VILNIUS UNIVERSITY
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DEEPTECH ENTREPRENEURSHIP [6211LX013]

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MASTER'S THESIS:

THE IMPACT OF DIGITAL TRANSFORMATION AND BLOCKCHAIN MATURITY ON ORGANIZATIONAL PERFORMANCE: A CROSS-SECTORAL ANALYSIS WITH AI MATURITY AS A MEDIATING FACTOR	SKAITMENINĖS TRANSFORMACIJOS IR BLOKŲ GRANDINĖS BRANDOS POVEIKIS ORGANIZACIJŲ VEIKLOS REZULTATAMS: TARPSEKTORINĖ ANALIZĖ, DIRBTINIO INTELEKTO BRANDĄ LAIKANT TARPINE GRANDIMI

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Summary

The thesis examined the smooth inter-relationships between Digital Transformation, Artificial Intelligence (AI) Maturity, Blockchain Maturity, and Organizational Performance with the objective of learning how the emerging digital technologies can work together to create value in organizations. The study created and tested an overall conceptual model, based on digital transformation theory, technology maturity perspectives, and views of the firm as a capability based on its responsiveness to emerging digital technologies, in response to growing organizational investment in digital technologies and the lack of integrated empirical evidence on how these interact. The study gave solid empirical information on both the direct and indirect processes by which digital technologies have an impact on organizational performance using a Partial Least Squares Structural Equation Modelling (PLS-SEM) approach.

The thesis began by pinpointing a critical research gap in the available literature. Although previous research has thoroughly investigated digital transformation, AI, and blockchain as a single phenomenon, little attention has been given to their relationships and to their maturity-related impact on organizational performance. To fill these gaps, the research proposed a model that conceptualized AI and blockchain maturity as distinct yet complementary technological capabilities operating within broader digital transformation projects. It premise that digital transformation automatically entails enhanced AI capabilities has seldom been empirically validated.

A quantitative research design was employed, and a structured survey instrument was used to collect primary data. The establishment of reliability and convergent and discriminant validities was based on numerous criteria, such as factor loadings, Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), HTMT ratios, and Fornell-Larcker. The validated scales helped measure the items, thereby providing content validity. Smart-PLS was used to analyze the data, following a strict two-step process that included evaluating the measurement and structural models. The evaluation of the structural model included path coefficients, t-values, and p-values, mediation analysis, R2 values, and multi-group analysis, providing a thorough assessment of the hypotheses presented.

The study contributes to the development of theory and practice by integrating several emerging technologies into a single explanatory framework, providing a strong basis for future research on the constantly evolving field of digital transformation and organizational performance. It is concluded that the thesis presents a holistic, empirically supported

framework for the effects of digital transformation, AI maturity, and blockchain maturity on organizational performance.

Santrauka

Disertacijoje nagrinėjamas sklandus skaitmeninės transformacijos, dirbtinio intelekto (DI) brandos, blokų grandinės brandos ir organizacijos veiklos tarpusavio ryšys, siekiant išsiaiškinti, kaip besiformuojančios skaitmeninės technologijos gali veikti kartu kurdamos vertę organizacijose. Tyrime sukurtas ir išbandytas bendras konceptualus modelis, pagrįstas skaitmeninės transformacijos teorija, technologijų brandos perspektyvomis ir įmonės, kaip gebėjimo, pagrįsto jos reagavimu į besiformuojančias skaitmenines technologijas, požiūriu, reaguojant į augančias organizacijų investicijas į skaitmenines technologijas ir integruotų empirinių įrodymų apie tai, kaip šios technologijos sąveikauja, trūkumą. Tyrime pateikta tvirta empirinė informacija apie tiesioginius ir netiesioginius procesus, kuriais skaitmeninės technologijos daro įtaką organizacijos veiklos rezultatams, naudojant dalinių mažiausių kvadratų struktūrinės lygties modeliavimo (PLS-SEM) metodą.

Disertacija pradėta nustatant esminę tyrimų spragą prieinamoje literatūroje. Nors ankstesni tyrimai nuodugniai tyrė skaitmeninę transformaciją, DI ir blokų grandinę kaip vieną reiškinį, mažai dėmesio skirta jų santykiams ir su branda susijusiam poveikiui organizacijos veiklos rezultatams. Siekiant užpildyti šias spragas, tyrime pasiūlytas modelis, kuris DI ir blokų grandinės brandą apibrėžė kaip atskirus, tačiau vienas kitą papildančius technologinius pajėgumus, veikiančius platesniuose skaitmeninės transformacijos projektuose. Ši prielaida, kad skaitmeninė transformacija automatiškai reiškia patobulintas dirbtinio intelekto galimybes, retai buvo empiriškai patvirtinta.

Buvo naudojamas kiekybinis tyrimo planas, o pirminiams duomenims rinkti – struktūrizuota apklausos priemonė. Patikimumas ir konvergentinis bei diskriminantinis validumas buvo nustatyti remiantis daugybe kriterijų, tokių kaip faktorių įkrovos, Cronbacho alfa, sudėtinis patikimumas, vidutinės dispersijos ekstrakcija (AVE), HTMT santykiai ir Fornell-Larcker. Patvirtintos skalės padėjo išmatuoti elementus, taip užtikrinant turinio validumą. Duomenims analizuoti buvo naudojamas Smart-PLS, laikantis griežto dviejų pakopų proceso, kuris apėmė matavimo ir struktūrinių modelių vertinimą. Struktūrinio modelio vertinimas apėmė kelio koeficientus, t ir p reikšmes, mediacijos analizę, R2 reikšmes ir daugiagrupę analizę, pateikiant išsamų pateiktų hipotezių vertinimą.

Tyrimas prisideda prie teorijos ir praktikos plėtros, integruodamas kelias naujas technologijas į vieną aiškinamąjį pagrindą, suteikdamas tvirtą pagrindą būsimiems tyrimams nuolat besikeičiančioje skaitmeninės transformacijos ir organizacijų veiklos srityje. Apibendrinant

galima teigti, kad darbe pateikiama holistinė, empiriškai pagrįsta skaitmeninės transformacijos, dirbtinio intelekto brandos ir blokų grandinės brandos poveikio organizacijos veiklos rezultatams vertinimo sistema.

Raktiniai žodžiai: dirbtinio intelekto branda, organizacijos veiklos rezultatai, skaitmeninė transformacija, blokų grandinės branda.

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Chapter 1

Introduction

1.1 Chapter Introduction

Digital transformation (DT) is reshaping how organizations redesign processes, services, and decision-making by leveraging digital technologies as a strategic response to disruption (Vial 2019). In healthcare, DT is especially consequential because operational efficiency, data quality, and service outcomes are tightly coupled, yet implementation is fragmented across stakeholders and units (Kraus et al., 2021). At the same time, blockchain is increasingly examined as an infrastructure for integrity, traceability, and trusted data exchange capabilities that align strongly with healthcare's privacy and coordination demands (Araújo et al., 2022). However, "technology adoption" alone rarely translates into performance unless the organization develops complementary capabilities to sense opportunities, reconfigure routines, and scale learning across functions (Teece, 2007). This study addresses that gap by linking digital transformation and block chain maturity to organizational performance, while positioning AI maturity as a mechanism that helps convert technology maturity into measurable value. The logic is resource-based organizations gain performance advantages when technology-related resources and capabilities become valuable and deployable at scale. The logic is resource-based: organizations gain performance advantages when technology-related resources and capabilities become valuable and deployable at scale (Barney, 1991). AI maturity is treated not merely as "having AI tools" but as organizational readiness data, skills, governance, and integration that determines whether digital initiatives produce superior outcomes (Mikalef & Gupta, 2021). By combining DT, blockchain maturity, and AI maturity in one integrated framework, the study aims to explain not only whether technology maturity matters, but how and where it becomes performance-improving in a complex healthcare organization. The expected contribution is actionable: informing investment sequencing (DT → data readiness → AI maturity), governance priorities, and capability-building pathways that are specific to functional realities inside hospital.

This study is relevant because healthcare digitalization often produces uneven results across departments, and leaders need evidence on which maturity dimensions translate into performance. It is timely due to growing interest in blockchain-enabled data integrity and interoperability in healthcare settings. It is practically significant by clarifying AI maturity as a value-realization pathway rather than a standalone trend.

1.2   Object of the Research

The object of the paper is an integrated, theory-informed examination of the relationships among digital transformation, blockchain maturity, AI maturity, and organizational performance in a hospital context, including whether these relationships differ across functional domains treated as internal sectors within one organization.

1.2.1   Aim of the Study

To investigate how digital transformation and blockchain maturity influence organizational performance in a healthcare organization, and to determine whether AI maturity mediates these relationships, including potential differences across functional domains.

1.2.2   Objectives of the Study

1. Measure DT, BM, AIM, and OP using validated multi-item constructs and consistent scaling.
2. Test the direct effects of DT and BM on OP using structural modelling.
3. Test whether AIM mediates the DT $\rightarrow$ OP and BM $\rightarrow$ OP relationships via bootstrapped indirect effects.
4. Compare structural path differences across functional domains using multi-group analysis (MGA).
5. Translate results into actionable recommendations for capability building, governance, and investment prioritization in healthcare digitalization.

1.3   Research Methods

Methodologically, the research follows a positivist, deductive quantitative approach and uses a cross-sectional survey within a single-case study design with embedded units of analysis. The target organization is Bahawal Victoria Hospital in Bahawalpur, Pakistan, with five embedded functional domains serving as comparative internal sectors. Data were collected via structured questionnaires administered through both Google Forms and paper-based distribution to accommodate departmental access constraints; the final usable sample is N=204 employees stratified across the five domains, and the instrument includes five items each for DT, blockchain maturity, AI maturity, and organizational performance on five-point Likert scales. Instrument rigor includes expert review and pilot testing (n=30) with reliability checks before full deployment. Analysis proceeds with SPSS for screening and preliminary statistics, then SmartPLS 4 for PLS-SEM measurement and structural assessment, mediation testing via bootstrapping (5,000 resamples), and multi-group analysis across domains an approach aligned

with established PLS-SEM reporting guidance

1.4 Structure of the Work

The work is organized to move from foundations to testing and implications: it begins with an introductory framing of digital transformation, emerging technologies, and performance issues; then develops the conceptual framework and hypotheses (including domain-variation hypotheses); next details the research methodology (case context, sampling, measurement development, data collection, and PLS-SEM procedures); then reports results (measurement model, structural paths, mediation, and multi-group differences); and finally discusses implications, conclusions, limitations, and directions for future research.

1.5 Difficulties and Limitations

This study is limited by its cross-sectional design, so the results indicate associations rather than confirmed causality. Because the data come from a single hospital and use self-reported survey measures, the findings may not fully generalize to other healthcare settings and may be influenced by common method bias or respondent perception differences across departments. In addition, subgroup (domain) comparisons can have lower statistical power because each group has a smaller sample size.

1.6 Declaration due to AI tools

This document may be prepared with AI-based writing support tools used strictly for language polishing (grammar, clarity, cohesion, and formatting). AI tools were not used to invent data, fabricate citations, generate survey responses, manipulate statistical outputs, or replace the author's methodological decisions and interpretation. Full responsibility for the study design, data collection, analysis steps, findings, and academic integrity remains with the author.

Chapter 2

Literature Review

2.1 OVERVIEW OF THE FOUNDATIONS OF DIGITAL TRANSFORMATION AND EMERGING TECHNOLOGIES

This chapter, we initiate a theoretical underpinning of the digital transformation, blockchain maturity, artificial intelligence adoption, and organizational performance in the context of highly topical macro-economic developments happened in the current business sphere. This chapter contributes conceptual bases for the combined framework devised in Chapter 2 by synthesizing prior research in these fields.

2.2 Digital Transformation: Conceptual Framework and Organizational Implications

2.2.1 Defining Digital Transformation

Digital transformation (DT) is the deep and fundamental re-imagining of the business processes, customer interactions, and the way firms create value through business in a specific strategic-contextual milieu created by the application of a digital technology platform (Favoino et al., 2025). Digital transformation deviates from the more common adoption of IT toolsets or even broad organizational change that has its impact solely at the individual or single role level, but must also impact culture, processes, business models, and the interaction of stakeholders (Bloedorn et al., 2023).

There are various definitions of digital transformation in academic and practitioner literature. Vial (2019) defined digital transformation as "a process that seeks to make an entity better by inducing changes of a nontrivial nature to the attributes of the transformed entity by using a combination of information, computing, communication, and connectivity technologies" (Wei et al., 2025). This definition highlights transformation as a process, instead of outcome, accentuating the fluidity of digital transformation. IBM (2022) defines it as "digital transformation is a strategic initiative that digitally enhances every area of an organization by assessing and modernizing an organization's processes, products, operations and technology stack to support an environment of continuous, fast, and customer-centric strategy innovation". This lens also highlights a general and strategic view of the requirement for digital transformation.

Gopi, K. (2025) presents digital transformation as "the re-programming of an organization to bring the value through regularly organizing technology at scale," putting weight on organization restructuring & sustained tech positioning. This definition emphasizes that not only technology acceptance but also a broader, more fundamental organizational reform is part of transformation, which in turn reflects the most common section across these viewpoints, and that is the understood or explicit acknowledgment that digital transformation is much more than technology distribution and will require integrated changes to organizational strategy, operations, culture and stakeholder engagement. Digital transformation is not a project; it is a journey of being an adaptive organization embracing opportunities for digital technologies and evolution in market demand (Ramadania et al., 2024).

2.2.2 Dimensions of Digital Transformation

This research has conceptualized digital transformation, their frameworks contain some overlap; for example, framework in addition proposed four main body of facets: including use of technologies, changes in value creation, changes in structures and changes in finance; others, i.e. include business model transformation, organizational transformation and domain transformation as essential dimensions (Tracey & Ruamsook, 2021). Building upon these perspectives, this study approaches the research from a four-dimensional model:

Technology Dimension: Covers the adoption and integration of digital technologies such as cloud computing, big data analysis, Internet of Things, mobile technologies, and emerging technologies, such as blockchain and AI Technology. This dimension addresses the technological backbone that supports transformation (Putra et al., 2024).

Process Dimension: digital transformation and optimization of business processes, automation of workflows and To Make Data Driven Decision Systems. Process transformation significantly increases operational productivity and agility by optimizing business workflows (Wulandari et al., 2024).

Organizational Dimension: The modifications to org design, culture, capabilities, and governance models (Fish, 2024). This involves having digital skillsets, innovation culture, and leadership that are not afraid to lead through the change.

Business Model Dimension: The Requires a complete rethinking of your value proposition, revenue models and how you connect with customers. Transforming business models is often the most radical expression of digital change as it allows new types of organizations to play in the digital marketplace (Szczepaniuk & Szczepaniuk, 2022).

2.3 Digital Transformation Drivers and Barriers

There are several aspects that trigger organizations towards digital transformation, externally, competitive pressure from digitally native participants and more demanding customer expectations and constant technological progression makes a need to transform. The internal front of digital initiatives is driven by opportunities for efficiency improvement, potential for data driven decision making, and of course, innovation necessities (Petek et al. 2021).

The implementation of advanced technologies is also mostly challenging for small and medium enterprises due to financial restrictions. Although the resources may be in the pipeline, organizations recurrently find themselves forced to define a scattered transformation effort without following an action plan, causing each initiative to reduction short in expected value distribution (Weber & Schaper-Rinkel, 2017). Another major barrier is cultural resistance and this resistant Ness of Employees to Digital Changes, Employees used to the existing ways of working may struggle digital changes, especially when automation endangers job security. The organizations can beat these barriers but only if help from the top is matched by effective change management capabilities.

2.3.1 Digital Transformation and Organizational Performance

An abundance of research demonstrations that digital transformation positively relates to organizational performance consequences at various levels of analysis. The process Automation, shortening the cycle times and better utilization of resources lead to the operational efficiency improvement. Customer-oriented values include higher satisfaction, increased engagement, and stronger loyalty determined by better digital experiences. The organizations build capacity to create and test new products, services, and business models at speed, capabilities for innovation multiply, Fin stop the improvements from financial performance appear by refining revenue, margin enhancement as well as the opportunity of innovative revenue streams (Azzahra et al., 2025).

The performance consequences for companies digitizing themselves or their products are like digital gold, at the initial stages of transformation and organizations may temporarily experience degradation in performance as they struggle with new truths and learning curves. There is also a gap between expectations and reality in relationships with investment performance that digital transformation can achieve. How much value lies in that dream and another factor that diminishes the digital transformation-performance connection is the

organization's willingness for change. For example, size will affect both resource availability and how complicated a transformation becomes (because the larger it is, even if each change has more potential benefits than smaller changes can deliver). Different shapes of the revolution matter, too, and not all industries will undergo this metamorphosis in the same way or measure of drama, with one sector: Financial Services. The ability to orchestrate transformation itself, and to lead organizations with leaders that are both compassionate in their dealings and can. They need a clear and achievable digital vision that aligns with the organization they are running Virtual maturity. In other words, an organization's overall capability for exploiting digital technologies has a decisive bearing on its profitability regardless of how quickly we all grow tired of digital and move back to thinking in gasps again. (Kurniawan & Dachyar, 2021).

