. This empowers the field team members to thrive, innovate, and adapt to the rapidly evolving 4IR technologies landscape (Amadi-Echendu et al., 2021; Tran, 2021; Erkoyuncu et al., 2021).

This insight highlights the importance of providing the direction, vision, and operational coordination necessary to deliver effective asset maintenance management practices.

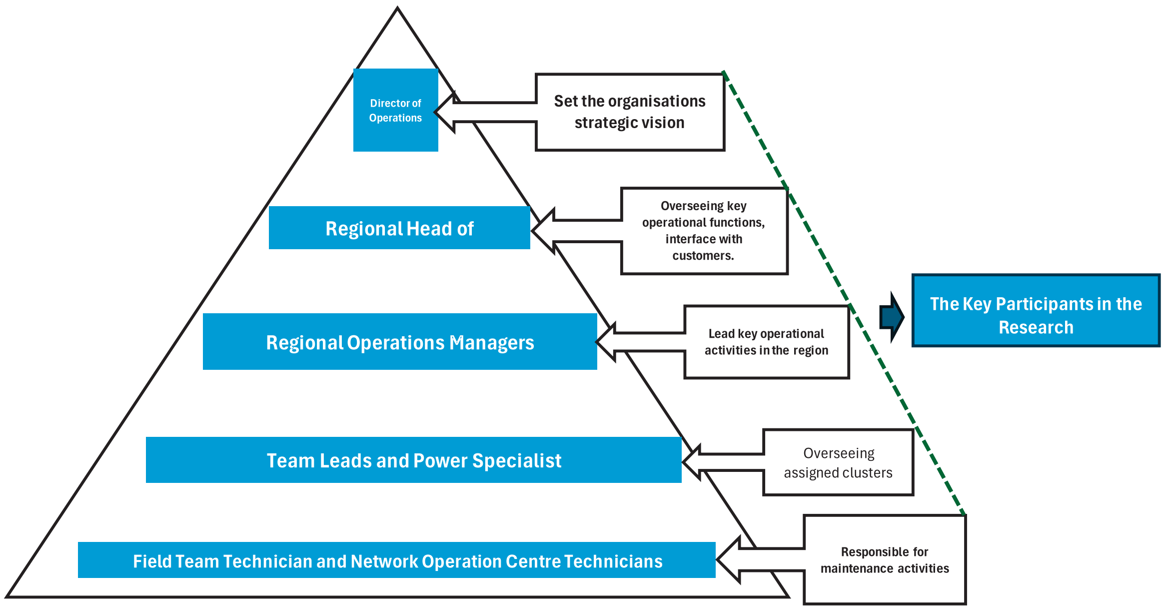

Figure 1Organisational hierarchy - operational workflow chart

The network operation centre (NOC), operated by highly skilled field technicians, serves as the base of the telecoms tower organisation ecosystem. It continuously monitors and tracks real-time asset functionality and performance, identifying and resolving asset outages and malfunctions, and implementing proactive measures to ensure continuous asset performance, thereby improving sustainable network availability.

Field technicians play a crucial role in the telecom tower organisation ecosystem. They report to the Network Operations Centre (NOC) and are responsible for the physical maintenance and repairs of the distributed assets. Their tasks range from servicing generators and cooling systems to diesel distribution, haulage, and delivery, as well as tower spot checks and maintenance, including non-routine repairs and upgrades. The field technician's knowledge of these distributed assets and functionalities, as well as their ability to respond rapidly to on-site outages and problems, is vital for reducing downtime and degradation. Thus, sustaining and maintaining the overall asset functionality, reliability, and performance is key to improving sustainable network availability.

Furthermore, with asset management planning and optimisation, alongside the operations and maintenance field teams, the telecom tower organisation employs power specialists and planners who are responsible for constantly evaluating and improving distributed asset functionalities and performance using predictive-based models. These power specialists and planners identify areas for asset upgrades and improvements, then plan and implement intelligent 4IR technologies to increase power efficiency and capacity (Heaton and Parlikad, 2020; Tran, 2021), reduce downtime, and enhance asset resilience.

Additionally, this insight explains that the field technicians' efforts ensure the distributed asset remains at the forefront of 4IR technological advancements, meeting the increasing demands for network availability (Amadi-Echendu et al., 2021). Thus, the assertion means that these field technicians possess a deep understanding of telecom-managed services and assets, enabling them to conduct root cause analysis (RCA) of asset outages and problems and implement designed resolutions. However, by bridging the gap between asset maintenance activities, real-time monitoring, functionality, and performance, the field technicians' teams ensure that even the most intricate outages are addressed and resolved effectively and efficiently, thereby improving network availability.

Asset hierarchies include dedicated field teams for escalation and resolution of disputed solutions in the event of intermittent asset outages and unexpected downtime, as well as complex and unresolved asset failures. In this context, skilled power specialists are trained to traverse the organisation's internal and asset management processes and leverage cross-functional resources for effective and equitable resolution (Heaton and Parlikad, 2020). Thus, their capability to quickly and efficiently address the most challenging distributed asset problems is essential for sustaining and maintaining responsiveness and integrity in maintenance activities.

2.4. Distributed telecoms infrastructure asset management overview

Distributed telecom infrastructure assets include passive, active, or separable components that can independently create value (Sacco, 2020; Hobday, 2023). In this research context, distributed telecom infrastructure assets encompass diesel generators, cooling systems, towers, hybrid systems, diesel tanks, cables, and lighting systems. However, the reviewed literature on managing distributed telecom infrastructure assets using conventional technologies and tools highlights a gap stemming from unpredictable factors such as automation, real-time monitoring, tracking, diagnosing, and processing asset functionality and behaviours.

Accordingly, there is a critical need to utilise 4IR technologies due to their capabilities and characteristics. However, the reviewed extant literature studies have shown that 4IR technologies, such as IoT, blockchain, and digital twin technologies, support business processes, operational optimisation, and efficiency, thereby closing the gap between conventional systems (Singh et al., 2023; Haun and Zukarnain, 2024; Ressi et al., 2024). Telecom operations and maintenance activities consist not only of the components necessary for the passive infrastructure assets, such as the research focus and content (Rha and Lee, 2022), but also of active infrastructure assets necessary for digital data and voice access, as well as transmission channels that interrelate with the passive infrastructure assets. Thus, assets are interpreted based on the access network's considerations about distributed telecom infrastructure.

2.5 Key features of blockchain technology

The key features of blockchain technology, as observed and identified in the extant literature, include a peer-to-peer interface, transparency, a decentralised and distributed database, authentication, trust, immutability, security, tamper resistance, and synchronisation across activities under a consensus mechanism (ELMessiry and Messiry, 2024; Khan et al., 2023). These features were supported by Yermack (2017), who noted the advantages of increased efficiency, enhanced traceability, and cost reduction. Han et al., (2024) argued that BCT could transfer values such as asset real-time conditions without compromising the data. For instance, adopting BCT and DT technologies will help the research context address the identified challenges, as outlined in Table 2.

Table 2: Blockchain technology benefits and challenges

Critical Value Drivers	Blockchain Technology Benefits	Present Operational Challenges
Operations and Maintenance efficiency and performance	Automation and Cost reduction Integrity and Reduced Human Error Real-Time faults detection	Manual fault update Semi-automation No real-time visibility
Asset security and Diesel management	Actual daily consumption CPD Supply approved quantity Report actual root cause failure	Manipulation of daily consumption and Theft Time consuming (MTTR)
Counterpart risk decrease and reduction	Asset records immutable Codified and implemented	Lack of tools for tracking escalation from individual components

Source: Han et al. (2024). Benefits of blockchain technology.

Conversely, Hughes et al. (2019) argue that organisations' increased adoption of BCT will take many years because of organisational, technical, and legal constraints (Table 1). Unfortunately, this prediction is not the case as several organisations have adopted BCT in their operations (Deloitte, 2020); thus, it is another likely reason for adopting BCT in this research context. This assertion is also within the remit of Lumineau et al. (2021) and ELMessiry and Messiry (2024), noting that consensus governs the actual state of information between collaborating organisations, which improves transparency, reduces information asymmetry, and encourages close collaboration among various stakeholders. This research highlighted the adoption of BCT in telecoms asset maintenance management practices to provide real-time asset maintenance management conditions and functionality, thereby facilitating better decision-making processes that align with trust and integrity in asset maintenance activities.

2.5.1. Blockchain and peer-to-peer network

Blockchain technology is a decentralised ledger for one or more digital assets, or simulated and artificially generated, using a peer-to-peer network to create a distributed ledger for cryptocurrency. This digger constructs a continuous chain of hashes to create immutable records. This insight is beneficial in conducting the actual root cause analysis (RCA) of asset outages in this research context, as it helps prevent misinformation and manipulation of facts regarding asset maintenance activities. This, in turn, facilitates proper decision-making on asset lifecycle management.

The peer-to-peer network in this context is decentralised, and each peer represents each of the passive assets in the base station, which is also known as a node, taking responsibility for providing the required and necessary support services to the network or operations (Viriyasitavat et al., 2019; Jain et al., 2025). However, the block should be validated using consensus mechanisms and mirrored and replicated in the updated block and the updated ledger before being incorporated into the distributed ledger, which could be referred to in this research context as the asset maintenance performance register. Therefore, all nodes have the authority to read and retrieve data, as well as to assign or act, support, and feed data to other nodes within the system. This insight is true because these assets are interrelated; a failure in one asset impacts the overall performance of the network systems. For instance, power failure impacts cooling systems, active infrastructure, and network performance.

2.5.2. Hash algorithm in blockchain technology

The blockchain system is composed of associated blocks that form chains, whereby the structure of the block includes a header and body for each block, the value of the preceding block hash, the timestamp for identifying, knowing and categorising the time of the block creation, the random root hash for the existing block based on the network configuration and regulations, and the body containing encoded and hashed vital transactions or activities; each block residing in several transactions or activities (Huang et al., 2020; Patra and Rani 2025). This assertion and descriptions of blockchain hash value are unique. If any alterations are made to any block in the chain, the block's corresponding hash value would be directly altered (Patra and Rani, 2025), as proof of work is a procedure used to verify or test the blockchain's validity. This understanding addresses the challenge in the research context of asset maintenance activities; whereby improper activities are implemented during asset maintenance tasks and not recorded according to the activities performed. Such an act will not be possible with this action, as the hash value will record all the activities performed.