2.4   Blockchain Technology: From Innovation to Enterprise Maturity

2.4.1   Blockchain Technology Fundamentals

The blockchain is a modern technology created in 2008 when the first cryptocurrency bitcoin appeared, but its features can have other applications far away from digital currency. In simple terms, blockchain is a shared ledger technology which ensures the recording and sharing of transactions among network participants in a secure, transparent, and immutable manner (Fauzi et al., 2024). Unique features that differentiate blockchain from a traditional database are decentralization (no meta-authority to govern it), immutability of data (cannot change transactions after being recorded), transparency (all participants can view transaction history) & cryptographic security (data integrity is secured by advanced encryption). There are several blockchain architectures designed for different use cases. Public blockchains are a completely open system open to anyone and anywhere. On private blockchains, only specific entities can participate, which results in more privacy and control but may give up some of the decentralization advantages. Unlike private blockchains where access or participation is limited to a single organization, consortium blockchains are run by a limited number of organizations; therefore, their governance touches both thresholds. Enterprise blockchain platforms like Hyperledger Fabric, R3 Corda and Quorum offer tailored enterprise-ready solutions focusing on the needs of organizations by providing features like scale, privacy, and compliance with regulations. These platforms are fundamentally different from public blockchain networks, by offering permissioned access, a modular architecture, and performance optimization (Al-Ariqi & Alhakimi, 2025).

2.4.2 Blockchain Implementation Challenges

While blockchain is being put into organizations, there are many technical, organizational, and environmental challenges faced by these organizations. Technical challenges involve scalability limitation, integration complexity with legacy systems, interoperability of cross blockchain platforms, and especially energy consumption concern about public blockchains (Toufaily et al., 2021). They point to internal barriers such as the shortage of blockchain knowledge, ambiguous ROI, difficult change management, and the challenges of designing an appropriate governance structure. There are environmental hurdles such as regulatory uncertainty, lack of standardization, and network effects that require ecosystem contribution. But the implementation costs are a major problem, especially for smaller organizations. Nevertheless, organizations cannot limit themselves to just acquiring technology. A part of their investment should go for capability development, process redesign, and change management. The immaturity of blockchain talent pools and the need to pay salary premium requirements.

When a blockchain solution is being adopted, problems with data quality and standardization continuously arise. The Problem The "garbage in, garbage out" nature of blockchain If the quality of data the existing system used for transactions is challenging, it transfers over to the blockchain implementation and eventually destroys the trust benefits of blockchain. A lot of authorities have regulatory uncertainty, and this makes these players (especially those in heavily regulated sectors like the financial services and healthcare sectors) cautious. When regulatory frameworks are undefined, or change frequently, organizations have trouble implementing blockchain solutions. However, research suggests that implementing barriers is more easily realized, and value from blockchain can be considerable through systematic consideration of such obstacles.

2.5 Artificial Intelligence: Maturity Models and Organizational Readiness

Artificial Intelligence refers to technologies that allow machines to execute tasks that would typically require human intelligence like perception, learning, reasoning, problem solving, and natural language comprehension. Modern AI applications include everything from machine learning and deep learning to natural language processing, computer vision, robotic process automation, and expert systems. ML, a fundamental subdomain of AI, makes it possible for systems to develop their understanding of the data and then continuously, without

being specifically programmed, increasing performance. Recent advances in AI, especially in the fields of image recognition, language translation, and game playing, have been driven by deep learning, which uses neural networks with many layers.

2.5.1 AI Adoption Drivers and Barriers

Organizations have several reasons for why they want to adopt AI and led competitors create valid urgency from competitive pressure and especially in parts of the business where AI services can lead to dramatic improvement in customer experience or cost efficiency and thus operating profit. The ability to hard ROI justification through improved decision-making efficiency through process automation. Innovation imperatives drive enterprises to adopt AI to develop new products, create new services, and establish new business models. When organizations realize that AI and ML can convert its data assets to value, we see new opportunities open for data monetization. The ability to create a better customer experience through personalization and more intelligent service delivery has been a leading factor driving investment in customers facing AI. But there are huge roadblocks that block AI adoption. The usual challenges that arise around data quality and availability are that organizations lack sufficient quality data to train stronger models. This makes it an uphill climb for organizations that do not have the right data science and AI engineering skills and experience; such is the technical complexity. Some of this cost is associated with not just the purchasing of technology but hiring the best talent, infrastructure and change management. Two, the competitive landscape for AI talent increases salaries and makes hiring more difficult. Time-honored organizational challenges such as resistance to change, insufficient leadership-level understanding of what AI can do, and poorly defined business cases for AI investments are also at work While factors related to culture have a large influence on the adoption of AI within organizations firms with more experimental, data-driven cultures use AI more effectively than those with risk-averse, hierarchical cultures. More entanglements and hurdles come in the shape of ethics and regulatory uncertainty. Enterprises contend with bias in AI, explain ability requirements, impacts on privacy and potential impact on employees. New and developing sets of regulations such as the EU AI Act will create compliance problems and uncertainty. (Chen et al., 2024) Show that overcoming these challenges by adopting systematic processes for AI adoption provides organizations with drastic competitive edges. The tie between top management involvement, strategic clarity, and organizational change management as critical success factors.

2.5.2 AI and Organizational Performance

Extensive research demonstrates positive relationships between AI adoption and organizational performance. (Chen et al., 2024) Identify that creativity, AI-enabled management, and AI-enabled decision-making pathways mediate the positive relationship between Ai capability and firm performance. The repetitive tasks are automated, the complex processes are optimized, and the resource utilization is improved to achieve operational efficiency gains. Firms already adopting AI are obtaining productivity gains at scale, cost savings, and improvements in quality. AI systems, at scales and speeds beyond the grasp of human analysts, sort through data and detect patterns to guide more informed decisions. Predictive capability enables managed processes to be proactive rather than reactive to events as they occur. AI also enhances performance on innovation, with faster test cycles to develop new offerings and mass personalization in addition to the ability to produce solutions to complex problems that were previously impractical to solve. Enhancing customer experience with personalization, intelligent service, and proactive engagement delivers increases in satisfaction and loyalty. Ismail et al. (2025) Corroborates that the effect of AI on performance is mediated by digital leadership indicating the centrality of human factors in enhancing performance through technology augmentation. Organizations are significantly more effective with leaders who better integrate AI into strategy and operations. However, the way AI performance will impact others is not absolute or ubiquitous. Less mature organizations in their data and AI journey may face larger implementation challenges and limited results. As organizations move the maturity scales for more systematic AI, performance benefits follow. In this context, the relationships between AI and performance outcomes become mediated and moderated in important ways. Understanding readiness for digital transformation is another enabling condition, with organizations that have invested in developing strong digital foundations in a better position to leverage AI. How quickly and effectively an organization can learn will shape how successfully it is able to convert capabilities toward building and deploying AI. Function context matters substantially. AI gains are greater in high-tech sectors, such as financial services, retail, and technology, than in traditional construction or manufacturing sectors. The difference in data availability, digitization of processes, and AI use case maturity between the sectors gives rise to this divergence.

2.6   Organizational Performance in the Digital Era

2.6.1   Conceptualizing Organizational Performance

Organizational performance is a multi-dimensional construct, which refers to the extent to which an organization is effective and efficient. Earnings, return on equity and sales growth, for instance, are common indicators of financial performance in traditional conceptualizations. Yet, modern views recognize a need for stakeholder perspectives and performance dimension integration in performance assessment. Kaplan and Norton (2001) Provided a multi-faceted view of performance by offering four perspectives, including customer, financial, internal process and learning and growth. The multidimensional conception of sustainable performance recognizes that sustainable performance is dependent on the performance of diverse organizational dimensions. So, performance itself is increasingly not only being seen through the lens of traditional metrics, but also innovation potential, agility, user experience, and the ability to participate in a wider ecosystem. Performance metrics that should differ for digital organizations due to their distinct value creation logic. Because of the fact that performance is the discretionary construct as different scholars partition performance into four (operational performance, financial performance, market performance and strategic performance) disciplines each with their own perspective (process efficiency and effectiveness, economic outcomes, competitive position and market share, and achievement of long-term objectives respectively), the effects of technology-enabled performance improvements can manifest in various dimensions.

2.6.2   Technology Adoption and Performance

There is a large body of research that looks at the relationships between some aspects of technology adoption and some measure of organizational performance. Positive relationships are found where organizations that successfully adopt digital technologies outperform several dimensions. This is not a direct relationship mediated by only one variable; however, these things are always complex systems. Previous IT research has experienced a productivity paradox that shows large investments in technology do not equal large productivity increases, thus reiterating that technology is not a performance panacea. The performance benefits of technology investments often require complementary organizational changes such as process redesign, skill development, and cultural evolution. The success of adopting an enterprise technology is determined by about 90% by how it has been implemented, used, and aligned with strategy. Lack of change management or user training

before implementing technologies in organizations can lead to disappointing results. Organizational capabilities for moderate technology-performance relationships. Firms with a robust absorptive capacity the ability to identify, absorb and apply new knowledge capture greater value from modern technologies. Specific technologies vary in effectiveness, dependent upon the digital maturity levels of the organizations deploying them. Technology-performance relationships are contingent on environmental factors such as competition intensity, regulation, and technology turbulence. In environments where there is stiff competition, technology adoption may very well be necessary for survival as opposed to competitive edges.

2.6.3   Cross-Sectoral Performance Variations

Sector level differences in drivers and outcomes of organizational performance are dramatic. Capital intensity, regulatory environment, customer expectations and competitive dynamics shape which factors have the most significant influence on performance are Function Characteristics Flow both inside and outside the organizational walls Digital technologies create larger transformational performance gains in technology sectors like financial services and telecommunications than in traditional sectors such as building or hospitality These are different levels of process digitalization, data access, and readiness for tech adoption. Performance effects are evident across sectors with high regulatory intensity (e.g., healthcare, financial services). Compliance may limit certain implementations of a technology, but it may also create opportunities for the technologies that create value in answer to regulation. Unlike the generalities we covered in our earlier posts, customer expectations vary by sector, which leads to different sets of digital capabilities having the highest impact on performance. Competitive dynamics shape technology-performance relationships. For technology- disrupted sectors, digital capabilities are table stakes, not differentiators. Understanding how these patterns vary across sectors is key to making sense of technology-performance research findings and adapting them to action-oriented recommendations.

This part presents the integrated theoretical framework guiding this research. Drawing on the theoretical foundations established in Chapter 1. This framework articulates relationships between digital transformation, blockchain maturity, AI maturity, and organizational performance. This chapter develops formal hypotheses and explains the theoretical rationale for predicted relationships.

2.7   Theoretical Foundations and Hypothesis Development

2.7.1   Theoretical Perspectives

Multiple theoretical lenses inform this research framework. The **Resource-Based View (RBV)** posits that sustainable competitive advantage derives from valuable, rare, inimitable, and non- substitutable organizational resources. Digital transformation capabilities, block chain implementation expertise, and AI maturity represent strategic resources potentially conferring competitive advantages.

An RBV logic assumes that organizations with superior technology competences outperform competitors that lack strong capabilities, but this framework admits that technology resources are not enough on their own either complementary organizational capability are needed to receive value from technology driven investments.

Dynamic Capabilities Theory RBV is extended by stressing what the organizations can do; that is integrating, building, and reconfiguring internal and external competencies to address rapidly changing environments. The dynamic capabilities such as the ability to sense opportunities and threats, seize opportunities and reconfigure resources are the key to sustaining high performance in unstable digital environments.

Dynamic capability is essential to digital transformation, blockchain adoption, and AI implementation. Firms are essential to sense the opportunities enabled by technology, seize and implement them, and then transform and operate differently to extract value. This theoretical lens also articulates why technology does not by themselves but also produce better performance success depending on the ability to transform itself.

Technology-Organization-Environment (TOE) Framework They offers a nuanced view by considering that technology adoption decisions and results are influenced by a combination of technological characteristics, organizational background, and environmental factors. This permits us to provide a brief explanation of inter-sectoral variation in technology adoption patterns and performance outcomes.

Institutional Theory This Theory is about work demonstrations that normative pressures from the institutional environment shape organizational behaviors. This context of technology adoption, institutional theory clarifies the phenomenon of mimetic isomorphism where organizations within the similar sectors end up adopting similar technology despite the individual business case being murky at best and simply because the technology in question is

perceived as legitimate. Together, these theoretical perspectives guide the development of hypotheses, direct relationships, and mediating mechanisms in the research framework.

2.7.2 Direct Effects: Digital Transformation and Organizational Performance

Hypothesis 1 (H1): Digital transformation positively influences organizational performance.

There is extensive literature in academia establishing the relationship between digital transformation and business outcomes. Using it, the institutes can derive insights that can be actionable towards the performance responsible for the operational activities and data-driven workflows in the best manner for better efficiency through digital transformation. Cost less, do more and do better – these are the hallmarks of digital transformation in organizations that embrace digital technologies. dig into Digital Transformations: Linking Performance and Customer Experience Enhancements by Driving Higher Satisfaction, Loyalty, and Word-of-Mouth. It is enabling businesses to interact with customers in a customized way and service them through a self-service channel at the same time to provide services with you saving your time through digital mediums. Digital Transformation expands the innovation capabilities with rapid experimentation, shortened time-to-market, and testing of new business models. More advanced organizations in terms of digital maturity not only take products and services to market more often, but they also succeed at that more often than their less digitally-savvy peers. Through digital transformation which bolsters agility to act strategically, businesses are challenged to cover more ground in responding to market disruptions. Digital enables the flexibility of service providers to respond to shifting customer preferences, competitive moves, and technology changes. This proposition is aligned with Resource-Based View rationale: digital transformation capabilities are unique, valuable, and imperfectly non-imitable resources that endow direct competitive benefits and performance increments to firms. Dynamic Capabilities Theory also highlights that the performance differential between organizations in effective exploitation of digital technologies stems from better sensing, seizing, and transforming capabilities.

H1a: The relationship between digital transformation and unit performance varies across functional domains.

The positive relationships are hypothesized, and sector specific factors likely moderate effect magnitudes. Technology laden industries that are digitally more advanced might be benefiting more in terms of performance than less technology concentrated traditional sectors

with lower a priori level of digitization. The Regulatory environments, customer expectations, and competitive dynamics create sector specific backgrounds shaping technology performance relationships.

2.7.3 Direct Effects: Blockchain Maturity and Organizational Performance

Hypothesis 2 (H2): Blockchain maturity positively influences organizational performance.

Blockchain maturity leads to more value in investments in technology. Companies that are at the future stages of maturity have built competence, governance, and integration skills needed to capture benefits from blockchain.

When blockchain enables automated processes, fewer reconciliation touchpoints, and quicker transaction flows, operational efficiencies become feasible for the enterprise. Reducing the costs of verification subsequently makes transactions faster; it finally leads to improvements in trust and transparency. Increased performance of strategic importance is more achievable through new model opportunities, ecosystem participation, and differentiation arising from blockchain-derived capabilities.

Blockchain natives can also offer unique and previously unavailable value propositions to competitors. We will see Risk Management as another avenue to perform. Auditability is enhanced and fraud risk is lowered, and regulatory commitments are reinforced by the responsibility of blockchain to be immutable and transparent Being more effective at-risk management has resulted in performance benefits through reduced losses and compliance costs. A maturity model construction assumes that these performance gains are nonlinear with diminishing returns to scale, specifically that performance gains are disproportionately greater as organizations transition from one level of conditioning toward higher levels. Then the implementation costs are revenue based and as a result, the early-stage organizations see net performance expense while controlled and optimizing companies experience a significant return.

H2a: The relationship between blockchain maturity and unit performance is moderated by the department's data intensity.

The maturity uses cases in a sector on blockchain to influence performance impacts. Moreover, the developed blockchain applications are likely to lead to a stronger performance effect than sectors with greater nascent usage of blockchain such as financial services and supply chain. The monitoring framework in particular influences blockchain-performance

dynamics within highly regulated industries.

2.7.4   Mediating Role of AI Maturity

Hypothesis 3 (H3): AI maturity mediates the relationship between blockchain maturity and organizational performance.

The main theoretical contribution of this study is introducing AI maturity as the significant mediating factor explanation, how and why blockchain implementations result in performance consequences. This mediation hypothesis is supported by numerous theorized mechanisms.

Data Processing and Analytics: Blockchains produce massive volumes of data, and processing this data into useful knowledge requires advanced analytics. Mature AI organizations can use machine learning and predictive analytics to understand commercial value within blockchain data identifying patterns, streamlining processes, and delivering strategic anticipation from companies that lack AI and they can successfully deploy blockchain but fail to realize overall value from the data that is not fully exploited.

Process Automation Synergies: Blockchain and AI, and you get additional, complementary automation gains. On the one hand, blockchain facilitates the automation in recording transactions as well as their execution with smart contract, and on the other hand AI makes possible automating decision-making processes in a much complex manner. Companies with more advanced AI capabilities could build elaborate automation systems that integrate blockchain's trust infrastructure and AI's cognitive tools.

Trust and Intelligence Integration: Blockchain offers trusted data infrastructure and AI, intelligent data reading. This combination is especially potent where both data integrity and complex processing are needed, such as in supply chain optimization which needs trusted provenance data and intelligent demand predictions.

Innovation Enablement: Advanced AI capabilities enable organizations to envision and implement novel applications of blockchain technology. Organizations limited to basic blockchain implementations may achieve operational improvements, but those with sophisticated AI can develop transformative applications creating new value propositions.

Resource Complementarity: RBV logic is based on the proposition that, together, complementary resources provide more value than when deployed alone. If Blockchain is the data infrastructure you can trust, then AI is what makes the most of that data. Firms that

develop both capabilities at the same time gain further advantages that exceed the additive effect of each of these technologies.

H3a: The mediating effect of AI maturity on the blockchain maturity-organizational performance relationship varies in strength across business functions.

The mediating effects are dependent on function characteristics. It is expected that function where AI applications are more mature and blockchain use cases have been widely developed have a stronger mediation effect. Functions with high data intensity may be more likely to see stronger mediation effects because they offer more possibilities for AI-blockchain complementarities.

2.7.5   Control Variables and Moderating Factors

The numerous organizational and functional factors likely impact the hypothesized relationships and are merged as control or moderating variables. In the context of a single-organization study, these variables account for internal variations between different business units.

Unit Size: Unlike organizational size in cross-firm studies, this study controls for the size of individual business units or departments (measured by headcount). Larger units naturally possess greater resources for technology investments and may achieve different consequences than smaller teams, however, the size can create implementation complexity potentially offsetting resource advantages.

Functional Domain: As the internal equivalent to "Industry Sector," this variable categorizes business units by their primary function (e.g., Operations, Finance, IT). As articulated in sector-specific hypotheses, the functional context significantly shapes technology-performance relationships. This variable acts as a key moderator to analyze cross-functional performance variations.

Unit Digital Maturity: Pre-existing digital abilities provide the foundation for blockchain and AI implementations. Business units with higher baseline digital maturity such as those with lower legacy system dependency may more successfully implement advanced technologies.

Operational Dynamism: Replacing external market uncertainty, this refers to the intensity of change within a specific department's operational scope. High task turbulence and operational pressure influence technology adoption of imperatives and outcomes. Dynamic operational environments may strengthen technology-performance relationships as technological

capabilities become crucial for adaptation.

Compliance Intensity: Principally relevant for blockchain and AI, internal governance and compliance frameworks form implementation approaches and business case viability. Supportive but rigorous compliance environments may enable stronger technology-performance relationships by ensuring alignment with organizational standards.

2.8 Framework Components and Relationships

2.8.1 Conceptual Framework Overview

The integrated conceptual framework synthesizes hypothesized relationships into a comprehensive model. Figure 4 provides visual representation of the framework.

Table 2.1: Conceptual Framework Overview

Component	Theory Base	Type	Example Indicators	Key References
Digital Transformation	RBV / TOE	Digital Resource	Digital processes, digital strategy, cloud, big data	Kane et al. (2015), Vial (2019)
Blockchain Maturity	RBV / Innovation Diffusion	Digital Resource	Smart contract readiness, interoperability, security, decentralization	Wang (2016), Ronaghi (2021), GBA Model (2023)
AI Maturity	Dynamic Capabilities	Mediating Capability	Data readiness, AI talent, lifecycle governance, scaled AI use-cases	Bloedorn et al. (2023), IMD (2024), Accenture (2022)

Organizational Performance	RBV / BSC	Outcome	Financial, operational, innovation, customer performance	Venkatraman (1989), Zhang (2023)
Functional Area	Contingency Theory	Moderator	Unit size, data intensity, function domain	Valaskova (2025), Zandi et al. (2023)

Independent Variable: Digital Transformation

Digital transformation represents a primary independent variable, encompassing an organization-wide combination of digital technologies into operations, processes, and business models. The measurement captures four proportions: technology adoption, process digitization, organizational capabilities, and business model innovation.

Independent Variable: Blockchain Maturity

Blockchain maturity represents the second independent variable, reflecting an organization's sophistication in implementing and leveraging blockchain technology. Measurement utilizes the five-level maturity model: Initial, Repeatable, Defined, Managed, Optimizing.

Mediating Variable: AI Maturity

AI maturity presents as the central mediating variable and represents an organization's capability to leverage artificial intelligence technologies. The measurement encompasses five proportions: strategy and governance, data infrastructure, technical capabilities, organizational culture, and AI deployment.

Dependent Variable: Organizational Performance

The organizational performance signifies the ultimate consequence variable, encompassing multiple performance dimensions. Measurements include operational performance (efficiency, quality), financial performance (profitability, growth), market performance (internal service quality, customer satisfaction), and strategic performance (innovation, agility).

Control Variables

The framework includes unit size, functional domain, unit digital maturity, operational dynamism, and compliance intensity as control variables influencing relationships.
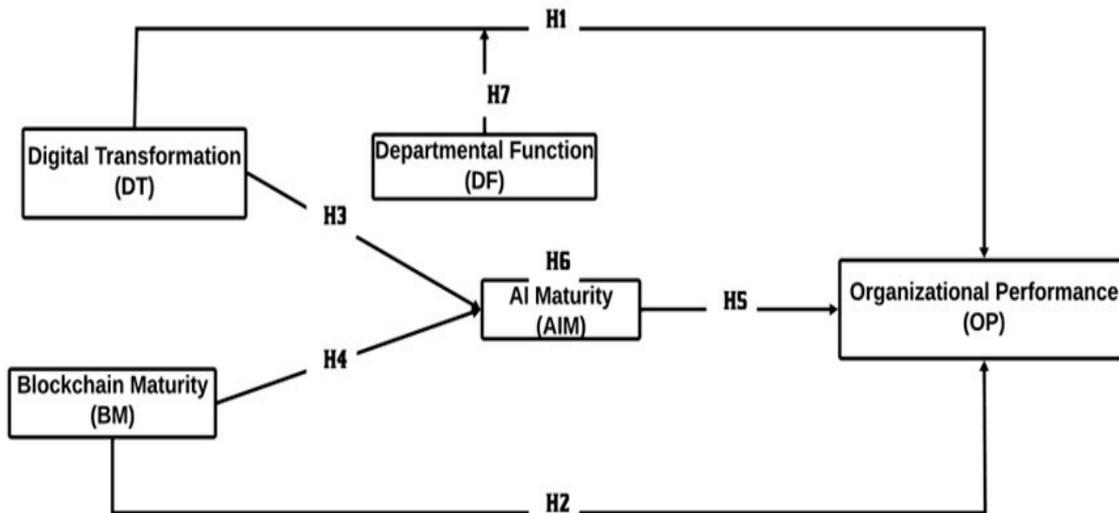
Figure 2.1: Research Framework

2.8.2   Pathways and Mechanisms

This framework articulates many pathways through which independent variables influence organizational performance:

Direct Pathway 1: Digital transformation directly affects organizational performance through efficiency improvements, customer experience improvement, innovation enablement, and strategic agility.

Direct Pathway 2: Blockchain maturity directly impacts organizational performance through operational improvements, risk reduction and planned opportunities and ecosystem benefits.

Direct Pathway 3: AI maturity directly inspirations on organizational performance through automation, enhanced decision-making, innovation acceleration, and customer intelligence.

Mediated Pathway: Blockchain maturity influences AI maturity, which in turn impacts organizational performance. This mediation happens through numerous mechanisms: blockchain data enables AI applications, AI enhances blockchain value capture and complementary resources create synergies, and combined capabilities enable novel innovations.

Interactive Effects: The outline acknowledges potential collaborating effects between digital

transformation and both blockchain and AI maturity. The organizations with strong digital basics may more effectively tool and leverage blockchain and AI.

Chapter 3

Research Methodology

3.1   Introduction

Chapter gives the methodological framework that was used to empirically examine the effect of digital transformation and blockchain maturity on organizational performance, having AI maturity as an intermediate. Based on the theoretical background and conceptual framework provided in Chapter 2, the proposed research uses a stringent quantitative methodology to prove the hypotheses by identifying the data collection and analysis in a systematic manner. The paper discusses these relations in the background of one of the hospitals Bahawal Victoria Hospital, Bahawalpur, Pakistan and how the various functional departments that are considered internal sectors in the organization experience different degrees of technology adoption and organizational performance.

The healthcare industry is one of the most promising research areas to explore the digital transformation, blockchain application, and the use of artificial intelligence. The global healthcare organizations are experiencing a significant technological change characterized by digitalization of health records, implementation of data analytics as the tool of clinical decision-making, the blockchain exploration due to the need to provide secure management of health data, and the introduction of the AI-powered diagnostic and managing tools. Pakistan in particular, big teaching hospitals such as Bahawal Victoria Hospital are in the process of investing heavily in digital infrastructure and up-and-coming technologies and would, therefore, be the best place to study technology-performance relationships.

One of the key features of the approach is a single-case study with integrated units of analysis. This research does not involve multiple organizations and work in the various industries; on the contrary, it pays close attention to one enterprise with many branches, which is undergoing digital transformation, and the functional domains (Clinical Services, Administrative and Management, Finance and Billing, IT and Digital Services, and Operational Support) act as an internal substitute to the industry sectors. This novel design has a number of methodological benefits: it is able to control external environmental factors (e.g. regulatory setting, market-force, and competitive pressure) that differ among organizations, and it is also able to explore how the different functional settings with different levels of data intensity, operational demands, and compliance requirements adopt technology at different rates.

This chapter has been systematically presented to cover the following aspects: research philosophy and paradigm (Section 3.2), research design and strategy (Section 3.3), target population and sampling procedures (Section 3.4), research instrument development and measurement (Section 3.5), data collection procedures (Section 3.6), data analysis techniques (Section 3.7), ethical considerations (Section 3.8) and limitations imposed by the methodology (Section 3.9). Essentially, every section has in depth defense of methodological options, openness of procedures and recognition of inherent limitations to allow critical assessment of the research quality.

3.2 Research Philosophy and Approach

3.2.1 Research Philosophy: Positivism

The research is based on the positivist research philosophy that believes that social reality could be objectively perceived, measured and analyzed by application of systematic and scientific methods as applied in natural sciences. Positivism has a number of assumptions that are central to its character and which are consistent with the objectives of this study:

Within the framework of this study, the digital transformation maturity, the performance levels of blockchain implementation, the levels of AI application, the organizational performance results are some real and measurable organizational factors objectively present and measurable with the help of appropriate measurement tools.

The only scientific knowledge that is legitimate is a phenomenon that can be observed, measured, and verified using empirical data. This research epistemology explains the reason why structured questionnaires were used to gather measurable data regarding technology maturity and performance in order to scientifically analyze them to test propositions of theory.

Axiological assumption (play of values): Positivism aims at the value-free, objective investigation when the researcher is not part of the research subject and personal values have no impact on results. This research uses standardized measures, systematic processes, and statistical methods in order to reduce the bias of the researcher and increase objectivity.

Methodological implication: The positivist philosophy requires the quantitative research methods of structured data collection instruments, large samples to allow generalization, statistical analysis to test hypotheses and focus on reliability, validity and replicability.

This is mainly due to the fact that the positivist paradigm is the most suitable paradigm to be used in this research. Second, the study aims at testing the specific and falsifiable hypotheses based on the existing theories (Resource-Based View, Dynamic Capabilities Theory) as opposed to the exploration of the theory generation. Second, the study aims to measure the relationship between clearly defined constructs which include digital transformation, blockchain maturity, AI maturity, organizational performance which needs measurement and statistical analysis. Third, cross-sectoral comparative research design that looks into the difference in relationships between functional areas requires systematic measurement that facilitates the valid comparison of the relationships, and this is offered by the positivist methods. Lastly, the research objectives which are determining the presence of and extent to which technology maturity impacts on organizational performance are compatible with the focus of positivism on prediction and explanation by identifying causal relationships.

3.2.2 Research Approach: Deductive Reasoning

This research follows a deductive research strategy, one that proceeds towards the specific empirical observations out of the general theoretical propositions by a series of logical inferences. The deductive method has a systematic approach:

As an example, RBV proposes that, useful, rare, inimitable resources (like the latest digital transformation, blockchain development, AI level, etc.) should improve the organizational performance, which results in the Hypotheses H1 and H2.

Observation: The researcher gathers empirical data as structured questionnaires to which the theoretical constructs of interest are measured in a sample of organizational members.

The deductive method has a number of methodological strengths in regard to this study. To begin with it offers a clear logical framework with links theory, hypothesis, measurement and empirical test, therefore increasing transparency and facilitating critical assessment. Second, it permits cumulative knowledge construction in that propositions of current theory are explicitly tested thus leading to the refinement of theory and their validation. Third, the deductive method aids in easy interpretation of results, when the pattern of empirical results coincides with theoretical judgment, its confidence is high of the theory; when patterns do not coincide, this indicates the necessity of theory change. Fourth, deductive research ensures that studies with similar hypotheses can be compared in terms of outcomes as researchers who have tested the same hypothesis can compare their results to determine whether they can observe similar patterns in different environments.

The deductive method is compared with the inductive method of reasoning, which starts with empirical observations and constructs theory by identifying patterns. Although inductive method can be useful in exploratory research in under-theorized areas, the present research deals with the phenomena (digital transformation, technology adoption, organizational performance) that already have plenty theoretical underpinnings, and deductive hypothesis testing may be more suitable.

3.3   Research Design and Strategy

3.3.1   Research Design: Cross-Sectional Survey

The proposed research design is the cross-sectional one based on gathering data concerning the respondents at one moment in time (July-August 2025) and capturing the situation with digital transformation, the use of blockchains, maturity of AI, and the performance of the organizations at Bahawal Victoria Hospital. Cross-sectional designs or snapshot designs are those studies that record the situations of phenomena at a certain point in time and not the development of the same over a period.

Cross sectional design characteristics:

Single temporal measurement: All the variables are assessed at the same time over a specific time frame of data collection.

Prevalence focus: It focuses on recording the current prevalence, maturity and relationship pattern as opposed to looking at the change over time.

Effective data collection: Once the respondents are contacted, they are not contacted again, which decreases the burden on the participants, and the process of data collection is accelerated.

Multiple variable analysis: Allows many constructs and their relationships to be investigated in a single analysis,

The benefits of cross-sectional design to this study are:

Time feasibility: Master thesis research is highly time-constrained (in general not less than 12 weeks and not more than 18 months since the idea of the project was formed to its finalization). Cross-sectional design allows the research to be completed within the available time and longitudinal design with repeated measures over a period of time (years) would have been impossible.

Resource efficiency: Cross-sectional data collection reduces expenses in monetary terms and time commitments on the part of researcher in contrast to longitudinal alternatives that demand recurrent contact with respondents, tracking of the respondent over time, and dealing with attrition.

Snapshot of the current organizational condition: The study is expected to capture the present maturity rates of digital transformation, blockchain, and AI at the Bahawal Victoria Hospital in the process of digital transformation that is underway. This is an appropriate capture of a modern snapshot of cross-sectional.

Hypothesis testing capability: The cross-sectional data possibilities cannot be certain when it comes to determining causality, yet, they can readily test whether hypothesized associations exist and give estimates of the magnitude of relationships, which are the top research objectives.

Background to future studies: Findings at cross-section can be used as the basis of future longitudinal studies to track the advances in technology maturity and the performance trends over time.

Seen weaknesses of cross-sectional design:

Temporal ambiguity: Cross-sectional measurement is unable to establish definitively a temporal order- of-the-art: is the maturity of technology a cause of later improvements in performance or is it the case that high-performing departments allocate more than others to technology. Although theory and previous longitudinal studies indicate that technology is a driving force of performance, the cross-sectional data are not able to test this cause-effect relationship.

Static representation: Cross-sectional design is one that only portrays a point in time, and it lacks the dynamic processes, like the stages of implementation of the technology or learning curves or performance changes after technology introduction.

Limitations in causality inference: To prove causality, we must prove: (1) that variables covariate, (2) that the cause precedes the effect periodically and (3) that we have excluded other possible causes. Cross-sectional designs represent the covariation, and though they answer limited evidence regarding the temporal precedence and alternative explanation elimination.

Cohort effects: When there are systematic differences in functional domains on other characteristics other than technology maturity (e.g. workforce demographics, resource

allocation), these observed differences may be due to such confounding factors and not technology effects.

Such restrictions are tackled using a number of strategies. To begin with, there are solid theoretical rationale and a previous longitudinal research that can logically justify the hypothesized causal directions. Second, alternative explanations are minimized by the statistical controls of possible confounding variables (experience level, domain size). Third, careful interpretation takes findings as being associated but not causal. Fourth, longitudinal extension recommendations admit this study as the basis of temporal studies in the future.

Table 3.1: Research Design

Research Component	Methodological Choice	Justification
Research Philosophy	Positivism	Testing objective relationships between defined constructs using statistical analysis
Research Paradigm	Quantitative	Quantifying maturity levels and examining causal relationships through numerical data
Research Approach	Deductive	Testing hypotheses derived from RBV and Dynamic Capabilities Theory
Research Strategy	Survey Research	Structured questionnaire enables systematic data collection from large sample
Research Design	Cross-sectional, Descriptive	Captures current state of technology adoption and performance at specific point
Time Horizon	Single point in time (2024)	Provides snapshot of organizational technology maturity and performance
Unit of Analysis	Individual employee (embedded in functional departments)	Employees as primary users/observers of technology implementation
Research Context	Single-case study with embedded units	Controls external factors; examines internal variation across functional domains

3.3.2   Research Strategy: Survey Methodology

The study uses survey research as its major approach to data collection. The methodology of the survey is the systematized gathering of information about respondents in the form of systematized questions put in questionnaires that allow quantifying the constructs and carrying out a statistical investigation.

3.3.3   Rationale for survey methodology:

Big data: Surveys can be used to collect data on large samples (n=204 in this case), which is sufficient to identify relationships as well as to use multivariate data, including structural equation modeling.

Standardization: The respondents use the same scales and the same number of questions and respond to the same questions regardless of the respondent, thus ensuring the consistency and comparability of the results across different respondents.

Quantification: Likert scale surveys convert perceptions and experiences to numerical data, which can be analyzed through inferential statistics, and tested using a hypothesis.

Efficiency: Surveys can be used to measure multiple constructs at the same time, which requires only one administration of a questionnaire, and thus the data collection becomes time and cost-efficient.

Anonymity: Anonymous surveys minimize the social desirability bias and help yield truthful responses especially on topics related to organizational issues or problems in implementing technology.

3.3.4   Descriptive Research Design

Descriptive research design is also factored in the study. Descriptive research describes attributes of phenomena in a systematic way, which means that it records what is, not why using causal statements. The descriptive element relates to such research objectives as:

Measuring the present levels of maturity of digital transformation, blockchain, and AI application in Bahawal Victoria Hospital.