2.5.3. Organisational application of blockchain technology

Organisations have various BCT applications depending on the features, business areas, or business perspective. Casino and Patsakis (2019) noted that BCT could be applied in organisations in a fully transparent and tamper-resistant manner, effectively and efficiently managing record-keeping and activities. For instance, automated transactional agreements through smart contracts, record or status updating, maintenance transparency, and traceability of asset conditions and outages (Dib et al., 2018). The following areas related to the research scope are presented accordingly.

Smart contracts are agreements among various stakeholders that facilitate business transactions in an ethical, transparent, and secure manner. Morabito (2017), Li et al. (2020), and Sawayz and Kavitha (2025) suggest that smart contracts can differ in scope and complexity, and several factors must be considered to ensure they are lawfully binding. Therefore, adopting a smart contract in a BCT system requires self-implementation, and the application varies depending on the specific needs of the user. As an element of BCT, smart contracts share features with activities that are traceable and irreversible. Aligning this proposition with the research context reveals that asset maintenance management practices and activities should be traceable, transparent, and visible regarding both maintenance activities and the real-time escalation and monitoring of asset conditions and functionality. For instance, the issues with manipulating RCA and asset conditions reports have led to poor decision-making and performance concerns.

These revealing concerns have severe implications for telecommunications providers, such as broken trust between network providers and customers. These network providers have recognised the need to enhance network quality of service, transparency, and value in their traceability systems, ensuring complete and reliable data that accurately reflects their agreed-upon KPIs. Benton et al. (2018) proposed a potent solution for total transparency in business activities, providing full traceability and visibility, as the tamper-resistant and distributed record technology will prevent the manipulation of data and feedback from individuals responsible for asset management.

2.5.4. Blockchain technology sustainability limitations

Although blockchain technology theoretically offers limitless opportunities, it is not without limitations (Yaga et al., 2018; Chen and Yu, 2024). Therefore, the limited adoption and actual understanding of BCT's technological and technical features impose economic and societal limitations. The practical application in daily business and operational settings is limited, particularly in terms of knowledge and experience regarding the advantages and risks associated with it. Chang et al. (2020) noted that the likely risks and expenditures outweigh the potential benefits. However, the limited insight, in conjunction with the fact that BCT is highly unexplored, might create friction and resistance regarding trust in the asset's functionality and integrity.

Furthermore, the inadequate legal and regulatory frameworks for the BCT network (Chang and Chen, 2020) and the distributed characteristics of the BCT network suggest a potential global geographic distribution of members, making regulatory and legal management problematic due to the absence of a uniform framework across geographical limitations. However, smart contracts are perceived as valid and lawful, making their use and implementation problematic from a legal and regulatory viewpoint.

Additionally, resource demand is another sustainability limitation, depending on the BCT features, consensus algorithm and hashing approaches. For instance, the characteristic economic limitation is the extensive diesel (fuel) consumption by the power generators (electricity) and the consumption per day (CPD) calculation or computation power that is needed to process and validate activities on BCT systems.

Human and system errors are other limitations because BCT is as prone to human and digital system errors as any other digital system (Yaga et al., 2018). This insight is because BCT could record fabricated or inaccurate data activities available on blockchain technology. However, where the network accepts that the information is attached to and mirrors reality, the BCT becomes trusting of external systems and humans to confirm the accuracy of the transferred information on the network. Chen and Yu (2024) posit that, although BCTs are evaluated as secure and trusted systems, they still rely on the system's capacity to develop bugs and loopholes that can be identified and eliminated.

2.6 Structure of digital twin technology

Digital twin technology is an innovative solution that significantly bridges the gap between physical assets, digital simulation, data, and services. Costello and Omale (2019) suggest that IoT organisations, such as those in the research context, most likely use digital twin technologies for operational excellence and future business activities. This assertion is based on the understanding that digital twin technologies merge various domains or assets. In the case of this research, there is an interconnection between passive assets, including power generating sets, cooling systems, power rectifiers, and diesel monitoring devices. Tao et al. (2019) supported this proposition with the insight that the needed digital twin system is constructed of a critical part comprising a digital model, data processing, and a database.

The digital model is an imitation or replication of the physical asset or item, including its components, a representation of the system's or asset's performance, functionalities, and defects, as well as a telecommunication model (Algabroun et al., 2022; Alshathri et al., 2023; Hobday, 2023). This insight supports the structure of subsystems, subassemblies, and modules, and develops a simulated explanation of every component based on the realised receiving measurements from creation, actions, activities, and operations.

Conversely, to enhance the maintenance services and reliability in activities, a replica of the sensors can be introduced inside the digital component of the systems based on the research and assertion by (Wang et al., 2019; Alshathri et al., 2023; Hobday, 2023), that the digital simulation could mirror the image of the physical asset by detecting and grouping the critical component of the actual assets. Additionally, the devices or sensors networks, storage systems and data transmission are essential factors or denominators for digitally modelling the systems and analysing the data in digital twin technologies (Algabroun et al., 2022; Alshathri et al., 2023) both for operations and maintenance analysis such as this research context, validation of the virtual model of the processing in numerical models and the needed simulation.

Furthermore, data fusion and merging are other critical characteristics of digital twin technologies (Blasch et al., 2021), which are applied to diagnose, predict, and recommend actual asset behaviour and functionalities by processing and optimising data (Qi et al., 2022). It analyses the performance of physical assets by processing a vast amount of information and data. For instance, to diagnose and prognosticate faults in physical assets, analysis is performed through knowledge rule-based systems, which, however, involve merging data from multiple sources to create a more comprehensive and accurate representation of the systems or environments (Blasch et al., 2021). This insight, in the context of digital twin technology, explains that data fusion algorithms can assist in combining data from multiple devices or sensors and sources to build a fused or combined view of the modelled physical asset.

Despite the various specific data fusion techniques that are generally used in digital twin technologies (Blasch et al., 2021), such as the Kalman filtering technique that involves a recursive algorithm that estimates or evaluates the state of the systems by combining noisy measurements with a dynamic model of the systems, (Bai et al., 2023), Bayesian networks technique that comprise a probabilistic model that applies graphical images to model the relations among the variables and perform probabilistic inferences (Shafer 1992), Dempster-Shafer theory techniques that have a mathematical framework for combining evidence from multiple sources that use belief functions to represent uncertainty; Fuzzy logic technique involves the use of fuzzy sets to characterise imprecise or uncertain information (Ahn et al., 2019) and can be employed to model complicated connections concerning the variables and Neural networks techniques that use a class or kind of machine learning model that can be applied to learn patterns in data and make predictions.

Given the description of these data fusion techniques, this research will apply neural network and Bayesian network techniques based on their characteristics of learning patterns, prediction, representation, and probabilistic inference, which align with the intended objectives and issues to be addressed using these innovative technologies (Qi et al., 2022). However, the specific technique chosen depends on the nature and context of the modelled systems and the available data.

The connections and operations are the final element that addresses complex systems and activities in digital twin technology. This is because a complicated function that any single unit cannot perform can be undertaken by assisting the elements in transferring significant data and information between elements and continuously processing the digital model.

With facility and asset maintenance management processes, such as modelling, operations and maintenance activities, asset functionality tracking, and monitoring, as well as asset fault escalation and tolerance, digital twin technology can describe a real-time view. It can also recognise malfunctioning data and propose a suitable resolution.

This assertion is based on the fact that digital twin technology is a key advantage for improving efficiency in asset maintenance management activities and reducing operating expenditure (OPEX), a critical focus of this research. It also reduces issues experienced during asset maintenance, operational activities, and the asset lifecycle. As a result, it detects and recognises the problems in the future, preventing unpredictable and unforeseen outage operations and simply projecting spare parts dimensioning. Thus, stakeholders can quickly access real-time reports, relevant data, and information because the digital twin facilitates effective interaction and records maintenance activities.

3. Methodology and Data

Academic research works are established on several underlying philosophical assumptions concerning good research and the appropriate methods of knowledge creation or problem resolution in a given study (Burrell and Morgan, 2019). Therefore, to conduct and explore any research, it is essential to understand these assumptions and the different philosophical perspectives that inform this research, as well as the philosophical paradigms used. With the research philosophy, the researcher makes critical assumptions about the worldviews and the approach through which the findings will be understood. The researcher also assists in capturing deductive and inductive research, as well as the various perspectives of ontology, epistemology, and axiology.

Figure 2 provides specified research philosophical assumptions, paradigm, research approaches, design, analysis, and description, aiming to develop a theoretical framework for telecoms asset maintenance management practices. The methodology employs a mixed-methods approach, presenting both quantitative and qualitative research methods in detail, along with their respective features and specifications. The ontology of objectivism and the epistemology of constructivism or interpretivism are adopted, considering the research aims and delivery objectives.