Technology maturity distribution Profiling technology maturity distribution across functional areas to determine high and low-maturity departments.

Recording perceived organizational performance results in relation to technology programs.

Defining the demographics of respondents and the features of functional domains.

Although all the research is focused on explanatory (testing relationships and mediation), the descriptive part offers valuable contextual knowledge and answers useful stakeholder interests when documenting the state of maturity in organizational technologies.

3.4   Research Context: Single-Case Study with Embedded Units

3.4.1   Methodological Approach

Another characteristic approach used in the methodology is the single-case study with embedded units of analysis. This design gives intensive research on a single organization and analyzing various subunits within the organization and viewing the subunits as cases to compare.

Target Organization: Bahawal Victoria Hospital (BVH), Bahawalpur, Pakistan. BVH is a large teaching hospital based in Southern Punjab which serves a population catchment of over 10 million people in several districts. The hospital has a workforce of about 1,090 employees in clinical, administrative and operational areas, offers a full range of medical services in 30-plus specializations, and is in the process of digital transformation with adoption of Hospital Information Management Systems (HIMS), eHealth records, laboratory information systems and consideration of blockchain to monitor pharmaceutical supply chains and AI to support diagnosis.

Embedded Units of Analysis: There exist five functional domains, which are internal sectors:

- **Clinical Services:** Doctors, Nurses, Paramedics that deal directly with the patients.
- **Administrative & Management:** HR, Admin, Procurement
- **Finance & Billing:** Accounts, Revenue, Audit
- **IT & Digital Services:** IT Support, Data Center, Records
- **Operational Support:** Pharmacy, laboratory, Maintenance, Logistics.

External variability: Research on various organizations of various industries presents significant external variability- the organizations are different in terms of the competitive environment, regulatory environment, market forces, organizational culture, leadership, and financial resources, and strategic focus. Such outside disparities may blur the connection between technology and performance. The design removes external variance by controlling these external factors to a single organization and isolates internal variation in the technology adoption within functional domains.

Cross-sectoral analysis in organization: This theoretical framework suggests a conceptual model of the relationships between sectors that will observe variation in relationships. Instead of contrasting manufacturing with healthcare with financial services organizations (where the confounding industry-specific factors are introduced), this design considers functional domains to be internal sectors. There is meaningful within-organization sectoral difference equivalent to industry differences in the operational characteristics, data intensity, and workflow structures, and compliance requirements in clinical Services departments and Finance departments.

Rich contextual knowledge: One-case in-depth research allows a deep insight into organizational context the particular digital transformation initiatives that are occurring, blockchain pilot projects that are under trial, AI apps that are already in action, performance issues that are being tackled, and that multi-organization surveys tend to lose.

Practical feasibility: There are significant practical challenges in obtaining research access to various organizations of significant size, permissions, and sufficient response rates across organizations. Targeting one organization where the researcher has developed relations with it is easy to access, higher chances of participation can be achieved, and clarification may be done later.

Generalization logic: This design uses analytical as opposed to statistical generalization. Results are transferred to theoretical propositions (e.g., RBV predictions regarding the ability of technologies to improve performance) as opposed to a population. As long as the technology maturity-performance relationships are noticed in several functional settings within a single organization, this gives support to some theoretical propositions that can be subjected to tests in other organizational settings.

3.5 Target Population and Sampling Strategy

3.5.1 Target Population

The target population will include all employees of the Bahawal Victoria Hospital that engage with digital, blockchain applications (when available), or AI in their work duties. This definition of population will include employees of all levels of the organization senior management, middle management, supervisory staff, technical specialists, and frontline operational staff in all areas of functionality.

Justification of the scope of population: This idea of involving employees at every level instead of limiting to the management has a number of benefits. First, different views: It is possible that different views exist between frontline staff who interact with digital systems on a daily basis and managers who make decisions regarding technology investments and their influence on maturity and performance of technology. The diverse nature of this is a rich source of insight. Second, sufficient sample size: It would be a disastrous limitation in terms of sample size to only managers, which might not suffice to conduct structural equation modeling. The sampling frame is increased by inclusion of all the users of technology. Third, performance perception validity: Although senior managers might be more exposed to organizational performance, frontline workers have direct exposure to operational efficiency, service quality, and impacts on the workflow and thus, their performance perception can be useful.

Population size: According to the records of the HR department, the amount of population is approximated at around 1,090 employees in the five functional areas. The distribution of population is not balanced across the domains, with Clinical Services taking the largest share (c. 450 staff), then Operational Support (c. 250 staff), Administrative and Management, Finance and Billing, and IT and Digital Services (c. 90 staff).

3.5.2 Sampling Technique: Stratified Random Sampling

The paper has utilized stratified random sampling, which is a type of probability sampling that classifies the population into homogeneous subgroups (strata) then randomly samples the members of each stratum. The functional domain is a stratification dimension, whereby the five departments are the strata.

Stratified random sampling procedure

Step 1: Stratification: The five mutually exclusive strata are formed based on the functional domain affiliation and the population (N) is divided into five groups (N=1,090).

Step 2: HR employee lists used to determine the size of each stratum: The size of each stratum will be determined using lists of HR employees.

Step 3: Sample allocation: The allocation of the sample in each stratum is based on proportional allocation- the sample size in each stratum is based on its representation in the population. In this case, 41% of the population should be represented in the sample (450/1,090) should the population of Clinical Services be 41%.

Step 4: Random sampling in strata: Within each of the functional areas, the respondents will be selected randomly on employee lists. Random selection minimizes selection bias and maximizes sample representativeness.

Step 5: Invitation and participation: The chosen employees are invited to take part through email and departmental meetings with questionnaire links (Google Forms) and paper copies being sent.

The benefits of stratified random sampling are as follows:

Ensures representation: Stratification ensures that all the functional domains are well represented in the sample though some functional domains may have a small population. Simple random sampling in the entire population might give inadequate observations of the smaller departments such as IT Services.

Minimizes sampling error: When strata are more homogenous within than they are between sampling strata can reduce sampling error than simple random sampling with the same sample size, which increases the precision.

Facilitates weighting: When the analysis should be post-stratified, the weighting can be adjusted using known population proportions so that the sample statistics can reflect the population parameter.

Sample size determination: The number of the target of 200-300 respondents was arrived at after various considerations:

PLS-SEM requirements: The research makes use of the Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses. The PLS-SEM sample size requirements can be usually calculated using the so-called 10-times rule, i.e. the minimum required sample size must be at least 10 times the highest number of structural paths that lead to any latent construct in the model. Digital Transformation, Blockchain Maturity, AI Maturity, and control variables are the sources of paths into Organizational Performance in the conceptual model (about 6-7 paths). Using 10 times rule: 7 times 10 = 70 minimum observations. Nevertheless, this is a rule of thumb, the bigger the sample, the better.

Consideration of power analysis: Statistical power analysis based on Power software shows that to find medium size effects (Cohen f 2 = 0.15) at low significance levels (0.05) with an adequate power (1- 0.80) in a multiple regression with 6-7 predictors, the sample size should

be about 153-176. In order to add margins to data quality problems and multi-group analysis, the target of 200-300 gives comfortable power.

Multi-group analysis requirements: The study involves multi-group analysis of comparison of path coefficients between functional domains. It is recommended that PLS-SEM multi-group analysis should have 30-50 observations per group. This would be achieved with five functional domains and a target of 200-300 total sample which would mean 40-60 observations per domain.

Practical feasibility: The sample size of 250 questionnaires in an organization with 1,090 employees using technology is about 23% sampling fraction, which is empirically feasible and the organization is not overburdened.

Expected response rate: According to organizational surveys in similar settings, the response rates of 70-85% are expected when there is organizational backing of the surveys and conducting several follow-ups. The 238 questionnaires with the projected response of 80% were to give an approximate of 190-210 valid questionnaires, which comprise the 200-300 target.

3.5.3   Actual Sample Achieved

The actual data collection yielded the following results:

Questionnaires distributed: 238

Questionnaires returned: 238 (100% return rate)

Invalid/incomplete responses excluded: 34 (incomplete demographic information, extensive missing data, response patterns indicating insufficient attention such as straight-lining all items with same response)

Final valid sample size: 204 usable responses

Effective response rate: 85.7% (204/238)

The achieved sample of **N=204** exceeds minimum PLS-SEM requirements (10-times rule: 70, power analysis: 153-176) and falls within the target range of 200-300, providing adequate statistical power for planned analyses. Table 3.3 presents the distribution of the 204 valid responses across functional domains, showing good representation ranging from n=27 (IT & Digital Services) to n=68 (Clinical Services).

Table 3.2: Sampling Details

Sampling Element	Description
Target Organization	Bahawal Victoria Hospital, Bahawalpur, Pakistan
Target Population	All employees across functional departments who interact with digital systems, blockchain applications, or AI tools
Sampling Frame	Employee roster from HR department covering all functional domains
Functional Domains (Strata)	5 domains: Clinical Services, Administrative & Management, Finance & Billing, IT & Digital Services, Operational Support
Sampling Technique	Stratified Random Sampling (proportional allocation by department size)
Sample Size Determination	Minimum 200-300 for PLS-SEM (10-times rule); Target = 250
Questionnaires Distributed	238 questionnaires
Questionnaires Returned	238 responses
Invalid/Incomplete Responses	34 responses excluded (incomplete or response patterns)
Final Valid Sample Size	204 valid responses
Response Rate	85.7% usable response rate (204/238)
Data Collection Period	July - August 2025 (6 weeks)

3.6 Research Instrument: Questionnaire Development

3.6.1 Questionnaire Structure Overview

A structured, self-administered questionnaire entitled Research Survey: Digital Transformation, Blockchain & AI in Healthcare was the tool used to gather data. The questionnaire was to be filled in around 10-15 minutes to ensure that the respondent burden is minimized and at the same time the data obtained is comprehensive.

The questionnaire will have two major sections:

Section 1: Demographics and Sector Profile (4 items) – Collects respondent demographic information and functional domain affiliation

Section 2: Variable Measurement (20 items) – Measures the four primary constructs using 5-point Likert scales:

- Part A: Digital Transformation (5 items)

- Part B: Blockchain Maturity (5 items)

- Part C: AI Maturity (5 items)

- Part D: Organizational Performance (5 items)

Total questionnaire length: 24 items (4 demographic + 20 construct measurement).

3.6.2 Section 1: Demographics and Control Variables

Four demographic and contextual variables were collected to enable sample profiling and serve as potential control variables in analysis:

1. Gender (Nominal, 2 categories)

- Male

- Female

Purpose: Demographic profiling; potential gender differences in technology perception can be explored as supplementary analysis.

2. Age Group (Ordinal, 5 categories)

- 18-25 years

- 26-35 years

- 36-45 years

- 46-55 years

- 56 years and above

Purpose: Age may relate to technology adoption attitudes (younger employees potentially more comfortable with digital technologies); can serve as control variable.

3. Functional Domain/Department (Nominal, 5 categories)

Clinical (Doctors, Nurses, Paramedics) Services.

Administrative/ Management (HR, Admin, Procurement)

IT Support, Data Center, Records IT & Digital Services.

Table 3.3: Functional Domains

Functional Domain	Description	Estimated Population	Target Sample (n)	Valid Responses (n)	Percentage of Sample (%)	Response Rate (%)
Clinical Services	Doctors, Nurses, Paramedics	~450	80	68	33.3%	85%
Administrative & Management	HR, Admin, Procurement	~180	45	38	18.6%	84%
Finance & Billing	Accounts, Revenue, Audit	~120	35	29	14.2%	83%
IT & Digital Services	IT Support, Data Center, Records	~90	30	27	13.2%	90%
Operational Support	Pharmacy, Lab, Maintenance	~250	60	42	20.6%	70%
TOTAL	All Departments	~1090	250	204	100%	85.7%

4. Work Experience (Ordinal, 5 categories)

- Less than 1 year

- 1-3 years

- 4-6 years

- 7-10 years

- More than 10 years

Purpose: Experience level may influence technology familiarity and performance perceptions; serves as potential control variable.

3.6.3 Section 2: Construct Measurement

All construct measurement items are 5-point Likert scales with 1 (Strongly Disagree) to 5 (Strongly Agree) points. The reason why Likert scales find extensive application in the research of organizations is their capability to describe gradation levels in terms of agreement, relative ease of administration to respondents, and interval level data may be subjected to parametric statistical analysis.

The scale anchors were clearly labeled:

- 1 = Strongly Disagree

- 2 = Disagree

- 3 = Neutral

- 4 = Agree

- 5 = Strongly Agree

Part A: Digital Transformation (DT) – 5 Items

Digital transformation has been operationalized as a multidimensional concept that mirrors the form of adoption of technology, digitalization of processes, use of data to make decisions, and organizational support of digital innovation. The five measurement items were based on the existing literature of digital transformation:

DT1: "Our department actively adopts modern digital technologies (e.g., E-Health records, cloud systems)"

- *Dimension*: Technology Adoption

- *Source*: Adapted from Vial (2019), Verhoef et al. (2021)

DT2: "Critical workflows are digitized rather than paper-based"

- *Dimension*: Process Digitization

- *Source*: Adapted from Matt et al. (2015)

DT3: "Our department uses data analytics to make informed decisions"

- *Dimension*: Data-Driven Decision Making

- *Source*: Adapted from Davenport & Harris (2007)

DT4: "Hospital leadership encourages digital innovation"

- *Dimension*: Leadership Support

- *Source*: Adapted from Singh & Hess (2017)

DT5: "We regularly upgrade digital infrastructure"

- *Dimension*: Infrastructure Investment

- *Source*: Adapted from Fitzgerald et al. (2014)

These five aspects are able to cover the major dimensions of digital transformation maturity that have been proposed in theoretical literature, i.e., technological capability (DT1, DT5), operational digitization (DT2, DT3), and organizational culture/leadership support (DT4).

Part B: Blockchain Maturity (BM) – 5 Items

The operationalization of blockchain maturity was based on blockchain maturity models and literature on healthcare blockchain. Since the use of blockchain in healthcare is still new, the items were created to reflect both the defining blockchain features and the state of the actual implementation:

BM1: "Once data is entered, it cannot be altered without authorization"

Dimension: Data Immutability (core blockchain characteristic)

Source: Adapted from Wang et al. (2019) - Blockchain in Healthcare

BM2: "Secure mechanisms exist to share data transparently across departments"

- *Dimension*: Transparency and Data Sharing

- *Source*: Adapted from Yaga et al. (2018) - NIST Blockchain Technology Overview

BM3: "Department is ready or uses distributed ledger technologies"

- *Dimension*: Distributed Ledger Technology (DLT) Readiness/Adoption

- *Source*: Adapted from Casino et al. (2019)

BM4: "High-level cryptographic security is prioritized"

- *Dimension*: Security (Cryptographic Protection)

- *Source*: Adapted from Mackey et al. (2019)

BM5: "Clear governance exists for shared data and transactions"

- *Dimension*: Governance Framework

- *Source*: Adapted from Kuo et al. (2017)

These items evaluate both readiness features (data immutability regimens, security prioritization, governance models) that pre-exist blockchain adoption and actual adoption (DLT use, open-data sharing processes) since blockchain execution in healthcare is still in its infancy.

Part C: AI Maturity (AIM) – 5 Items

AI maturity was operationalized across five dimensions reflecting infrastructure, deployment, strategy, capabilities, and analytical sophistication identified in AI maturity frameworks:

AIM1: "Necessary data infrastructure exists to support AI tools"

- *Dimension*: Data Infrastructure

- *Source*: Adapted from Davenport & Ronanki (2018)

AIM2: "Automated tools assist in routine tasks"

- *Dimension*: Automation/AI Deployment

- *Source*: Adapted from Rai et al. (2019)

AIM3: "There is a strategic vision to implement AI"

- *Dimension*: Strategic Vision/AI Strategy

- *Source*: Adapted from Ransbotham et al. (2017)

AIM4: "Staff have skills/training for intelligent systems"

- *Dimension*: Skills and Capabilities

- *Source*: Adapted from Fountaine et al. (2019)

AIM5: "Predictive insights are used for planning"

- *Dimension*: Predictive Analytics/Advanced Applications

- *Source*: Adapted from Shrestha et al. (2019)

These five items progress from foundational requirements (data infrastructure - AIM1, skills - AIM4) through strategic orientation (vision - AIM3) to operational deployment (automation - AIM2) and advanced applications (predictive analytics - AIM5), reflecting the AI maturity progression from basic readiness to sophisticated implementation.

Part D: Organizational Performance (OP) – 5 Items

The measurement of the organizational performance was using self-reported, perception-based measures of various performance dimensions that were applicable in the healthcare settings. The five items were formulated as being specific to this healthcare context:

OP1: "Technology adoption improved process speed"

- *Dimension*: Process Efficiency

- *Rationale*: Digital transformation should enhance operational efficiency through automation and streamlined workflows

OP2: "Digital tools reduced operational costs"

- *Dimension*: Cost Performance

- *Rationale*: Technology investments should yield cost savings through efficiency gains and resource optimization

OP3: "Patient/end-user satisfaction increased"

- *Dimension*: Customer (Patient) Satisfaction

- *Rationale*: Technology should improve service delivery quality, wait times, and patient experiences

OP4: "Department adapts quickly to change"

- *Dimension*: Organizational Agility

- *Rationale*: Technology capabilities should enhance organizational responsiveness and adaptability

OP5: "Overall service quality improved"

- *Dimension*: Service Quality

- *Rationale*: Holistic performance indicator capturing comprehensive service delivery improvement

Justification for self-reported performance measures: Although objective performance indicators (financial information, patient outcomes, metrics of efficiency) would be the best fit, there were a number of considerations that made self-reporting the right choice in this study. To start with, the constraints of access- objective financial or clinical outcome data cannot be received at departmental level without with a lot of organizational approvals and data access which could not be accessed within the time frame of the thesis. Second, aggregation suitability the study deals with perceptions of technology-using employees in various departments; the individual-level technology experiences may not relate to aggregate departmental performance-based data. Third, in the literature, perception-based performance measurements are successfully implemented in literatures that adopt technology and organizational performance through the use of precedent studies that have been proven by comparison with objective measures. Fourth, mitigation of common method bias with self-reported independent and dependent variables takes the risk of common method bias, this may be statistically tested and remedied using procedural remedies and Harman test.

3.6.4 Questionnaire Development Process

The questionnaire development followed established scale development procedures:

Step 1: Literature review and item generation overview Based on the extensive review of the literature on digital transformation, blockchain, AI maturity, and organizational performance, the existing measurement scales and dimensions were discovered. The first item pools were created by transforming validated scales into the healthcare setting.

Step 2: Expert Review Prof. Tadas Limba, thesis supervisor and two members of the faculty who have expertise in information systems and healthcare management reviewed the draft questionnaire. Content validity was determined by expert feedback on the comprehensiveness of items in representing construct domains and face validity was determined by clarity, relevance, and unambiguity of items.

Step 3: Refinement of items According to the feedbacks of the experts, the items underwent revision in terms of their clarity, relevance with the healthcare setting, and the length. The use

of overly technical terminology was made simple enough to allow the respondents who had different levels of technical backgrounds to understand.

Step 4: Pilot Testing The revised questionnaire was pilot-tested with a convenience sample of **n=30 employees** from Bahawal Victoria Hospital representing different functional domains. Pilot respondents completed the questionnaire and provided feedback on:

- Clarity of instructions

- Item comprehensibility and ambiguity

- Response scale appropriateness

- Questionnaire length and completion time

- Technical issues with Google Forms platform

Pilot data were analyzed for preliminary reliability assessment (Cronbach's alpha for each construct). All constructs demonstrated acceptable alpha values ($\alpha > 0.70$), indicating satisfactory internal consistency.

Step 5: Final Refinement – Minor wording adjustments based on pilot feedback produced the final questionnaire version used for main data collection.

3.6.5   Questionnaire Administration Modes

The questionnaire was administered through two modes to accommodate respondent preferences and technological accessibility:

Mode 1: Online (Google Forms), The questionnaire on the main administration mode was through Google Forms sent via email to employee institutional email accounts and forwarded in departmental WhatsApp groups. Online administration has the following benefits: speed of distribution, data capture which eliminates transcription errors, easy to use on mobile devices such that it can be completed in breaks and lastly is environmentally friendly.

Mode 2: Paper-based, In the departments where access to computers was limited during working hours (mainly Clinical Services and Operational Support with field-based staff), the disseminated and collected printed questionnaires were through department coordinators. The researcher then entered the paper responses into the Google Forms database and random doubling verification of 10% of the paper responses was carried out to guarantee accuracy of data entry.

The content of the question and response options in both modes were equal, thus, measurement was equivalent. The responses were received through online mode and paper mode in nearly 65 percent (n=133) and 35 percent (n=71) respectively. Data Collection Procedures

3.6.6 Ethical Approval and Organizational Permission

Prior to data collection, formal ethical approval and organizational permissions were obtained:

Step 1: University Ethics Approval The ethical analysis of the research protocol comprising of questionnaire, consent procedures and data handling protocols were sent to the Business School of Vilnius University. A protocol approval was made to ensure that ethical standards were met in case of research that involved human participants.

Step 2: Hospital Permission The ethical analysis of the research protocol comprising of questionnaire, consent procedures and data handling protocols were sent to the Business School of Vilnius University. A protocol approval was made to ensure that ethical standards were met in case of research that involved human participants.

Step 3: Informed Consent The questionnaire included an informed consent statement explaining:

- Research purpose and objectives

- Voluntary participation (no penalties for non-participation or withdrawal)

- Confidentiality and anonymity (no personally identifiable information collected; data reported only in aggregate)

- Approximate completion time (10-15 minutes)

- Academic use of data

- Contact information for questions or concerns

Respondents indicated consent by proceeding with questionnaire completion.

3.6.7 Data Collection Timeline

Data collection occurred during a **6-week period from July to August 2025**. This timeframe was selected to avoid peak hospital operational periods and major holidays that could reduce participation.

Week 1-2: Initial Distribution and Sensitization

- Departmental meetings conducted by coordinators to explain research and invite participation

- Initial questionnaire distribution via email and via departmental WhatsApp groups

- Paper questionnaires distributed to clinical and operational departments

- Posters displayed in common areas with QR codes linking to online survey

Week 3-4: First Follow-up

- Reminder emails sent to all employees emphasizing voluntary participation and confidentiality

- Coordinators conducted brief verbal reminders during departmental meetings

- Additional paper copies provided to departments with lower initial response

Week 5-6: Second Follow-up and Collection Closure

- Final reminder communications sent

- Paper questionnaires collected from departments

- Online survey remained open until end of Week 6

- Data collection officially closed with 238 total responses received

3.6.8 Response Enhancement Strategies

An official written request was provided to the Medical Superintendent of Bahawal Victoria Hospital about the purpose of the research, the criteria that will be used to select the participants, how the data will be collected, how the data will be kept confidential, and how the findings will be of help to the organization (feedback report on technology maturity status). The hospital management provided the permission and assigned departmental coordinators to make it easier to collect data.

Step 1: Research Design

Deductive research of Theory (Normelizational)

Behaytior Wellness Hospital Subsector

Step 2: Population

Target admittees, management. & and clinical employees.

Total agehcy emplayees appro, 1000

Step 4: Stratified Random Sampling

Clinical Services
N68

Admin & Management
N38

Finance & Billing
N29

IT & Digital Services
N27

Step 5: Data Collection

Oinline collection date **August 2025**

204 respondents ahieved

5P56 28
Descriptive Statistics
Chi-square
Mann-wlhttney
Normailty tests

Shapiro's & l silructured model testing
Monn-whitney
Multi-group analyses

Figure 3.1: Research Methodology Process

Figure 3.2: Research Methodology Process Flow - This flowchart illustrates the systematic nine-step research process from research design through data collection and analysis at Bahawal Victoria Hospital.

3.7　Data Analysis Strategy

Data analysis followed a systematic, multi-stage process employing both SPSS and SmartPLS software platforms.

3.7.1　Stage 1: Data Preparation and Screening (SPSS)

Step 1: Data Entry and Verification

Google Forms online respondents were automatically captured in electronic form, and exported to SPSS. The paper-based responses were entered manually in the SPSS database and the data entry was checked on a random 10 percent subsample to detect and rectify the transcription errors.

Step 2: Data Screening and Cleaning

Missing data analysis: The dataset was examined for missing values. Patterns of missingness were assessed to determine whether data were missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) using Little's MCAR test. Missing data handling strategies were determined based on extent and pattern:

- Variables with <5% missing: Mean imputation or expectation-maximization (EM) algorithm

- Variables with 5-15% missing: Multiple imputation procedures

- Cases with >20% missing values: Excluded from analysis

- Items with >20% missing: Flagged for potential removal

- In the real dataset, the percentage of missing data was low (below 3 percent) because the Google Forms required the response to all questions and the checking of the paper questionnaires in the collection process, which reduced the level of missing data issues.

Detection of outliers: Univariate outliers were determined by the use of normalized z- scores: values above 3.29 were noted to be checked. Mahalanobis distance was used to identify the multivariate outliers, and the investigations focused on the observations which have a Mahalanobis distance greater than the critical value at $p < 0.001$. The outliers were identified and analyzed to establish whether they were:

- Data entry errors (corrected)

- Response patterns indicating insufficient attention (e.g., straight-lining all items with "5"; excluded)

- Legitimate extreme values representing genuine perceptions (retained)

Based on this screening, **34 responses were excluded** due to incomplete demographics, extensive missing data on construct items, or response patterns indicating insufficient attention, yielding the final sample of N=204.

Normality assessment: In the real dataset, the percentage of missing data was low (below 3 percent) because the Google Forms required the response to all questions and the checking of the paper questionnaires in the collection process, which reduced the level of missing data issues.

Step 3: Composite Variable Construction

Mean scores for each construct were calculated by averaging responses across the five items within each construct:

- Digital Transformation score (DT) = (DT1 + DT2 + DT3 + DT4 + DT5) / 5

- Blockchain Maturity score (BM) = (BM1 + BM2 + BM3 + BM4 + BM5) / 5

- AI Maturity score (AIM) = (AIM1 + AIM2 + AIM3 + AIM4 + AIM5) / 5

- Organizational Performance score (OP) = (OP1 + OP2 + OP3 + OP4 + OP5) / 5

Composite scores range from 1.00 to 5.00, with higher scores indicating higher maturity or performance.

3.7.2 Stage 2: Descriptive and Preliminary Analysis (SPSS)

Demographic Profiling

Categorical demographic variables (gender, age group, functional domain, work experience) were determined using frequencies and percentages in order to describe the sample. Cross tabulations were used to look at the distribution of demographics in the various functional areas to determine any possible imbalance of the demographics that need to be considered.

Descriptive Statistics

For all continuous variables (DT, BM, AIM, OP composite scores), descriptive statistics were calculated:

- Mean (central tendency)

- Median (central tendency, robust to outliers)

- Standard deviation (dispersion)

- Minimum and maximum values (range)

- Skewness and kurtosis (distribution shape)

Descriptive statistics were calculated overall and disaggregated by functional domain to enable cross-domain comparison.

Reliability Analysis

Internal consistency reliability for each construct was assessed using Cronbach's alpha (α):

- $\alpha \geq 0.70$: Acceptable reliability

- $\alpha \geq 0.80$: Good reliability

- $\alpha \geq 0.90$: Excellent reliability

Item-total correlations were examined to identify poorly performing items that do not correlate well with the construct total score. Items with item-total correlations < 0.30 or alpha-if-item-deleted suggesting substantial reliability improvement were flagged for potential removal.

3.7.3   Stage 3: Measurement Model Assessment (SmartPLS)

SmartPLS 4 software was used to compute Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM analysis is conducted in two steps; measurement (relations between latent constructs and indicators) and structural (relations among constructs) analysis.

Why PLS-SEM?

PLS-SEM was selected over covariance-based SEM (CB-SEM) for several methodological reasons:

Sample size flexibility: PLS-SEM achieves adequate statistical power with smaller samples than CB-SEM, making it appropriate for samples of 200-300 and enabling multi-group analysis across functional domains.

Distributional assumptions: PLS-SEM does not require multivariate normality, accommodating potential non-normal distributions in survey data.

Predictive orientation: PLS-SEM maximizes explained variance in endogenous constructs (AI Maturity, Organizational Performance), aligning with this study's focus on prediction and explanation.

Complex model capability: PLS-SEM handles complex models with multiple constructs, mediation paths, and multi-group comparisons efficiently.

Formative vs. reflective flexibility: PLS-SEM accommodates both reflective measurement models (indicators reflect underlying constructs) and formative models (indicators form/define constructs), providing modeling flexibility.

Measurement Model Evaluation Criteria:

1. Indicator Reliability

- **Metric**: Outer loadings (standardized loadings of indicators on constructs)

- **Criterion**: Loadings ≥ 0.70 indicate that the construct explains ≥49% of indicator variance

- **Decision rule**: Items with loadings < 0.40 removed; items with loadings 0.40-0.70 retained if removal does not improve reliability or validity

2. Internal Consistency Reliability

- **Metrics**: Cronbach's Alpha (α) and Composite Reliability (CR)

- **Criteria**: $\alpha \geq 0.70$ and CR ≥ 0.70 acceptable; α/CR ≥ 0.80 good; α/CR ≥ 0.90 excellent (but > 0.95 may indicate redundancy)

3. Convergent Validity

- **Metric**: Average Variance Extracted (AVE) – proportion of variance in indicators explained by the construct

- **Criterion**: AVE ≥ 0.50 indicates construct explains majority of indicator variance

4. Discriminant Validity

- **Metrics**: Heterotrait-Monotrait (HTMT) ratio of correlations.

- **Criterion**: HTMT < 0.85 (conservative threshold) or < 0.90 (liberal threshold) indicates constructs are empirically distinct.

- **Alternative**: Fornell-Larcker criterion (square root of AVE > inter-construct correlations), though HTMT is preferred for its superior performance.

If measurement model criteria are not satisfied, problematic indicators are removed and the model is re-estimated iteratively until acceptable measurement quality is achieved.

3.7.4 Stage 4: Structural Model Assessment (SmartPLS)

Once the measurement model demonstrates adequate quality, the structural model is evaluated to test hypotheses:

Path Coefficient Estimation

Standardized path coefficients (β) represent the strength and direction of relationships between constructs:

- **Positive β:** Positive relationship (increases in predictor associate with increases in outcome)

- **Negative β:** Negative relationship (increases in predictor associate with decreases in outcome)

- **|β| magnitude:** 0.10 (small effect), 0.30 (medium effect), 0.50 (large effect)

Significance Testing via Bootstrapping

PLS-SEM uses **bootstrapping** (resampling with replacement) to generate standard errors and test path coefficient significance. The analysis employs **5,000 bootstrap resamples**, a conventional number providing stable standard error estimates. For each path coefficient, bootstrapping produces:

- Standard error

- t-statistic = β / SE

- p-value (two-tailed test)

- 95% confidence interval

Significance criterion: $p < 0.05$ (two-tailed) indicates statistically significant relationship.

Coefficient of Determination (R²)

R² indicates the proportion of variance in endogenous constructs explained by their predictors:

- R² for AI Maturity: variance explained by DT and BM

- R² for Organizational Performance: variance explained by DT, BM, AIM, and control variables

Interpretation: R² values of 0.25 (weak), 0.50 (moderate), 0.75 (substantial) in behavioral/organizational research.

The overall acceptable model will be calculated using Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI).

3.7.5 Stage 5: Mediation Analysis (SmartPLS)

Hypothesis H3 proposes that AI Maturity mediates the relationship between Blockchain Maturity and Organizational Performance. Mediation analysis tests whether the effect of BM on OP operates indirectly through AIM.

Mediation Testing Procedure:

Step 1: Total Effect – Test direct relationship BM → OP without including mediator AIM. Significant total effect establishes that relationship exists before testing mediation.

Step 2: Indirect Effect – Calculate indirect effect as product of two paths:

$$\text{Indirect Effect} = (BM \rightarrow AIM) \times (AIM \rightarrow OP)$$

Step 3: Bootstrapping Significance Test – Use 5,000 bootstrap resamples to generate confidence intervals for indirect effect. If 95% CI excludes zero, indirect effect is statistically significant.

Step 4: Direct Effect – Test direct relationship BM → OP while including mediator AIM.

Mediation Types:

- **Full Mediation**: Indirect effect significant, direct effect non-significant (BM effect fully transmitted through AIM)

- **Partial/Complementary Mediation**: Both indirect and direct effects significant (BM affects OP both through AIM and directly)

- **No Mediation**: Indirect effect non-significant (AIM does not mediate BM-OP relationship)

Variance Accounted For (VAF):

$$VAF = \frac{\text{Indirect Effect}}{\text{Total Effect}} = \frac{\text{Indirect Effect}}{\text{Direct Effect} + \text{Indirect Effect}}$$

Interpretation:

- VAF < 0.20: No mediation

- $0.20 \leq$ VAF < 0.80: Partial mediation

- VAF $\geq$ 0.80: Full mediation

3.7.6 Stage 6: Multi-Group Analysis (SmartPLS)

Hypotheses H1a, H2a, and H3a propose that relationships differ across functional domains. **Multi-group analysis (MGA)** tests whether path coefficients differ significantly between groups.

As data were gathered across five different functional domains, a post-hoc authority analysis specified that the sample sizes for individual departments (e.g., IT & Digital Services, n=27; Finance & Billing, n=29) were insufficient to handling a healthy five-way Multi-Group Analysis (MGA). To certify satisfactory statistical power and model strength, the five domains were combined into two strategic groups for cross sectoral analysis:

1. **Group A (Frontline & Operational, n=110):** Involving 'Clinical Services' and 'Operational Support'. These domains characterize the hospital's core value delivery and patient-facing physical operations.

2. **Group B (Administrative & Support, n=94):** Comprising 'Administrative & Management', 'Finance & Billing', and 'IT & Digital Services'. These domains characterize the backend, desk-based support functions important for organizational permanence.

This dual classification allows the study to link technology-performance connections between the hospital's operational core and its administrative strength.

3.8 Reliability and Validity

Ensuring measurement reliability and validity is critical for research quality.

3.8.1 Reliability Assessment

Internal Consistency Reliability assesses whether items measuring the same construct produce consistent results.

Cronbach's Alpha (α): Calculated in SPSS for each construct during preliminary analysis:

- $\alpha \geq 0.70$: Acceptable

- α ≥ 0.80: Good

- α ≥ 0.90: Excellent

Alpha values below 0.70 indicate insufficient internal consistency, potentially requiring item removal or construct reconceptualization.

Composite Reliability (CR): Calculated in SmartPLS during measurement model assessment:

- CR ≥ 0.70: Acceptable

- CR ≥ 0.80: Good

CR is generally preferred over Cronbach's alpha in PLS-SEM because it accounts for different item loadings rather than assuming equal item weights.

3.8.2 Validity Assessment

Content Validity assesses whether measurement items comprehensively represent all facets of the construct domain.

Assessment method: Systematic comparison of measurement items to theoretical construct definitions established in literature review (Chapter 2). Expert review by thesis supervisor and faculty members evaluated whether items adequately captured construct dimensions.

Face Validity assesses whether items appear to measure what they intend to measure based on subjective judgment.