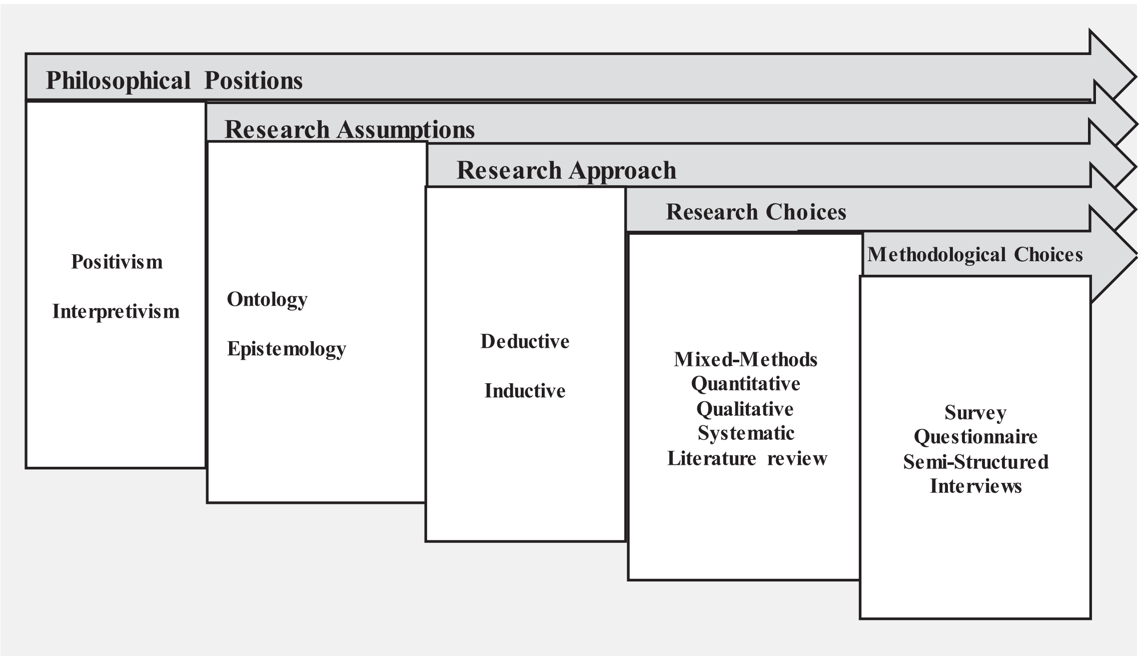

Figure 2: Research methodology

The research philosophy adopts a mixed-methods approach, combining positivistic and interpretivist methodologies, following the hypothesis-testing approach and employing both assumptions. The justification and choice are based on the assertion that positivism supports objectivism, interpretivism, and subjectivism. Additionally, the integration of deductive and inductive research approaches is crucial, as the research focuses on designing and developing a hypothesis to be tested and subsequently accepted or rejected. Following the integration of deductive and inductive research approaches, this research employed both explanatory and descriptive processes.

4.0 Data analysis and discussion

In theory, blockchain and digital twin technologies have transformed the structure of asset maintenance management practices in various organisations (Chang et al., 2019; Callcut et al., 2021; Chen et al., 2022). This is because these technologies work in a decentralised manner by adapting to industrial 4.0 principles. Studies have also shown that organisations that apply a decentralised structure based on these new technologies outperform organisations with the conventional centralised structure (Van Dinter et al., 2022; Mahmoodian et al., 2022). This is due to the decision flow among the asset peer-to-peer connect functionalities, which reduces human interface, irregularities, and inappropriate activities and actions.

However, the adoption of these technologies cannot address the issues of overhauling operational decisions and changes in maintenance practices. It is essential to initiate the adoption process by integrating a data and human governance framework, which ensures a seamless match between the conventional maintenance strategy and the intended predictive maintenance strategy. For instance, to avoid resistance from the operational team based on the decision to virtualise some maintenance activities, it is justifiable that they understand the process.

To bring the benefits of blockchain and digital twin technologies in asset maintenance management practices, human knowledge of these technologies is significant, based on the understanding that these technologies cannot operate in silos. Therefore, the change in asset maintenance management practices will be in alignment with less reactive and hierarchical, yet more predictive-based and collaborative practices, to remain agile in addressing issues in the evolving digital operating environment.

4.1 Comparative analysis of the developing countries' telecom industry

From the comparative analysis of these emerging telecom countries, the research found that the perception of telecom organisations in these countries, regarding telecom asset management, is that it is seen as a function that disposes of ageing or old assets, rather than a form of strategic asset management practice. Additionally, it was identified that there is an absence of applicable asset management best practices or standards tailored to the industry. Based on telecom asset management practices, the existing challenges and future opportunities identified from the reviewed extant literature on 4IR technologies, the research developed a conceptual framework for effective asset management utilising blockchain technology and digital twin capabilities.

However, in Figure 3, Nigeria and Ghana's telecom industries have seen significant operational growth, and the asset management practices and approaches differ in notable ways. For instance, given the reviewed literature and collected data, Nigeria's telecom industry faced challenges such as infrastructure and asset deficiencies (Ochuba et al., 2024), low public (grid) electricity, ageing assets (Simon 2021), low-level skilled workforce and operating environment issues, leading to a more reactive asset maintenance management approach. Despite these challenges, the research found a lack of systematic and effective telecom asset management practices in most of these analysed emerging countries.

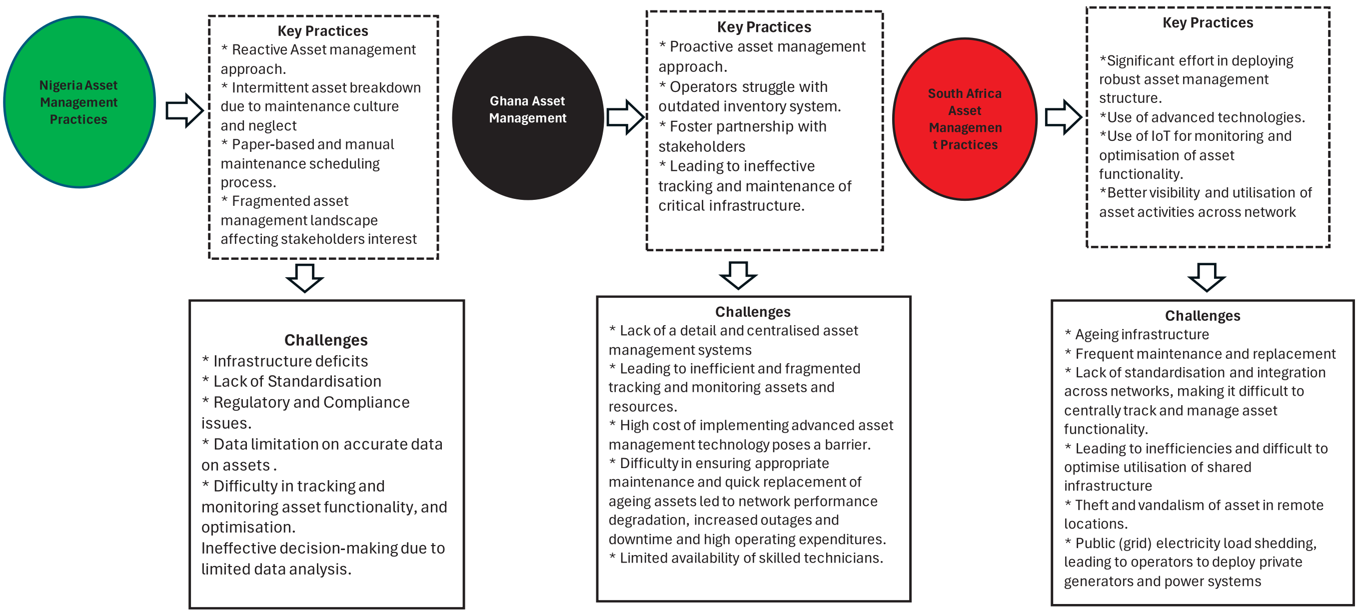

Figure 3: Developing country network operations

On the contrary, Ghana's telecom industry has adopted a proactive approach to asset maintenance management. This strategy involves robust and intelligent asset tracking and maintenance strategies to minimise network degradation, maximise uptime and outages, and improve maintenance efficiency. The difference in strategic focus between Nigeria and Ghana has led to divergent results. Ghana's distributed telecom assets are usually effectively maintained and optimised, in contrast to Nigeria's asset maintenance management practices.

Another significant difference between Nigeria's and Ghana's asset maintenance management practices is the level of collaboration and partnership between the private and public sectors. In Ghana, the telecom regulatory agencies have actively promoted and fostered strong cooperation and collaboration with telecoms and tower organisations. This support has allowed for joint initiatives that optimise assets and improve performance.

In contrast, Nigeria's telecom industry has struggled to support and align the attention and interests of telecom and tower organisations, leading to an incoherent and fragmented asset management landscape (Ochuba et al., 2024). Thus, the unsupportive relationship and alignment with these stakeholders have hindered the collaborative adoption of best asset management practices. However, individual telecom organisations realise economies of scale by adopting efficient asset management approaches to improve performance and reduce costs.

Furthermore, Nigeria and South Africa share similarities as major telecom operating markets in Africa and developing countries. However, the telecom asset maintenance management practices of the two countries differ significantly. The Nigerian asset maintenance management approach is more decentralised and less coordinated, as each telecom and tower organisation manages its assets independently (Ochuba et al., 2024). Contrarily, the South African telecom asset maintenance management approach features more centralised and standardised practices and systems for managing distributed assets (Mazele and Amoah 2022; Saba and David 2023), with government agencies playing active roles in oversight and regulation.

However, with the shift to public (grid) electricity, some telecom and tower organisations are beginning to manage their assets independently, supported by diesel generators and other efficient power solutions. One significant contrast between these two contexts is the level of asset and infrastructure investment (Robb and Paelo 2020). South Africa has demonstrated superior asset investment in innovative and 4IR technologies, characterised by high-capability networks, which enable and support more efficient and effective asset management practices (Sutherland 2015; Mazele and Amoah 2022).

Additionally, Nigeria has struggled with investing in ageing assets and infrastructure, as well as uneven development (Gedel and Nwulu, 2021), creating challenges for effective asset maintenance management practices. This divergence in asset and infrastructure investment and quality directly affects the telecom asset management practices in Nigeria and South Africa.

Additionally, Rwanda and Morocco are on the journey of the 4IR revolution, as they have limited solutions and ICT regulations that differ in kind, and they have not grown into globally accepted product divisions; thus, they operate and rely on working well with cross-border services. Generally, 4IR innovation continues to develop in Rwanda, Morocco, and other African countries, with a focus on advancing 4IR technologies (Doorsamy et al., 2021; Fox and Signe, 2021), thereby creating more opportunities for telecom asset management practices.

These actions and focus from the emerging countries as regards the adoption of 4IR are consistent with the assertions and findings from Hoosain et al. (2020) on the impact of 4IR digital technologies in attaining the SDGs, and also the proposition by Manyeke (2022) on the management of 4IR opportunities and challenges in Africa.