Assessment method: Expert review and pilot test feedback (n=30) evaluated item clarity, relevance, and apparent appropriateness.

Construct Validity assesses whether measures behave as theoretically expected.

Convergent Validity assesses whether items measuring the same construct correlate highly:

- **Assessment metric**: Average Variance Extracted (AVE)

- **Criterion**: AVE ≥ 0.50 (construct explains ≥50% of indicator variance)

- Calculated in SmartPLS measurement model assessment

Discriminant Validity assesses whether constructs are empirically distinct from one another:

- **Assessment metrics**: Heterotrait-Monotrait (HTMT) ratio

- **Criterion**: HTMT < 0.85 (conservative) or < 0.90 (liberal)

- Calculated in SmartPLS measurement model assessment

Criterion-Related Validity assesses whether measures correlate with outcomes they should theoretically predict.

Assessment method: Expected positive correlations between technology maturity (DT, BM, AIM) and organizational performance provide criterion validity evidence.

3.8.3 Ethical Considerations

Research ethics were rigorously observed throughout all phases:

Informed Consent: All participants received clear information about research purposes, voluntary participation, right to withdraw, confidentiality protections, and data use. Proceeding with questionnaire completion constituted informed consent.

Voluntary Participation: Participation was entirely voluntary with no incentives, penalties, or pressure. Employees could decline without consequences.

Anonymity and Confidentiality: No personally identifiable information (names, employee IDs, contact information) was collected. Questionnaires were anonymous, and data are reported only in aggregate form preventing individual identification.

Data Security: Electronic data stored on password-protected devices and cloud storage with access restricted to researcher. Paper questionnaires stored securely and will be destroyed after thesis completion.

Organizational Confidentiality: While Bahawal Victoria Hospital is named as research site (with permission), individual departmental results are not attributed to specific identifiable departments in reporting unless aggregated sufficiently to prevent identification of individuals.

Beneficence: Research benefits include: providing the organization with insights into technology maturity status, contributing to academic knowledge on digital transformation in healthcare, and informing evidence-based technology investment decisions.

Non-maleficence: Research posed minimal risk to participants. No sensitive personal information collected; questionnaire focused on technology perceptions and organizational performance assessments.

Institutional Approval: Research protocol received ethical approval from Business School of Vilnius University and organizational permission from Bahawal Victoria Hospital administration prior to data collection.

3.9   Methodological Limitations

This research acknowledges several methodological limitations:

Cross-Sectional Design

Limitation: Whereas the theoretical process proposes that performance is caused by technology maturity, the cross-sectional evidence cannot conclusively prove that technology has a causal impact on performance as opposed to the likelihood that high-performing departments put more money into technologies.

Mitigation: A well-developed theoretical rationale by RBV and Dynamic Capabilities Theory has offered some rational justification to the cause and effect directions, which are hypothesized. The existing previous studies favor technology→performance causality. Statistical controls decrease the effect of alternative explanations. The findings are also given in terms of association but not as hard-and-fast causality. Extension is suggested to be longitudinal research.

Single Organization Context:

Limitation: The study is limited to single organization data that cannot be generalized to different organizational settings, healthcare systems, or nations. Results might be particular to the unique attributes of Bahawal Victoria Hospital, culture, methods of technological adoption or Pakistani healthcare environment.

Mitigation: Intensive single-case study makes possible analytical generalization to theoretical propositions but not statistical generalization to populations. Having theoretical predictions (RBV, Dynamic Capabilities) to be true in the various functional situations of one organization, this is an indication that the theory can be applied. It is advised that multi-organizational replication is to be used.

Self-Reported Measures:

Limitation: Any construct measures are based on employee self-reports but not objective data (technology audits, financial performance records, patient satisfaction surveys). Social desirability bias and common method variance is likely to affect self-reports, as well as subjective perceptions that are in contrast with objective reality.

Mitigation: Anonymous surveys will decrease the social desirability issue. The common method bias was determined by the single-factor test developed by Harman and corrected by

procedural means (distinctness between items, time in question sequence with different question orders). Numerous technology adoption researches effectively employ perception-based measurements which have been checked on objective measures. Objective performance data could be introduced into future research.

Common Method Bias:

Limitation: It is possible that the correlation between independent and dependent variables collected at the same time with the same respondents using the same instrument will overstate relationships because of the common method variance.

Mitigation: Design solutions involve separation of predictor and outcome questions in the questionnaire, making it clear that there are no correct or incorrect answers and that the questionnaire targets anonymous respondents where they are expected to be honest. The statistical solutions are the single factor test by Harman (when the single factor accounts to over 50 percent variance, CMB is present) and the common latent factor models in PLS-SEM. In case of large CMB observed, there are other specifications to regulate method effects.

Sample Size for Multi-Group Analysis:

Limitation: This has a limitation; the general sample (N=204) is sufficient to perform PLS-SEM; however, due to the multi-group analysis, the sample is divided into five functional areas, and some groups have smaller samples (n=27 in the case of IT and Digital Services). The small group sizes can decrease the statistical power used to detect group differences.

Mitigation: the stratified sampling was used so that all domains were represented. PLS-SEM is comparatively resistant to the smaller sizes of groups than CB-SEM. The non-significant multi-group differences can show the true similarity or lack of power interpretation can accept this weakness.

Blockchain Measurement Challenges:

Strength: The use of blockchain in healthcare is still at an early stage. Measurement items are measured both in terms of readiness characteristics and actual adoption which may confound different stages of maturity. There is a possibility that some of the respondents are not well acquainted with blockchain and this can compromise the validity of responses.

Pilot testing ensured the understanding of the items. Descriptive analysis will look at the distributions of blockchain maturity scores; low variance would mean there is a low adoption and this needs to be looked at carefully.

Performance Measurement Scope:

SmartPLS 4 software was used to compute Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM analysis is conducted in two steps; measurement (relations between latent constructs and indicators) and structural (relations among constructs) analysis.

3.10 Summary

In this chapter, it was possible to provide a detailed methodological approach to the research of the effects of digital transformation and blockchain maturity on the performance of organizations, with the mediation of AI maturity, using cross-sectoral analysis and functional departments of the Bahawal Victoria Hospital. The philosophy and approach used in the research include the positivist philosophy and deductive approach that relies on cross-sectional survey methodology and single-case study, with embedded units design.

Structured questionnaires (Google Forms and paper-based) were used to conduct the primary data collection, and 204 employees were selected according to the five functional domains, namely, Clinical Services, Administrative and Management, Finance and Billing, IT and Digital services, and Operational Support, with 85.7 percent of the usable response rate. The questionnaire included four constructs Digital Transformation (5 items), Blockchain Maturity (5 items), AI Maturity (5 items), and Organizational Performance (5 items) assessed using 5-point Likert scales based on the already existing literature.

The analysis of the data has a logical sequence: SPSS to conduct the screening of the data, descriptive statistics, and initial reliability check; SmartPLS 4 to conduct the PLS-SEM analysis including the assessment of the measurement model (reliability, convergent validity, discriminant validity), the structural model analysis (hypothesis testing through path coefficients, R 2), mediation analysis (indirect effects through bootstrapping), and multi-group analysis (cross-domain comparisons).

Chapter 04

Data Analysis and Results

This chapter presents the results of the analysis of the collected data, extracted using Smart-PLS SEM. This chapter is divided into four parts: the first part includes demographic information; the second part consists of descriptive statistics; the third part contains results from the measurement model estimated using the PLS algorithm; and the final part presents results from the structural model.

4.1   Demographic Information

Table 4.2: Demographic information

No.	Name	Mean	Standard deviation	Excess kurtosis	Skewness
1	Gender	1.40	0.49	-1.83	0.43
2	Age	2.38	1.11	-0.20	0.57
3	Dept.	1.52	0.50	-2.01	-0.07
4	Exp	2.72	1.13	-0.39	0.33

4.2   Descriptive Statistics

The descriptive statistics include the list of items with standard deviation, kurtosis, and skewness.

Table 4.3: Descriptive Statistics

No.	Name	Mean	Standard deviation	Excess kurtosis	Skewness
1	Gender	1.40	0.49	-1.83	0.43
2	Age	2.38	1.11	-0.20	0.57
3	Dept.	1.52	0.50	-2.01	-0.07
4	Exp	2.72	1.13	-0.39	0.33
5	DT1	3.92	1.17	-0.05	-0.93
6	DT2	3.99	1.09	0.43	-1.04
7	DT3	3.90	1.21	-0.16	-0.90
8	DT4	4.04	1.09	0.81	-1.18
9	DT5	3.99	1.12	0.33	-1.04
10	BM1	3.90	1.24	0.07	-1.04
11	BM2	4.02	1.12	0.45	-1.10

12	BM3	3.94	1.17	0.07	-0.99
13	BM4	3.92	1.20	0.09	-1.01
14	BM5	3.99	1.17	0.60	-1.20
15	AIM1	3.89	1.20	0.10	-1.00
16	AIM2	3.84	1.25	0.01	-0.99
17	AIM3	3.89	1.16	-0.03	-0.89
18	AIM4	3.98	1.14	0.48	-1.12
19	AIM5	3.87	1.22	-0.00	-0.98
20	OP1	3.96	1.16	0.08	-0.99
21	OP2	4.01	1.09	0.46	-1.06
22	OP3	3.97	1.13	0.08	-0.95
23	OP4	3.98	1.14	0.27	-1.01
24	OP5	3.99	1.11	0.40	-1.04

The table presents descriptive statistics for demographic variables and several construct items. Overall, respondents reported most items in the construct as high, with mean scores ranging from 3.8 to 4.0, indicating overall positive perceptions or agreement. The standard deviations (around 1.1 -1.2) indicate moderate variability of responses. Demographic variables (Gender, Age, Department, and Experience) have lower means, in line with categorical coding and low dispersion. The skewness of the construct items is mostly negative (ranging from -0.9 to -1.2), indicating that responses are distributed to the right side of the scale, whereas the demographic variables have low skew. The construct items have excess kurtosis values that are generally near zero, indicating a distribution that is typically distributed around. In contrast, Gender and Department have lower excess kurtosis values, indicating a flatter distribution typical of binary or categorical variables. In general, the statistics indicate good distributional characteristics with no drastic changes in normality, suggesting the appropriateness of the data for multivariate analysis.

4.3 Measurement Model

The measurement model contains results from the PLS algorithm, including the factor loadings, Cronbach's alpha, composite reliability, and average variance extracted. Discriminant validity results are also part of these results, and they are divided into three parts: the results for the combined groups, and the results for groups A and B, presented separately.

The threshold values for factor loadings, Cronbach's Alpha, and Composite reliability are 0.70, which is acceptable; 0.80, which is considered good; and 0.90, which is excellent. At the same time, the threshold for average variance extracted (AVE) is 0.50 or higher.

Reliability and Validity

Table 4.4: Measurement Model Results (Combine Results for both Groups)

Variables	Items	Factors' Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Maturity (AIM)	AIM1	0.914			
	AIM2	0.911			
	AIM3	0.927	0.957	0.967	0.852
	AIM4	0.929			
	AIM5	0.936			
Blockchain Maturity (BM)	BM1	0.901			
	BM2	0.899			
	BM3	0.929	0.949	0.961	0.831
	BM4	0.912			
	BM5	0.916			
Digital Transformation (DT)	DT1	0.935			
	DT2	0.908			
	DT3	0.931	0.955	0.965	0.848
	DT4	0.910			
	DT5	0.921			
Organizational Performance (OP)	OP1	0.877			
	OP2	0.914			
	OP3	0.913	0.947	0.959	0.826
	OP4	0.905			
	OP5	0.934			

The table presents the measurement model findings and high reliability and convergent validity across all constructs. The loading for all item factors is high, ranging from 0.877 to 0.936, which exceeds the suggested cutoff of 0.70. This implies that all the items load their respective constructs well. The alphas for AI Maturity, Blockchain Maturity, Digital Transformation, and Organizational Performance range from 0.947 to 0.957, indicating strong internal consistency. In the same way, the composite reliability values (0.9590.967) are significantly high over the acceptable minimum of 0.70, and the values also confirm construct reliability. The Average

Variance Extracted (AVE) values, 0.826 to 0.852, exceed the recommended 0.50, indicating that each construct explains a significant percentage of the variance in the indicators. Generally, these findings affirm that the measurement scales are trustworthy and exhibit excellent convergent validity, and thus are apt to be used further in the analysis of the structural model.

Table 4.5: Measurement Model Results (Group A: Frontline & Operational)

Variables	Items	Factors' Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Maturity (AIM)	AIM1	0.903	0.957	0.967	0.852
	AIM2	0.912			
	AIM3	0.927			
	AIM4	0.951			
	AIM5	0.923			
Blockchain Maturity (BM)	BM1	0.923	0.953	0.964	0.843
	BM2	0.908			
	BM3	0.924			
	BM4	0.924			
	BM5	0.912			
Digital Transformation (DT)	DT1	0.933	0.954	0.965	0.845
	DT2	0.913			
	DT3	0.936			
	DT4	0.905			
	DT5	0.910			
Organizational Performance (OP)	OP1	0.875	0.947	0.960	0.826
	OP2	0.923			
	OP3	0.919			
	OP4	0.908			
	OP5	0.921			

The adjusted measurement model results are shown in the table and demonstrate that all constructs have high levels of reliability and convergent validity. The factor loadings are all high, ranging from 0.875 to 0.951, exceeding the suggested threshold of 0.70, indicating that the measurement items are highly reflective of the latent factors. The alpha values of Cronbach (0.947-0.957) indicate high internal consistency of all the constructs. Similarly, the related composite reliability ranges from 0.960 to 0.967, well above the acceptable level, further

confirming the scales' reliability. The Average Variance Extracted (AVE) values (0.826-0.852) exceed the minimum value (0.50), indicating that each construct accounts for a substantial percentage of the variance in its indicators. Altogether, these findings demonstrate that the measurement model is sound, that item reliability and convergent validity are high, and that the model can be used to conduct further structural equation modelling and test hypotheses.

Table 4.6: Measurement Model Results (Results for Group B: Administrative & Support)

Variables	Items	Factors' Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Maturity (AIM)	AIM1	0.927	0.957	0.967	0.855
	AIM2	0.909			
	AIM3	0.928			
	AIM4	0.909			
	AIM5	0.949			
Blockchain Maturity (BM)	BM1	0.878	0.945	0.958	0.820
	BM2	0.889			
	BM3	0.935			
	BM4	0.902			
	BM5	0.922			
Digital Transformation (DT)	DT1	0.938	0.957	0.967	0.853
	DT2	0.904			
	DT3	0.927			
	DT4	0.915			
	DT5	0.934			
Organizational Performance (OP)	OP1	0.880	0.948	0.960	0.829
	OP2	0.911			
	OP3	0.910			
	OP4	0.903			
	OP5	0.947			

The table reports the end-of-assessment results for the measurement model and provides strong indications of the reliability and convergent validity of all the constructs. The loading for each factor is high, ranging from 0.878 to 0.949, which exceeds the recommended 0.70, indicating that all items are good proxies for their corresponding constructs. The alpha values reported by Cronbach for AI Maturity (0.957), Blockchain Maturity (0.945), Digital Transformation

(0.957), and Organizational Performance (0.948) indicate excellent internal consistency. The scale reliability is also supported by the fact that composite reliability values (0.958, 0.967) are significantly above the acceptable level of 0.70. The Average Variance Extracted (AVE) values of 0.820 to 0.855 exceed the recommended threshold of 0.50, indicating that both constructs account for a significant percentage of variance in the measures. In general, these findings suggest that the measurement model is healthy, the items are highly reliable, and the model exhibits high convergent validity, and that it can be subjected to further structural model analysis.
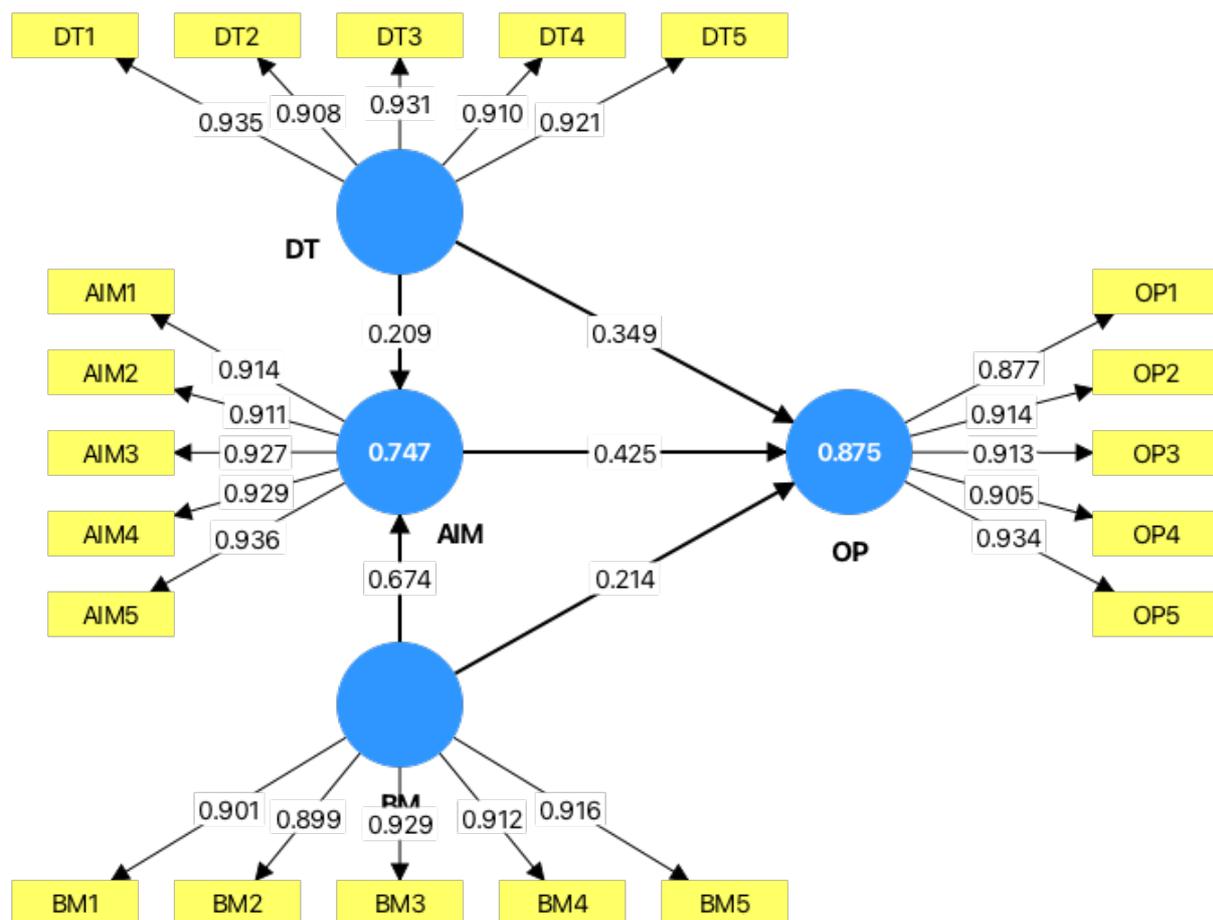
Figure 4.2: R-square Values

The figure presents the results of the structural equation model, showing the measurement and structural correlations among the constructs. The indicators (DT1- DT5, AIM1- AIM5, BM1- BM5, and OP1- OP5) all show high outer loadings, with most exceeding 0.90, indicating excellent reliability and consistency with the measurement model outcomes. The structural paths also show that Digital Transformation positively influences AI Maturity (0.209) and Blockchain Maturity (0.674), implying that the greater the level of digital transformation, the more the technological maturity in an organization. The positive effect on the Blockchain

Maturity (0.425) also shows the positive impact of AI Maturity on the development of blockchain (with a positive relationship). Moreover, the positive correlations between Digital Transformation (0.349), AI Maturity (0.214), and Blockchain Maturity (0.425) and Organizational Performance also demonstrate that these technologies are significant in enhancing organizational performance. The R^2 values indicate that the endogenous constructs (AI Maturity R^2 values (0.747) and Organizational Performance R^2 values (0.875)) are strongly explained by their predictors. In general, the model has high explanatory power and supports the assumptions about the relationships among digital transformation, technological maturity, and organizational performance.
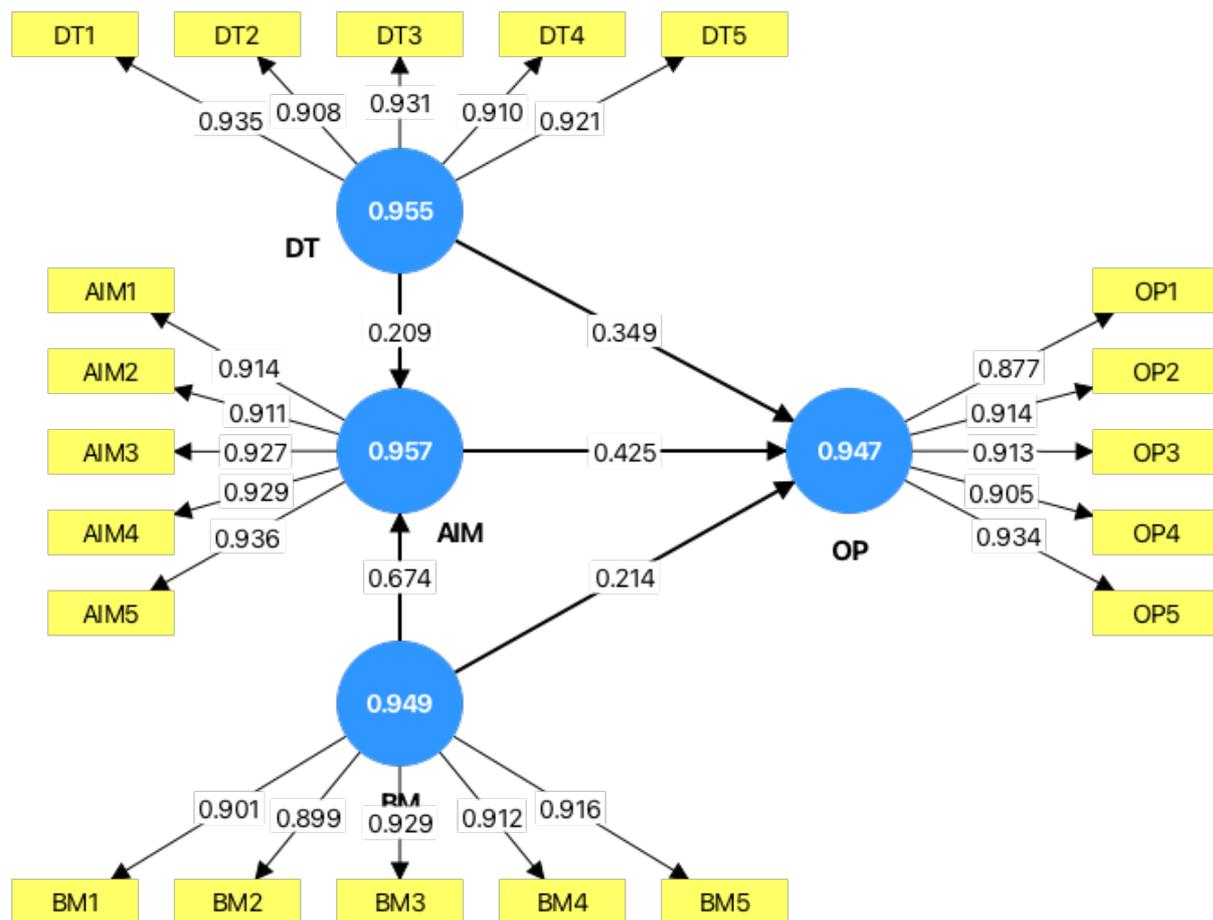
Figure 4.2: R-square Values

The figure shows the final PLS-SEM model, which combines the measurement and structural components, and it has very high reliability and explanatory power. Each of the measurement items of Digital Transformation (DT), AI Maturity (AIM), Blockchain Maturity (BM), and Organizational Performance (OP) has high outer loadings (around 0.88-0.94), which proves the high reliability of indicators. The values presented within the blue circles (DT = 0.955, AIM = 0.957, BM = 0.949, and OP = 0.947) indicate that the internal consistency reliability (Cronbach's alpha) is very high (all are above the recommended 0.70 value). Digitally, Digital

Transformation has a positive effect on AI Maturity (0.209) and Blockchain Maturity (0.674), indicating that digital efforts have a pronounced impact on technological maturity, particularly in the use of blockchain. AI Maturity, on its part, also shows a positive correlation with Blockchain Maturity (0.425), demonstrating the reinforcing nature of AI and blockchain capabilities. Digital Transformation (0.349), AI Maturity (0.214), and Blockchain Maturity (0.425) have a positive impact on Organizational Performance, indicating that these technological variables contribute to better organizational performance. In total, the model has good measurement quality, meaningful path relations, and strong support for the overall theoretical framework linking digital transformation, the maturity of emerging technologies, and organizational performance.
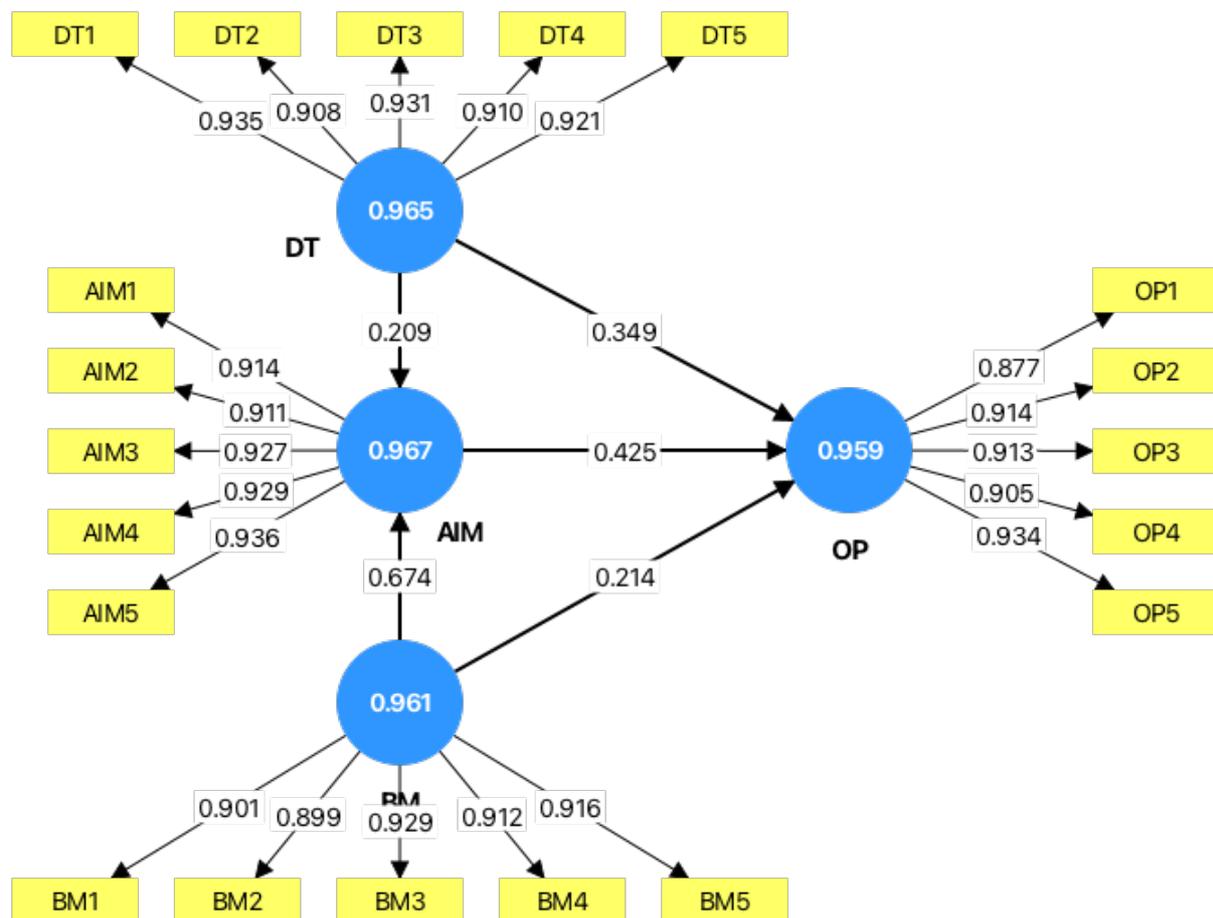
Figure 4.3: Composite Reliability Values

The results of the composite reliability analysis in the model suggest high internal consistency for all constructs. All the indicators have a higher CR of 0.965 (Digital Transformation), 0.967 (AI Maturity), 0.961 (Blockchain Maturity), and 0.959 (Organizational Performance), which are above the recommended threshold of 0.70 and even 0.90, which illustrates that the indicators are all measuring what they are expected to measure, namely their respective latent

constructs. These high composite reliabilities indicate that the measurement items account for a substantial portion of the variance and provide a reliable representation of each construct. The results also suggest that the measurement model has high reliability, indicating the strength of the constructs and their directness for use in further structural model analysis and hypothesis testing.
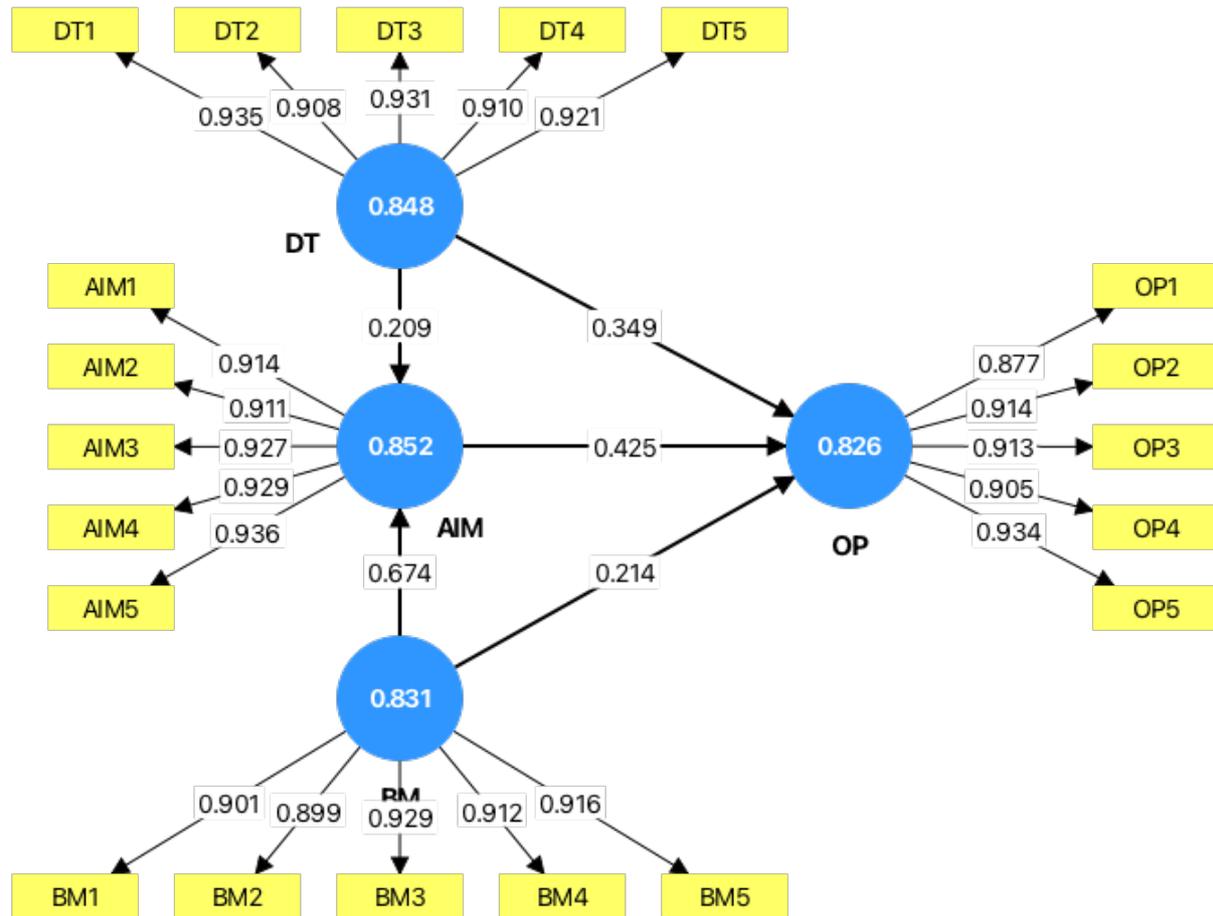
Figure 4.4: Average Variance Extracted (AVE) Values

The Average Variance Extracted (AVE) values presented in the model demonstrate high convergent validity for all constructs. Digital Transformation (AVE = 0.848), AI Maturity (AVE = 0.852), Blockchain Maturity (AVE = 0.831), and Organizational Performance (AVE = 0.826) have AVE greater than 0.50. This illustrates that both constructs explain more than 80 percent of the variance in their corresponding indicators, demonstrating that the measurement items are very representative of the latent variables they reflect. The evidently high AVE values confirm that the constructs account for a significant portion of the indicators' variance relative to measurement error, which is a strong indicator of convergent validity and provides evidence of the suitability of the measurement model for the following structural analysis.
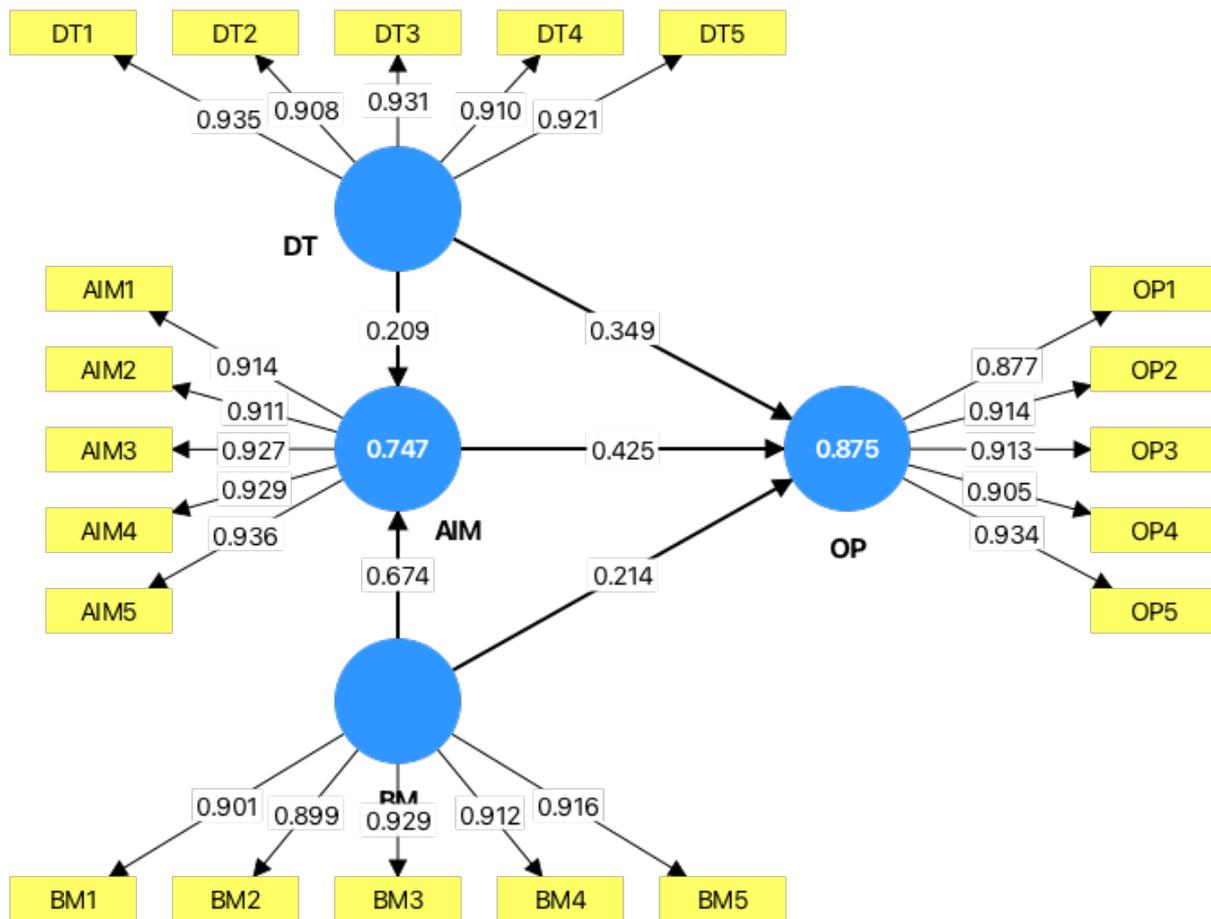
Figure 4.5: R-square Values

The R-Squared (R^2) values in the model indicate that the structural relationships have high explanatory power. The R^2 value for AI Maturity is 0.747, indicating that 74.7 percent of the variance in AI Maturity is accounted for by Digital Transformation, which is quite a reasonable degree of explanatory power. The R^2 value for Organization Performance is 0.875; hence, Digital Transformation, AI Maturity, and Blockchain Maturity together account for 87.5 percent of the variation in organizational performance, indicating very high predictive power for organizational performance. These R^2 values exceed the recommended thresholds for significant explanatory power in PLS-SEM, indicating that the developed model effectively captures the main determinants of technological maturity and organizational performance.