Thus, these emerging countries focus on evolving 4IR technologies through ICT capabilities and adopting smart contracts and intelligent technologies. The key results and findings demonstrate how these 4IR technologies and innovative solutions can be effectively applied to implement proactive and predictive-based asset maintenance management practices.

4.2 Path analysis with SPSS AMOS model

Given the model fit summary in Table 3, which indicates the model minimum was achieved with values of Model 1—Chi-square = 148.588, degree of freedom = 43, and probability level = .000, an RMSEA value of .05 or less implies a perfect fit, while a value of .08 or less implies an accepted fit (Marsh and Hocevar, 1985; Kline, 2016).

Table 3 Model fit summary - CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	93	158.588	43	.000	3.688
Saturated model	136	0	0		
Independence model	16	790.924	120	.000	6.591

Theoretically, a CMIN/DF value of less than two (2) is considered a good model fit, whereas a value of less than five (5) indicates an accepted model fit; thus, it can be observed that the value in model CMIN/DF is an accepted model fit (Marsh and Hocevar, 1985) based on the value of 3.688, which is less than five (5).

To interpret CMIN involves the discrepancy divided by the degree of freedom, as the value of interest is the default model CMIN/DF. Therefore, the research observed that the chi-square test indicates that the model did not depart from the actual fit X^2 (43) = 158.588, $p<.000$. However, Kline (2016) posited that the goodness of fit index (GFI) and adjusted goodness of fit index (AGFI) are absolute fit indices as indicated in Table 4.

Table 4 Model fit summary RMG and GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0.022	0.879	0.617	0.278
Saturated model	.000	1.000		
Independence model	0.16	0.525	0.462	0.464

Therefore, the goodness-of-fit index measures the relative extent of variance and covariance in the sample covariance matrix, which is justified as the model-implied population covariance matrix (Byrne, 2010, p. 79). This assertion is based on the understanding that GFI is a measure of fit between the hypothesised model and the observed covariance matrix, as the AGFI corrects the GFI, which is impacted by the number of indicators of each latent variable; this is the range of GFI and AGFI is between values of zero (0)) and one (1).

The ranges of the goodness of fit index and adjusted goodness of fit index begin from zero (0) to one (1), where greater values indicate superior fit, > .90 or .95 are classically considered as signifying acceptable to good model fit (Byrne, 2010; Whittaker, 2016; Schumacker and Lomax, 2016).

Table 5 indicates that a baseline comparison value of NFI = 1 is a good fit, as a model value of NFI = < 0.9 can generally be improved. (Bollen, 1998). For the model, the NFI of 0.799 indicated a close and reasonable fit. However, an NFI value of 0.9 indicates a reasonable fit (Bentler and Bonett, 1980), and values between 0.90 and 0.95 signify an acceptable fit (Hu and Bentler, 1999).

The RFI depends on the complexity of the model and the sample size. This model's RFI of 0.44 indicates an unaccepted fit; a value above 0.90 indicates an accepted fit, and a value above 0.95 indicates a good fit (Hu and Bentler, 1999).

Table 5 Model fit summary - baseline comparisons

Model	**NFI Delta1**	**RFI rho1**	**IFI Delta2**	**TLI rho2**	**CFI**
Default model	0.799	0.44	0.845	0.519	0.828
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Table 5 shows that the Incremental Fit Index (IFI) of this model is 0.845, indicating an acceptable fit, as suggested by Bentler (1990) and Marsh (2004), who propose that a value of 0.90 represents a reasonable fit and a cutoff value for a good fit. However, the TLI value for this model is 0.512, which is not an acceptable fit, as the benchmark proposed by Brown (2006) suggests that a model should have a TLI value greater than 0.9.

The comparative fit index (CFI) also indicates an acceptable goodness-of-fit model with a value greater than. 828 (>.90). This value is consistent with West et al.'s (2012) suggestion that values between 0,90 and 0,95 are an accepted fit and values above 0,95 are an excellent model fit. This is also supported by Kline's (2016) assertion that a CFI value of nearly 1 is a good fit.

Furthermore, Kline (2016) noted that the root-mean-square error of approximation (RMSEA) can be considered an absolute fit index, with a value of zero (0) indicating the best fit and values greater than 0 indicating a worse fit, as shown in Table 6. However, values of .05 or below on the root-square-error approximation generally indicate a close-fitting model.

Table 6 Model fit summary - RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.157	0.131	0.184	.000
Independence model	0.226	0.212	0.242	.000

According to Table 6, the RMSEA value is 0.157, which falls within the accepted range of 0.05 to 0.08 (MacCallum et al., 1996). However, applying the rule of thumb in this situation suggests that the null model, which is less than or equal to 0.157, could be accepted, provided the PCLOSE is less than 0.05, as is the case with this model's PCLOSE. The PCLOSE is the p-value for rejecting the null hypothesis that the model fits the subject data, indicating that a p-value of less than 0.05, as in this model's PCLOSE, suggests that the RMSEA is greater than zero (0); thus, the model does not provide a good fit.

However, the sample size could influence the result of this model, as other indicators measure a model's good fit. This output and contention are because a sample that is too small can prevent the findings from being deduced or generalised. At the same time, a sample that is too large can increase the likelihood of discovering differences, highlighting statistical variations that are not scientifically relevant to the context.

Therefore, according to the model, the root-square-error approximation equals 0.157, which falls outside the 0.05 (close fit) threshold; thus, the root-square-error approximation based on the model suggests that the model does not provide an entirely close fit to the data; however, it indicates an acceptable fit. This assertion aligns with Brown and Cudeck's (1993) findings, which suggest that values between .08 and Hu and Bentler's (1995) value of .10 are accepted. In contrast, Kline (2016) proposed that a root-square-error approximation value of ≥ .10 could create a problem with model specification.

The model fit can also be accessed from the PCLOSE test, which provides a base for the root-square-error approximation. If we agree that a root-square-error approximation value of ≤ .05 represents a close-fitting model, as indicated on the RMSEA Table 6, then the p=close text result where the p>.05 can be deemed as supporting the null hypothesis of close model fit. This proposition is consistent with Kline's (2016) findings on the accepted range of p-values for model fit.

Therefore, from the RMSEA analysis, the PCLOSE is 0.000, which suggests that the acceptance of the alternative hypothesis (which the research aims to prove) with evidence for the rejection of the null hypothesis (which the study attempts to disprove) of close fit does not support the model.

Additionally, we can use the 90% confidence interval (CI), which provides another approach to assessing model fit based on the root-squared-error approximation. Specifically, it is an interval estimate for the root-squared-error approximation, and when the upper bound (HI90) falls below .05, it is interpreted as supporting a close-fitting model (Kline, 2016); however, if the upper bound is > .10, which signifies a threshold for poor fit, then there is weaker evidence in support of a well-fitting model. In contrast, if the lower bound of the interval is > .05, which signifies a close fit, and the upper bound is < .10, which is a poor fit, then the model does not pass the test of close fit, as it may represent an acceptable fit to the data.

Furthermore, the broader the CI, the less confidence the researcher should have in the point estimate for the root-square-error approximation. For instance, 0.157 and the 90% CI range from 0.131 to 0.184, with the lower bound suggesting a close-fitting model, whereas the upper bound indicates a non-fitting model.

This model concern can be addressed by Kline's (2016) proposition that the seeming contradiction by stating that the model is just as consistent with a close-fitting hypothesis as it is with the poor-fitting hypothesis; thus, we have mixed results about the acceptability of the model fit using the CI because the lower bound of .131 and upper bound .184 values.

Therefore, these results indicated a reasonable confidence interval based on the wide confidence range of 0.50 to 1.0, suggesting limited knowledge concerning the effect (Greenland et al., 2016). This is because the first sample population is smaller than the second population, meaning that 95% of the intervals would be expected to include the population mean.

Table 7 presents the unstandardised factor loadings, which do not include a significance test, while the remaining test results are standardised factor loadings. From the critical ratio regression, dividing the regression weight estimate by the estimate of its standard error yields a value of z = 10.984.462 = 23.764. This output means that the regression weight estimate is 23.764 standard errors over zero (0). The regression weight estimate, 10.984, has a standard error of about 0.462. When PdM goes up by one (1), AMMP goes up by one (1)0.984.

Table 7: Estimate maximum regression weights

Estimates (Group number 1 - Default model)
Scalar Estimates (Group number 1 - Default model)
Maximum Likelihood Estimates
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
PdM	<---	Rtime	0.015	0.02	0.711	0.477
CMB	<---	Rtime	-0.132	0.158	-0.835	0.404
PPM	<---	Rtime	-0.02	0.712	-0.028	0.978
PdM	<---	Monitoring	-0.069	0.035	-1.976	0.048
CMB	<---	Monitoring	0.284	0.27	1.051	0.293
PdM	<---	DataRecords	-0.013	0.054	-0.25	0.802
CMB	<---	DataRecords	0.493	0.417	1.182	0.237
PPM	<---	Monitoring	0.688	1.214	0.567	0.571
PPM	<---	DataRecords	-2.651	1.873	-1.415	0.157
PdM	<---	Immutability	0.107	0.009	11.404	***
CMB	<---	Immutability	0.101	0.072	1.389	0.165
PPM	<---	Immutability	0.192	0.326	0.59	0.555
PdM	<---	Consensus	-0.003	0.008	-0.367	0.714
CMB	<---	Consensus	-0.026	0.058	-0.438	0.661
PPM	<---	Consensus	0.177	0.263	0.673	0.501
PdM	<---	Security	0	0.013	0.02	0.984
CMB	<---	Security	-0.424	0.099	-4.278	***
PPM	<---	Security	-0.45	0.446	-1.01	0.313
CMB	<---	Trust	-0.267	0.35	-0.762	0.446
PPM	<---	Trust	-1.925	1.573	-1.224	0.221
PdM	<---	ReduceRisk	-0.006	0.003	-1.998	0.046
PdM	<---	Trust	0.237	0.045	5.244	***
PPM	<---	ReduceRisk	-0.111	0.103	-1.084	0.278
CMB	<---	ReduceRisk	0.02	0.023	0.883	0.377
PPM	<---	Transparency	-0.055	0.104	-0.523	0.601
CMB	<---	Transparency	-0.001	0.023	-0.024	0.981
PdM	<---	Transparency	0.002	0.003	0.582	0.561
Cost	<---	PdM	-0.258	0.182	-1.417	0.157
OptimPerformance	<---	PdM	0.733	0.154	4.77	***
Cost	<---	CMB	0.062	0.045	1.373	0.17
Cost	<---	PPM	0.005	0.011	0.507	0.612
OptimPerformance	<---	CMB	0.114	0.038	2.975	0.003
OptimPerformance	<---	PPM	0.01	0.009	1.148	0.251
BCTDT	<---	Cost	0.003	0.033	0.105	0.917
BCTDT	<---	OptimPerformance	0.009	0.039	0.225	0.822
BCTDT	<---	PdM	0.574	0.07	8.197	***
BCTDT	<---	PPM	0.001	0.004	0.18	0.857
BCTDT	<---	CMB	-0.009	0.016	-0.57	0.568
AMMP	<---	BCTDT	-2.958	0.53	-5.586	***
AMMP	<---	PdM	10.984	0.462	23.764	***
AMMP	<---	PPM	-0.02	0.021	-0.96	0.337

The probability of reaching a critical ratio as large as 23.764 in absolute value is less than 0.001. In other words, the regression weight for PdM in the prediction of AMMP is notably different from zero at the 0.001 level (two-tailed). These assertions are approximately factual for large samples under appropriate assumptions. The justification is that in this model output, some factors are positive, while some are negative and statistically significant to the dependent variable. The negative aspects are combined with the asset management activities and BCTDT factors. Thus, the coefficients were positive. PdM was a positive and significant (b = .10.984, s.e = .462, p = .000) predictor of positive coping; CBM was a positive and significant (b = .114, s.e = .038, p = .003) predictor of positive coping; and BCTDT was a positive and significant (b = -2.958, s.e = .53, p = .000) predictor of positive coping.

Immutability was positive and significant (b = .1077 s.e .009, p .000); Security was positive and significant (b = -.424, s.e .009. p .000). Reduce risk (b = -.006, s.e .003, p 0.046, and trust was positive and significant (b = .237, s.e .045, p .000).

In contrast, PPM was a negative and significant (b = -.02, s.e = .021, p = 0.337) predictor of negative coping, whereas Optima performance was a negative and significant (b = -.009, s.e = .039, p = 0.822) predictor of negative coping, the cost was negative and significant (b = -.003, s.e = .033, p = 0.917) predictor of negative coping,

4.3. Standardised regression weights model

These are standardised path coefficients, which are interpreted as beta coefficients in the context of ordinary least squares (OLS) regressions (Huang et al., 2024). They estimate the coefficients of linear regression equations that describe the relationship between independent quantitative variables and the dependent variable.

Table 8 represents the degree of change in the dependent variable (AMMP), characterised by the standard deviation (SD) units of change in the independent variables.

For instance, the standardised regression in this model is less than one (1) value, which theoretically enables a direct comparison of the outcome of the several independent variables on the dependent variable, irrespective of the units of measurement. When real-time goes up by one (1) standard deviation, PdM goes up by 0.034 standard deviations. When DataRecords goes up by one (1) standard deviation, CMB goes up by 0.105 standard deviations, and when real-time goes up by one (1), PPM goes down by 0.003 standard deviations. Moreover, as shown in Table 7, the estimates resulting from this model's regression analysis (Ratner, 2009) are based on primary data that have been standardised to ensure the variances of both independent and dependent variables are equal to one (1).

Table 8 Standardised regression weights

			Estimate
PdM	<---	Rtime	0.034
CMB	<---	Rtime	-0.077
PPM	<---	Rtime	-0.003
PdM	<---	Monitoring	-0.094
CMB	<---	Monitoring	0.096
PdM	<---	DataRecords	-0.012
CMB	<---	DataRecords	0.105
PPM	<---	Monitoring	0.056
PPM	<---	DataRecords	-0.135
PdM	<---	Immutability	0.659
CMB	<---	Immutability	0.154
PPM	<---	Immutability	0.071
PdM	<---	Consensus	-0.017
CMB	<---	Consensus	-0.04
PPM	<---	Consensus	0.066
PdM	<---	Security	0.001
CMB	<---	Security	-0.385
PPM	<---	Security	-0.098
CMB	<---	Trust	-0.087
PPM	<---	Trust	-0.151
PdM	<---	ReduceRisk	-0.096
PdM	<---	Trust	0.312
PPM	<---	ReduceRisk	-0.108
CMB	<---	ReduceRisk	0.081
PPM	<---	Transparency	-0.054
CMB	<---	Transparency	-0.002
PdM	<---	Transparency	0.029
Cost	<---	PdM	-0.134
OptimPerformance	<---	PdM	0.398
Cost	<---	CMB	0.13
Cost	<---	PPM	0.048
OptimPerformance	<---	CMB	0.248
OptimPerformance	<---	PPM	0.095
BCTDT	<---	Cost	0.008
BCTDT	<---	OptimPerformance	0.019
BCTDT	<---	PdM	0.657
BCTDT	<---	PPM	0.013
BCTDT	<---	CMB	-0.043
AMMP	<---	BCTDT	-0.254
AMMP	<---	PdM	1.081
AMMP	<---	PPM	-0.033

This assertion is based on the concern that a standardised regression greater than one (1) raises questions about the legitimacy of the coefficients and issues with interpretation (Miles and Shevlin, 2000). Therefore, when PdM goes up by one (1) standard deviation, AMMP goes up by one (1).081 standard deviation. In comparison, when PdM goes up by one (1) standard deviation, BCTDT goes up by 0.657 standard deviations, and when PdM goes up by one (1) standard deviation, Optima performance goes up by 0.398 standard deviation.; including when PdM goes up by one (1) standard deviation, cost goes down by 0.134 standard deviations. Thus, the accepted range of the standardised regression coefficients is between zero (0) and one (1) or zero (0) and minus one (-1), depending on the direction of the relationship (Ratner 2009; Nieminen 2022). The nearer the standardised regression coefficient value is to one (1) or minus one (-1), the stronger and better the relationship.

Table 9 provides an estimation of the covariance between factors and measurement errors for the negatively expressed independent variables, which are modelled to capture the likely approach. Additionally, it indicates the covariance, which, according to the model, is represented by a double-headed arrow used to depict the covariance between the variables, also linking the error term icon in the AMOS regression analysis.

In the covariance between trust and real-time, the probability of finding a critical ratio as large as 2.468 in absolute value is .014. In other words, the covariance between real-time and trust is meaningfully different from zero (0) at the 0.05 level (two-tailed). Additionally, in the covariance between monitoring and real-time, the probability of reaching a critical ratio as large as 2.226 in absolute value is 0.026.

In other words, the covariance between real-time and monitoring is significantly different from zero at the 0.05 level (two-tailed). These reports are accurate for large samples under suitable assumptions, provided that the variable's relationships to blockchain technology features are taken into account.

Furthermore, there is a covariance between immutability and trust, as the probability of obtaining a critical ratio as large as 5.472 in absolute value is less than 0.001. In other words, the covariance between trust and immutability is significantly different from zero at the 0.001 level (two-tailed). These assertions are correct for large samples, provided suitable assumptions are made regarding the benefits of blockchain technology in asset maintenance management. There is a covariance between transparency and real-time, as the probability of obtaining a critical ratio as large as 3.209 in absolute value is approximately 0.001. In other words, the covariance between transparency and reduced risk is significantly different from zero at the 0.001 level (two-tailed). These contentions are nearly accepted for large samples under appropriate assumptions and a p-value of 0.05, which is considered acceptable.

Table 9 Covariance

			Estimate	S.E.	C.R.	P
Transparency	<-->	Rtime	-0.105	0.058	-1.825	0.068
Rtime	<-->	ReduceRisk	-0.024	0.055	-0.439	0.661
Rtime	<-->	Trust	0.011	0.005	2.468	0.014
Rtime	<-->	Security	-0.01	0.012	-0.827	0.408
Rtime	<-->	Consensus	-0.017	0.021	-0.806	0.42
Rtime	<-->	Immutability	0.035	0.021	1.634	0.102
Rtime	<-->	DataRecords	0	0.003	0.107	0.915
Rtime	<-->	Monitoring	0.011	0.005	2.226	0.026
Transparency	<-->	Monitoring	-0.056	0.034	-1.666	0.096
ReduceRisk	<-->	Monitoring	-0.04	0.032	-1.226	0.22
Trust	<-->	Monitoring	0.006	0.003	2.285	0.022
Security	<-->	Monitoring	0.003	0.007	0.392	0.695
Consensus	<-->	Monitoring	-0.015	0.013	-1.157	0.247
Immutability	<-->	Monitoring	0.014	0.012	1.116	0.264
DataRecords	<-->	Monitoring	0	0.002	0.004	0.997
Transparency	<-->	DataRecords	0.032	0.021	1.517	0.129
ReduceRisk	<-->	DataRecords	0.009	0.02	0.445	0.656
Trust	<-->	DataRecords	-0.002	0.002	-1.022	0.307
Security	<-->	DataRecords	0	0.005	0.077	0.939
Security	<-->	Immutability	-0.054	0.033	-1.639	0.101
Consensus	<-->	Immutability	-0.073	0.057	-1.29	0.197
Trust	<-->	Immutability	0.076	0.014	5.472	***
ReduceRisk	<-->	Immutability	0.06	0.146	0.41	0.681
Transparency	<-->	Consensus	0.323	0.156	2.071	0.038
Security	<-->	Consensus	0.063	0.034	1.848	0.065
Trust	<-->	Consensus	-0.004	0.012	-0.322	0.747
ReduceRisk	<-->	Consensus	0.139	0.149	0.935	0.35
Trust	<-->	Security	-0.01	0.007	-1.44	0.15
ReduceRisk	<-->	Security	0.061	0.086	0.705	0.481
Transparency	<-->	Security	-0.06	0.089	-0.679	0.497
ReduceRisk	<-->	Trust	0.028	0.031	0.885	0.376
Transparency	<-->	Trust	0.009	0.032	0.297	0.767
Consensus	<-->	DataRecords	-0.007	0.008	-0.879	0.379
Immutability	<-->	DataRecords	-0.01	0.008	-1.274	0.203
Transparency	<-->	Immutability	-0.014	0.15	-0.094	0.925
Transparency	<-->	ReduceRisk	1.331	0.415	3.209	0.001

Subsequently, the test of covariance in Table 8 between the real-time and trust characteristics of BCTDT was significant ($p < .014$), indicating that an increase in the real-time escalation variable is associated with an increase in the trust variable. Accordingly, the two variables can be observed to have a positive covariance.

The probability of attaining a critical ratio (C.R.) as large as 2.468 in absolute value is .14. For instance, the covariance between real-time and trust is significantly different from zero (0) at the 0.05 level (2-tailed). These assertions are approximately correct for large samples under suitable assumptions (Kline, 2016), which suggests that hypothesis testing procedures, confidence intervals, and claims for efficiency in maximum likelihood or generalised least squares estimation by SPSS AMOS depend on certain statistical distribution assumptions.

Similarly, the probability of attaining a critical ratio (C.R.) as large as 2.285 in absolute value is .022. This statement signifies that the covariance between trust and monitoring is significantly different from zero (0) at the 0.05 level (2-tailed. Additionally, the probability of getting a C.R. as large as 5.472 in absolute value is less than 0.001.

This output indicates that the covariance between trust and immutability is significantly different from zero at a 0.001 (2-tailed) level. The probability of getting a critical ratio as large as 2.071 in absolute value is .038. The covariance between Transparency and Consensus is substantially different from zero at the 0.05 level (two-tailed). The probability of finding a critical ratio as large as 3.209 in absolute value is .001. Specifically, the covariance between Transparency and ReduceRisk is significantly different from zero at the 0.001 level (two-tailed).

For instance, the real-time and trust variables, which are key characteristics of blockchain and digital twins, significantly influence asset management activities. These variables impact asset visibility, functionality, performance, and sustainability, thereby demonstrating the practical relevance of the research. Similarly, the positive covariance between trust and immutability suggests that these variables tend to move in the same direction, further underlining the practical implications of the research.

The research concludes that the covariance of this model specifies the values within the accepted range as minus (-1) and 1.1, representing a perfect positive linear relationship, minus one (-1) representing a perfect negative linear relationship, and zero (0) signifies no linear relationship. Therefore, there is a correlated error between the variables.

In contrast, the probability of getting a critical ratio as large as 1.634 in absolute value is .102. In a simple explanation, the covariance between Real-time and Immutability is not substantially different from zero at the 0.05 level (two-tailed). The probability of finding a critical ratio as large as 1.666 in absolute value is .096. In a simple explanation, the covariance between Transparency and Monitoring is not substantially different from zero at the 0.05 level (two-tailed).

The probability of obtaining a ratio as large as 1.022 in absolute value is .307. In addition, the covariance between Trust and DataRecords is not notably different from zero at the 0.05 level (two-tailed). The probability of finding a critical ratio as large as 0.297 in absolute value is .767. Put differently, the covariance between Transparency and Trust is not significantly different from zero (0) at the 0.05 level (two-tailed).

Table 10 contains the correlations between the factors and between the errors for the positively and negatively worded variables. For instance, -.178 is the estimated correlation between transparency and real-time, 0.243 is the estimated correlation between real-time and trust, and 0.000 is the estimated correlation between data records and monitoring.

Thus, the correlations between the independent variables (exogenous) and the dependent variables pointed toward them, as the disturbance terms are known as prediction errors. From the correlation, .000 is the estimated correlation between data records and monitoring. .010 is the estimated correlation between Real-time and data records. .028 is the estimated correlation between Transparency and Trust. 031 is the estimated correlation between Trust and Consensus. .007 is the estimated correlation between Security and DataRecords. .039 is the estimated correlation between ReduceRisk and Immutability. -.009 is the estimated correlation between Transparency and Immutability.

Furthermore, the estimated correlation between transparency and monitoring is- .162. .108 is the estimated correlation between immutability and monitoring. -.124 is the estimated correlation between Consensus and Immutability. -.077 is the estimated correlation between real-time and consensus. 0.010 is the estimated correlation between real-time and data records. .028 is the estimated correlation between Transparency and Trust. 0.224 is the estimated correlation between trust and monitoring. .202 is the estimated correlation between transparency and consensus. 0.043 is the estimated correlation between reduced risk and data records. .090 is the estimated correlation between reduced risk and consensus. .085 is the estimated correlation between reduced risk and trust.

Table 10 Correlations

			Estimate
Transparency	<-->	Rtime	-0.178
Rtime	<-->	ReduceRisk	-0.042
Rtime	<-->	Trust	0.243
Rtime	<-->	Security	-0.079
Rtime	<-->	Consensus	-0.077
Rtime	<-->	Immutability	0.159
Rtime	<-->	DataRecords	0.01
Rtime	<-->	Monitoring	0.218
Transparency	<-->	Monitoring	-0.162
ReduceRisk	<-->	Monitoring	-0.118
Trust	<-->	Monitoring	0.224
Security	<-->	Monitoring	0.038
Consensus	<-->	Monitoring	-0.111
Immutability	<-->	Monitoring	0.108
DataRecords	<-->	Monitoring	0
Transparency	<-->	DataRecords	0.147
ReduceRisk	<-->	DataRecords	0.043
Trust	<-->	DataRecords	-0.098
Security	<-->	DataRecords	0.007
Security	<-->	Immutability	-0.159
Consensus	<-->	Immutability	-0.124
Trust	<-->	Immutability	0.615
ReduceRisk	<-->	Immutability	0.039
Transparency	<-->	Consensus	0.202
Security	<-->	Consensus	0.18
Trust	<-->	Consensus	-0.031
ReduceRisk	<-->	Consensus	0.09
Trust	<-->	Security	-0.139
ReduceRisk	<-->	Security	0.068
Transparency	<-->	Security	-0.065
ReduceRisk	<-->	Trust	0.085
Transparency	<-->	Trust	0.028
Consensus	<-->	DataRecords	-0.085
Immutability	<-->	DataRecords	-0.123
Transparency	<-->	Immutability	-0.009
Transparency	<-->	ReduceRisk	0.323

Therefore, it is estimated that the predictors of BCTDT explain 43.6% of its variance. In contrast, the error variance of BCTDT is approximately 56.4% of the variance of BCTDT itself, as presented in Table 11. This result indicates that the error variance of AMMP is approximately 12.7% of the variance of AMMP itself. It is estimated that the predictors of PdM explain 78.2% of its variance. The error variance of PdM is approximately 21.8 per cent of the variance of PdM itself.

The squared multiple correlations, as presented in Table 11, are equivalent to R-squared, as these are provided for all endogenous (dependent) variables within the model, where the endogenous variables are specified as outcomes of other variables in the model. It is estimated that the predictors of AMMP explain 87.3% of its variance.

Table 11 Squared multiple correlations

	Estimate
PPM	0.066
CMB	0.194
PdM	0.782
OptimPerformance	0.251
Cost	0.034
BCTDT	0.436
AMMP	0.873

It is estimated that the predictors of Optima performance explain 25.1% of its variance. Generally, the error variance of Optima performance is approximately 74.9% of the variance of Optima performance itself. It is estimated that the predictors of cost explain 3.4% of its variance. In other words, the error variance of cost is approximately 96.6 per cent of the variance of cost itself. It is estimated that the predictors of PPM explain 6.6% of its variance.

This result indicates that PPM's error variance accounts for approximately 93.4% of its total variance. The predictors of CMB are estimated to explain 19.4% of its variance. Therefore, CMB's error variance is approximately 80.6% of its variance.

Cost is specified as a predictor of positive coping; the model accounts for approximately 0.033 x 100% = 3.3% % of the variance in positive coping. Optimal performance is specified as a predictor of positive coping; the model can say that it accounts for approximately 26.1% of the variance in positive coping. BCTDT is defined as a predictor of positive coping; the model can say that it accounts for approximately 43.5% of the variance in positive coping.

The standardised estimate loadings in Model Figure 4 are the correlations between the indicator variables represented in box forms. In contrast, the double-headed arrows between the boxes represent the correlation between each pair of boxes. In this model, the correlation between CMB and PPM is r = 0.11, whereas the correlation between PPM and PdM is r = -0.03. The correlation between CMB and PdM is r = 0.17.

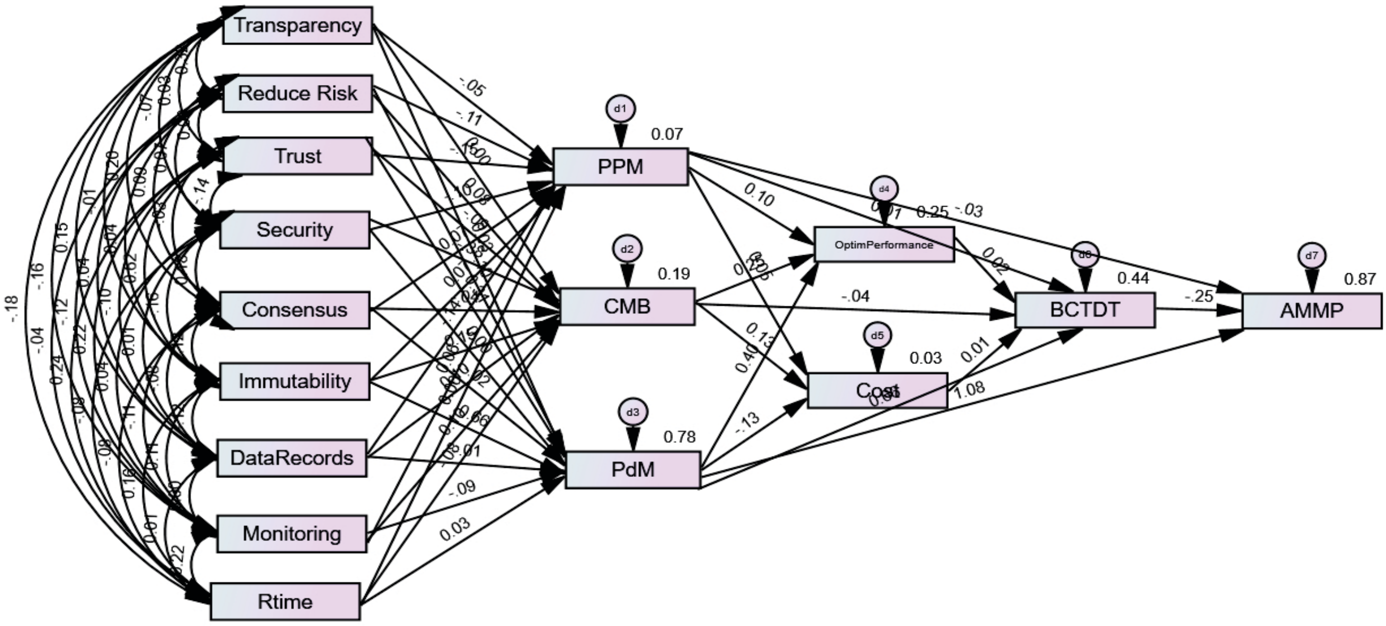

Figure 4 Standardised estimate

From Figure 4, AMMP = (0.46) BCTDT + () d7; BCTDT = (-.04) CMB + (0.01) Cost + () d6 + (0.02) Optimisation and performance + (0.66) PdM + (0.01) PPM; CMB = (-.04) Consensus + (0.10) DataRecords + (0.15) Immutability + (0.00) Transparency + () d2 + (0.10) Monitoring + (0.08) ReduceRisk + (-.08) Real-time + (-.38) Security + (-.09) Trust; Cost = (0.13) CMB + () d5 + (-.13) PdM + (0.05) PPM; Optimisation and performance = (0.25) CMB + () d4 + (0.40) PdM + (0.10) PPM; PdM = (-.02) Consensus + (0.66) Immutability + () d3 + (-.01) DataRecords + (-.09) Monitoring + (-.10) ReduceRisk + (0.03) Real-time + (0.00) Security + (0.03) Transparency + (0.31) Trust; PPM = (0.07) Consensus + (-.10) Security + (-.05) Transparency + (-.15) Trust + () d1 + (-.14) DataRecords + (0.07) Immutability + (0.06) Monitoring + (-.11) ReduceRisk + (0.00) Real-time.

These outcomes align with Chicco et al.'s (2021) assertion that a correlation coefficient greater than zero (0) signifies a positive relationship, while less than zero (0) indicates a negative relationship. Therefore, both positive and negative coping were independent variable predictors of AMMP; the model can say that these predictors jointly describe 0.874 × 100% = 87.4% of the variation in AMMP.

Standardised residuals can be managed by identifying the likely address of model misspecification. According to Byrne (2010), this description of standardised residuals posits that these residuals can be considered analogous to z-scores, noting that larger standardised residuals can indicate the likely misspecification of the model between two variables.

This assertion by Byrne (2010) regarding standardised residuals was supported by Whittaker (2016), suggesting further investigation of standardised residuals with an absolute value greater than 1.96. In contrast, those with an absolute value greater than 2.58 are considered significant (Byrne, 2010).

In the standardised residuals, the model perceives the most significant residuals for the CMB and PPM, which may suggest model misspecification that has created observed discrepancies in the covariances involving PdM, BCTDT, and AMMP. However, as a suggestion for modification indices, adding a path from the PPM to Optima performance and CMB to cost, and AMMP can review the standardised residuals.

This suggestion arises as a re-specification that capitalises on the chance characteristics of the model data; thus, the justification for the highly significant consideration in re-modelling and re-specification based on empirical criteria, and to ensure that the changes are implemented in accordance with a given theory or concept.

Additionally, in Figure 5, the unstandardised coefficients include the outcomes concerning the variance and the means that support the model's predictions. They also assist in interpreting the effects of independent variables on dependent variables.

AMMP = (5.34) BCTDT + (1) d7; BCTDT = (-.01) CMB + (0.00) Cost + (1) d6 + (0.01) Optimisation and performance + (0.57) PdM + (0.00) PPM; CMB = (-.03) Consensus + (0.49) DataRecords + (0.10) Immutability + (0.00) Transparency + (1) d2 + (0.28) Monitoring + (0.02) ReduceRisk + (-.13) Real-time + (-.42) Security + (-.27) Trust; Cost = (0.06) CMB + (1) d5 + (-.26) PdM + (0.01) PPM.

Optimisation and performance = (0.11) CMB + (1) d4 + (0.73) PdM + (0.01) PPM; PdM = (0.00) Consensus + (0.11) Immutability + (1) d3 + (-.01) DataRecords + (-.07) Monitoring + (-.01) ReduceRisk + (0.01) Real-time + (0.00) Security + (0.00) Transparency + (0.24) Trust; PPM = (0.18) Consensus + (-.45) Security + (-.05) Transparency + (-1.92) Trust + (1) d1 + (-2.65) DataRecords + (0.19) Immutability + (0.69) Monitoring + (-.11) ReduceRisk + (-.02) Real-time.

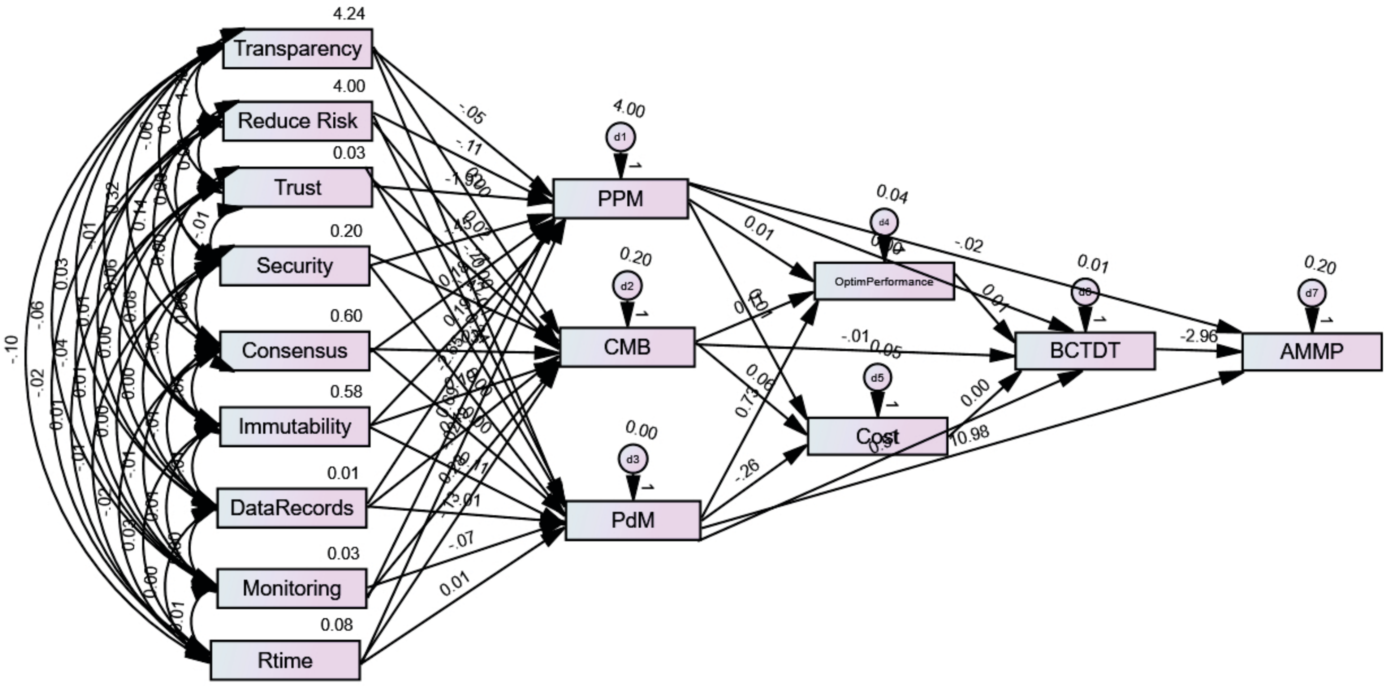

Figure 5: Unstandardised estimate

These unstandardised regression coefficients show how the change in the dependent variable (Y) was predicted and estimated to occur per unit change in the independent variable of PdM when all the other independent variables (CBM, PMM, Optima performance and costs) are held constant.

Additionally, with the unstandardised factor loading, the loading estimate fixed at 1.0 does not include a significance test; rather, the remaining test results pertain to the unstandardised factor loadings. In this model output, five (5) of the estimated factor loadings have accepted p-values and are positive and statistically significant and affect asset maintenance management practices.

5. Discussion on the adoption of blockchain and digital twin technology

Blockchain and digital twin technologies can offer several technical solutions to address the issues currently faced in asset maintenance management activities within the research context. As observed from the data, the mismanagement of diesel allocation, incorrect root cause analysis reporting, and a poor maintenance culture all impact the performance and functionality of these telecommunication infrastructures and assets. Thus, technological systems, such as the blockchain and digital twin, can address these issues based on their features of trust, transparency, security, and virtual replication of physical assets.

Additionally, trust is supported by numerical algorithms and actual evidence, as blockchain and digital twin technologies provide an innovative approach that increases transparency and reduces information irregularities. For instance,

"These new technologies will help the providers to adopt a more decentralised maintenance approach that brings more trust, transparency and security, with fewer opportunities for manipulation of records concerning asset maintenance activities" (PT4). Again, *"by adopting the blockchain and digital twins technologies will enforce more ethical approach to asset maintenance management activities" (PT7)*.

Legacy issues will occur when moving from the *"conventional planned preventive maintenance strategy to the intended predictive-based approach powered by these new technologies until the field technicians become comfortable with the operations" (PT5)*.

This assertion explains the significance of the features of these intended technologies for peer-to-peer asset functionality based on real-time monitoring and escalation. However, in this research context, the organisation should consider capital expenditures related to the adoption of new technologies, as well as the long-term benefits of improving asset performance and reducing operating expenses.

5.1 Addressing the research objective

Research Objective - to investigate the potential benefits and challenges of adopting blockchain technology and digital twins for improved infrastructure asset maintenance management.

The challenges in that context are the integration of disruptive technologies that are predictive-based with the legacy (existing) assets that are reactive-based due to their outdated architectural design and process (Bakar et al., 2019). However, in some situations, these legacy systems could be upgraded to be compatible with the 4IR technology (Hoosain et al., 2020; Mpofu and Nemashakwe, 2023). This assertion is related to incompatibility concerns of legacy systems (Habiyaremye and Monaco, 2023), which state that outdated systems are often not designed or designed to integrate new technologies, thus making them incompatible with 4IR upgrades and a challenge, as indicated in Figure 6.

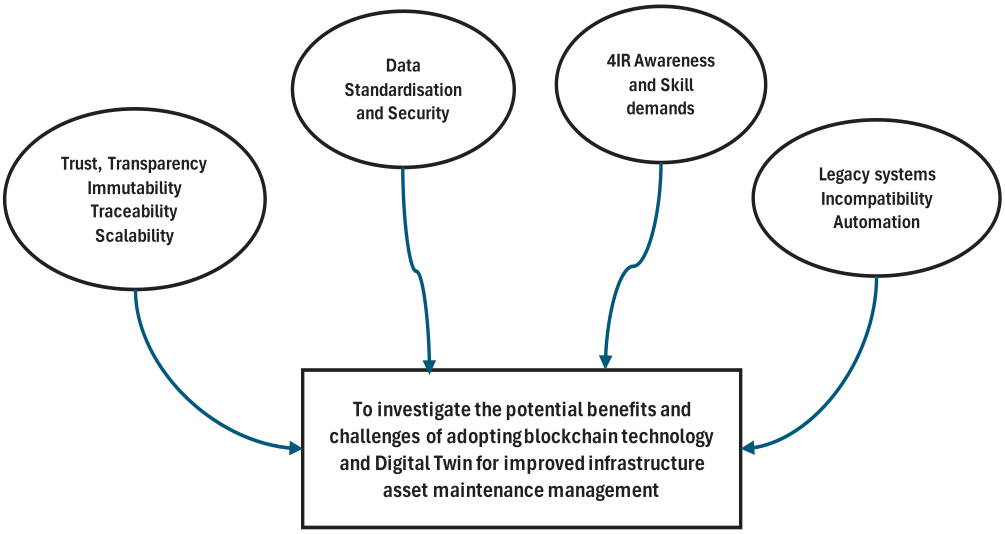

Figure 6: Addressing research objective.

Another challenge is the concern about the lack of scalability related to captured data. This concern relates to the vast amount of data required by these disruptive technologies to optimise their functionality and performance (Mamphiswana and Bekele, 2020; Manyeke, 2022). This assertion is linked to trust issues that affect maintenance activities in the research context (Lu et al., 2021), where records and information on asset maintenance management are not accurately captured. Therefore, integrating with the theme of trust, features of transparency, security, immutability, and traceability have become active in addressing these challenges.

Furthermore, the lack of skilled employees, stakeholders, and awareness is another challenge in research on the adoption of blockchain and digital twin technologies (Adepoju and Aigbavboa, 2021). Several telecom stakeholders are unaware of the potential advantages of adopting and implementing 4IR technologies and how these technologies can revolutionise their asset management practices. However, with the adoption of 4IR technologies in asset management in the research context, telecom organisations will be able to retain and upskill their field technicians and other stakeholders.

5.2 Addressing the hypothesis

Following the measurement model analysis, the research empirically examined and analysed the research hypotheses using the structural equation modelling (SEM) of SPSS AMOS analytical tools. Figures 5 and 6 in the model show the results of the structural equation modelling. This decision was based on Romano et al. (2010)'s suggestion for hypothesis testing, where the researchers estimated the coefficient of determination (R-squared) and the path coefficient, along with their corresponding t-values. The R-squared values for the endogenous variables (Asset maintenance management practices) exhibited adequate explanatory power for our model.

The hypotheses predict a strong relationship between blockchain technology, digital twin, and predictive-based maintenance. The research tested the hypotheses using the SPSS regression analysis to evaluate and compute the coefficient for the individual effects of blockchain technology and digital twin features on asset maintenance management practices. The results suggest a strong and positive relationship between predictive maintenance ($\beta = 1.041$; $p < .001$) and blockchain technology, as well as a negative and significant relationship between predictive maintenance and digital twin ($\beta = -.254$, $p < .001$). These results suggest that incorporating blockchain technology and digital twin systems into predictive maintenance approaches in asset maintenance management practices can enhance asset performance, maintain network availability, and reduce operating expenditures.

6. Conclusion, contribution, implications and direction of future research

4IR technologies in the management of distributed telecoms infrastructure assets have been evolving because of the innovative capabilities of these disruptive technologies. Implementing 4IR technologies, such as blockchain and digital twin technologies, in the management of distributed infrastructure assets enhances functionality, real-time fault escalation and visibility, performance, and lifecycle management. This framework includes a detailed approach to addressing energy supply challenges, utilising BCT and DT features and approaches to analyse key specific asset maintenance activities.

6.1 Research Contribution of knowledge to practice

Given the research background, overview, and context in Chapter One, the researcher, as an asset management practitioner in the telecom industry, developed a strong relationship with the telecom tower organisations in the research context. Thus, the researcher gained an understanding of the research terrain and stakeholders through industrial knowledge and perspective on the research subject.

Accordingly, the research contributed to the practice using 4IR technology, specifically adopting blockchain and digital twin capabilities and features in asset maintenance management practices, such as:

- Bridges the gap by analysing blockchain and digital twin technology-enabled decentralised systems to enhance operational efficiency and leveraging these technologies for the automation of asset maintenance activities.
- By eliminating manual processes and intermediaries, and improving transparency, asset maintenance management activities reduce intermittent outages and degradation, thereby enhancing network power availability.

Furthermore, the core use of this developed blockchain and digital twin technologies framework in managing distributed telecom assets is expected through the complete asset maintenance activities of asset management practices. Thus, it is helpful for asset practitioners, field technicians, network operations centre technicians, operations managers, and supervisors. However, the application of the developed framework is expected to occur through an overview of the adoption of 4IR technologies, such as blockchain and digital twin technologies, in the organisation's asset management practices by its decision-making team.

6.2 Implications on the maintenance of distributed telecoms assets

The management of distributed telecom assets in the explored research context has shown similarities and distinctions across developing countries due to recurring themes of infrastructure deficiencies, skilled workforces, regulatory agencies, and operating environments. Thus, the adoption and implementation of 4IR technologies, including blockchain and digital twin technologies, offer significant possibilities for advancing the management of distributed assets in the telecom industry of developing countries. Leveraging the capabilities of blockchain and digital twin technologies within the 4IR, asset practitioners and field technicians can benefit from enhanced transparency, security, asset visibility, and replication of maintenance or functionality activities, as well as improved effectiveness and efficiency, and enhanced asset monitoring, tracking, and traceability. This conclusion is based on the insight that blockchain technology provides a decentralised and tamper-proof database, ensuring transparent and trustworthy records. This allows asset practitioners and field technicians to access reliable data to support their decision-making processes.

Blockchain technology also provides automation and decentralising features, which can rationalise and modernise asset management processes, minimising delays and related operating costs. Thus, the capability to precisely track and trace the functionality and performance of assets throughout their lifecycle. This insight enhances the accuracy of asset assessment and reduces the risk of errors in manual maintenance activities. Lastly, blockchain technology enables predictive analytics by gathering and analysing data from various asset sources, allowing asset practitioners and field technicians to predict and preempt maintenance demands and requirements, proactively resolve potential problems, and optimise asset functionality and performance, thereby reducing operating costs.

Additionally, the integration of on-chain and off-chain databases provides a complete solution to address the concern on data volumes effectively (Salah et al., 2019) because they are stored in a public and private cloud; thus, adopting 4IR technologies capabilities assists in developing a predictive maintenance strategy that is proactive, compatible with asset management processes that enable swifty real-time monitoring and escalation of asset functionality and performance. These conclusions are consistent with the collected data and the reviewed extant literature and studies.

6.3 Limitations

Given that the research also focuses on predictive-based asset maintenance data from the perspective of real-time monitoring, tracking, and escalation of outages, it could also pose some challenges in capturing the data when offline. However, with blockchain technology's transparency and traceability, offline data can be captured, while standardisation and data tagging enhance data visualisation and structuring. Therefore, addressing these issues of managing large data volumes and ensuring data integration can improve understanding and efficient operations and maintenance practices.

6.4 Future research direction

Given the evolution of the telecom tower industry in the research context, adopting and integrating 4IR technologies, such as blockchain and digital twin technologies, will be necessary to manage distributed assets in developing countries efficiently. Therefore, as a future research direction, the study recommends a strategic approach that leverages the dominance of data-driven asset management decision-making processes. Thus, as blockchain technology and the Internet of Things (IoT) converge, several promising research directions are emerging that could reshape how related distributed assets interact in secure and decentralised systems. This insight into the automation, digitalised, and intelligent automation landscape will improve network availability based on asset reliability, sustainability, and resilience. However, existing studies emphasise the need for small consensus algorithms that can operate efficiently on assets with limited computational capacities and battery limitations. For instance, real-time dynamic resource management systems that include a consensus mechanism suitable for real-time monitoring of asset maintenance management activities.

By embracing these disruptive and transformative technologies, telecom tower organisations can drive and enhance operational and maintenance efficiencies and effectiveness, sustain reliable and stable network availability, and remain customers' choice in the fast-paced landscape.

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