4.4 Discriminant Validity

The discriminant validity can be determined with the help of Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker criterion. There are two tables below representing the HTMT and Fornell-Larcker criterion and also the description of these two tables are given below in details to explain theses results for understanding.

Table 4.7: Heterotrait-Monotrait ratio (HTMT)

Variables	AIM	BM	DT	OP
AIM				
BM	0.800			
DT	0.842	0.832		
OP	0.733	0.737	0.827	

The Heterotrait-Monotrait ratio (HTMT) indicates sufficient discriminant validity for all constructs in the model. The values of all the HTMT are lower than the conservative value of 0.85 (and far lower than the liberal value of 0.90), indicating that each construct is empirically distinct. In particular, the HTMT values between AI Maturity and Blockchain Maturity (0.800), AI Maturity and Digital Transformation (0.842), and Blockchain Maturity and Digital Transformation (0.832) are not above acceptable limits, indicating that they are related but distinct constructs. In the same way, Organization Performance presents a satisfactory discriminant validity with AI Maturity (0.733), Blockchain Maturity (0.737), and Digital Transformation (0.827). In general, the constructs demonstrated discriminant validity and assessed conceptually distinct phenomena in the research model.

Table 4.8: Fornell-Larcker criterion

Variables	AIM	BM	DT	OP
AIM	0.923			
BM	0.859	0.912		
DT	0.807	0.888	0.921	
OP	0.890	0.888	0.881	0.909

The results of the Fornell-Larcker criterion indicate the presence of discriminant validity between the constructs. The square root of the Average Variance Extracted (AVE) at the diagonal is maximized for each of the constructs relative to its respective relationships with the other constructs in the same row and column. In particular, AI Maturity (0.923), Blockchain Maturity (0.912), Digital Transformation (0.921), and Organizational Performance (0.909) are the diagonal values that are larger than their inter-construct-related correlations. It means that each construct has indicators with greater variance than those of the other constructs in the model. All in all, the findings demonstrate discriminant validity, which underlies the distinctiveness of AI Maturity, Blockchain Maturity, Digital Transformation, and Organizational Performance.

Table 4.9: Cross Loadings

Items	AIM	BM	DT	OP
AIM1	0.914	0.829	0.770	0.826
AIM2	0.911	0.752	0.667	0.766
AIM3	0.927	0.750	0.740	0.836
AIM4	0.929	0.835	0.794	0.853
AIM5	0.936	0.793	0.745	0.822
BM1	0.773	0.901	0.792	0.796
BM2	0.773	0.899	0.786	0.802
BM3	0.800	0.929	0.865	0.836
BM4	0.774	0.912	0.820	0.790
BM5	0.795	0.916	0.781	0.824
DT1	0.767	0.830	0.935	0.816
DT2	0.739	0.795	0.908	0.791
DT3	0.720	0.811	0.931	0.804
DT4	0.758	0.835	0.910	0.834
DT5	0.730	0.815	0.921	0.812
OP1	0.747	0.836	0.816	0.877
OP2	0.829	0.799	0.787	0.914
OP3	0.787	0.798	0.831	0.913
OP4	0.855	0.806	0.776	0.905
OP5	0.822	0.796	0.795	0.934

Other indicators of discriminant validity in the measurement model include cross-loadings. All measurement indicators, as measures of their intended constructs, have the highest loadings relative to other constructs, which shows that the indicators are more strongly correlated with their respective latent constructs. For example, all AI Maturity indicators load most strongly on AI Maturity (0.91136), all Blockchain Maturity indicators load most strongly on Blockchain Maturity (0.89932), all Digital Transformation indicators load most strongly on Digital Transformation (0.90836), and all Organizational Performance indicators load most strongly on Organizational Performance (0.87734). Though cross-loadings with other constructs are still relatively high, they are always lower than the primary loadings, which is reasonable in multidimensional models with conceptually related constructs. These findings overall support

that the indicators demonstrate sufficient discriminant validity and measure their respective constructs as intended.

Table 4.10: Model Summary

	Saturated model	Estimated model
SRMR	0.040	0.040
d_ULS	0.337	0.337
d_G	0.592	0.592
Chi-square	709.056	709.056
NFI	0.877	0.877

The coefficients of model fit indicate that the overall fit of the saturated and estimated models is acceptable to good, as the value is the same in this scenario. The recommended value of SRMR is 0.08, whereas the observed value is 0.040, which is much lower, indicating a good fit to the model. The discrepancies d ULS (0.337) and d G (0.592) are not significant, suggesting few differences between the model-implied and observed correlation matrices. The chi-square value (709.056) indicates the overall distance between the observed and estimated covariance matrices, but the difference is sensitive to sample size, so its interpretation in PLS-SEM is usually supportive but not conclusive. The Normed Fit Index (NFI) is 0.877, close to the generally accepted cutoff of 0.90, indicating that the model fits the data reasonably well. All in all, these fit indices suggest that the proposed model has good global fit and can be used to understand the structural relationships.

Table 4.11: Values of r-square (Combine)

Dependent Variables	R-square	R-square adjusted
AIM	0.747	0.745
OP	0.875	0.874

The values of R-squared and adjusted R-squared suggest that the structural model has strong explanatory power for the dependent variables. AI Maturity (AIM) indicates the value of R^2 is 0.747, or in other words, three-quarters of the variance in AI Maturity is covered by its predictor(s), and the adjusted R-2 is 0.745, which also shows that the explanatory capacity of the model will not decrease when the complexity of the model is considered. The R-square is even higher for Organizational Performance (OP): 0.875, and the adjusted R-square is 0.874, indicating negligible shrinkage. On the whole, these findings reveal that the model has very high predictive validity and strong explanatory power for AI Maturity and Organizational Performance.

**Table 4.12:** Values of r-square (Group A: Frontline & Operational)

Dependent Variables	R-square	R-square adjusted
AIM	0.834	0.831
OP	0.896	0.893

The values of R-squared and adjusted R-squared show that the structural model has very high explanatory power on the dependent variables. The R-square value for AI Maturity (AIM) is 0.834, indicating that its predictors can explain 83.4% of the variance in AI Maturity. The adjusted R-square for AI Maturity equals 0.831, suggesting that its predictors explain such a high level of variance despite controlling for model complexity. The even higher R-Sq value of 0.896 for Organizational Performance (OP) indicates that 89.6 percent of the variance in organizational performance is attributed to the antecedent constructs, and the adjusted R-Sq of 0.893 shows very little decrement. All in all, the results indicate the high quality of the predictive variables and the model's strength in predicting both AI Maturity and Organizational Performance.

Table 4.13: Values of r-square (Group B: Administrative & Support)

Dependent Variables	R-square	R-square adjusted
AIM	0.664	0.657
OP	0.859	0.855

Both the R-squared and adjusted R-squared values indicate that the structural model has strong explanatory power for the dependent variables. The R-square of AI Maturity (AIM) is 0.664, which implies that 66.4 percent of the variance in AI Maturity is captured by its predictors(s), and the adjusted R-squared at 0.657 also indicates that there is no significant change in adjusted R-squared when including the model complexity, hence indicating a stable model. Organization Performance (OP) also has a high R-square value of 0.859, suggesting that 85.9% of the variation in organization performance is attributed to the antecedent constructs, with an adjusted R-square of 0.855, affirming the strength. In general, these findings indicate that the model has significant predictive power for both the AI Maturity and Organizational Performance.
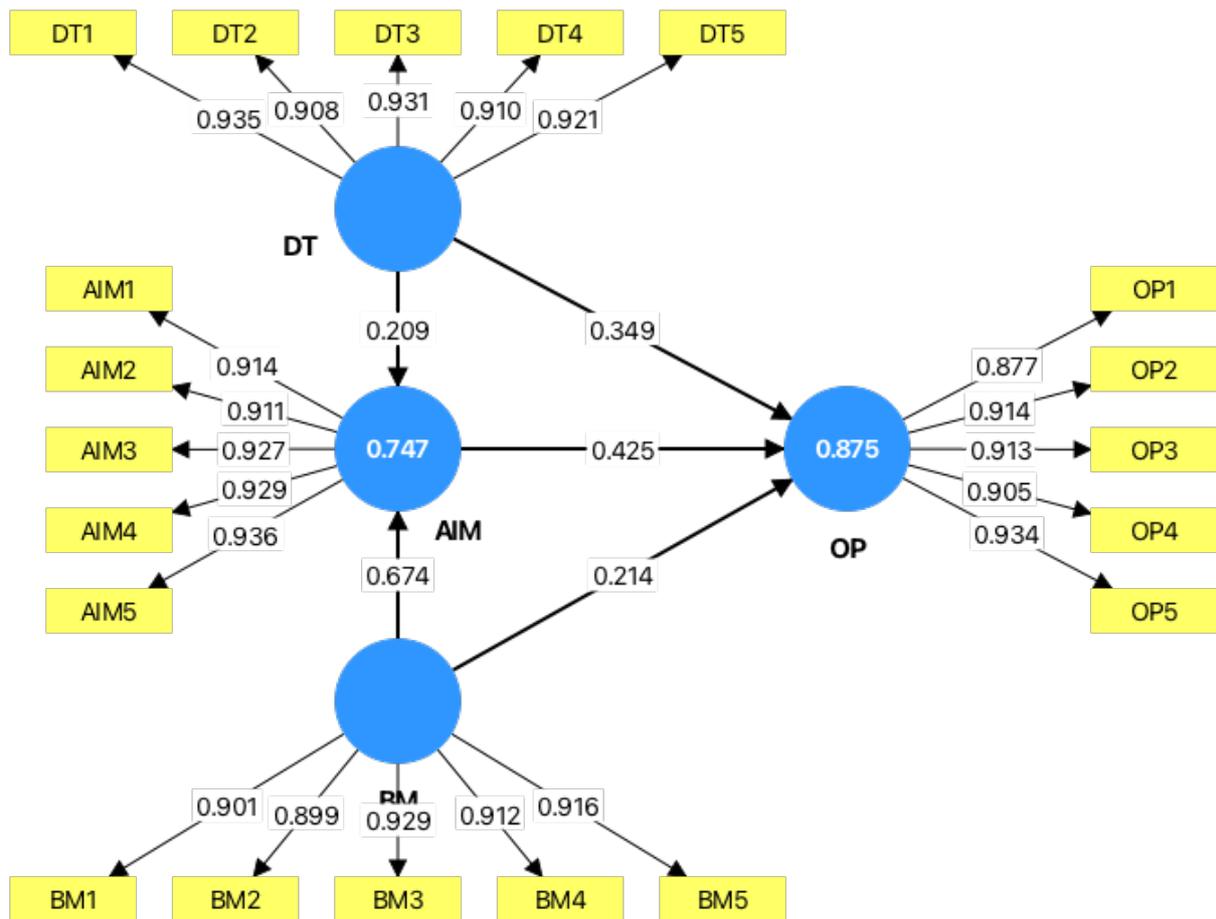
Figure 4.6: R-square Values

The R-square (R 2) values in the model suggest that the endogenous constructs are explained mainly. The R 2 of AI Maturity = 0.747, indicating that 74.7% of the variance in AI Maturity is predicted by antecedent variable/s, which is a high degree of prediction. The R2 for Organization Performance is even greater, at 0.875, indicating that the combination of Digital Transformation, AI Maturity, and Blockchain Maturity accounts for 87.5 per cent of the variation in organizational performance. Based on generally recognized guidelines for PLS-SEM, these R2 values may be considered meaningful, indicating that the suggested model is highly predictive and explains variations in both AI Maturity and Organizational Performance.

Table 4.14: Direct Relations (Combine)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
AIM -> OP	0.425	0.428	0.069	6.124	0.000	Supported
BM -> AIM	0.674	0.683	0.129	5.238	0.000	Supported
BM -> OP	0.500	0.512	0.119	4.209	0.000	Supported

DT -> AIM	0.209	0.199	0.135	1.544	0.123	Not-Supported
DT -> OP	0.438	0.426	0.114	3.830	0.000	Supported

The table shows the structural path coefficients and the results of testing the model's hypothesis. The correlation between AI Maturity and Organizational Performance is found to be positive and statistically significant (r = 0.425, t = 6.124, p < 0.001). Therefore, the more the AI maturity, the better the performance of any organization; thus, the hypothesis is proved to be valid. AI Maturity is positively and significantly affected by Blockchain Maturity (r = 0.674, t (5) = 5.238, p = 0.001), indicating that blockchain capabilities can be important for improving AI maturity. Also, Blockchain Maturity has a positive impact on Organizational Performance (= 0.500, t = 4.209, p < 0.001), indicating that it directly affects performance. Digital Transformation has a positive effect on Organizational Performance (=0.438, t=3.830, p=0.001), and it is clear that digital initiatives are essential factors that enhance performance. Nevertheless, the correlation between Digital Transformation and AI Maturity is not statistically significant (0.209, t = 1.544, p = 0.123), indicating that the effect of digital transformation on AI maturity is not directly positive. In general, the findings provide strong support for the proposed model, as most hypothesized relationships have been confirmed. Still, the direct impact of Digital Transformation on AI Maturity has not.

Table 4.15: Indirect Relations (Combine)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
BM -> AIM -> OP	0.286	0.292	0.070	4.111	0.000	Partial Mediation
DT -> AIM -> OP	0.089	0.087	0.062	1.439	0.150	Full Mediation

The table indicates the mediation analysis findings and the indirect effects using AI Maturity. The indirect relationship between Blockchain Maturity and Organizational Performance through AI Maturity is found to be positive and statistically significant (0.286, t = 4.111, p < 0.001), implying that AI Maturity partially mediates the relationship between Blockchain Maturity and Organizational Performance. This means that blockchain maturity positively and indirectly increases an organization's performance by improving AI maturity. Conversely, the indirect effect of Digital Transformation on Organizational Performance based on AI Maturity is not significant (0.089, t = 1.439, p = 0.150), indicating that AI Maturity does not play a vital

role in the relationship under discussion. Consequently, AI Maturity does not influence Organizational Performance through Digital Transformation. On the whole, the outcomes of the mediation highlight the importance of AI Maturity in transforming blockchain capabilities into performance rewards, and whether digital transformation is influencing organizational performance through mechanisms other than AI maturity.

Table 4.16: Direct Relations (Group A: Frontline & Operational)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ($\|O/STDEV\|$)	P values	Decision
AIM -> OP	0.328	0.349	0.110	2.966	0.003	Supported
BM -> AIM	0.698	0.690	0.176	3.958	0.000	Supported
BM -> OP	0.533	0.534	0.098	5.415	0.000	Supported
DT -> AIM	0.230	0.238	0.186	1.237	0.216	Not-Supported
DT -> OP	0.424	0.422	0.095	4.444	0.000	Supported

The results of the structural path analysis and hypothesis testing are provided in the table. The correlation between AI Maturity and Organization Performance is positive and statistically significant ($= 0.328, = 2.966, = 0.003$). Therefore, the higher the level of AI maturity, the better the organization's performance, which supports the proposed hypothesis. The positive impact of Blockchain Maturity on AI Maturity is very high and significant ($r = 0.698$, $t = 3.958$, $p < 0.001$), indicating that advanced blockchain capabilities are crucial for improving AI maturity in organizations. Organizational Performance is also directly and substantially influenced by Blockchain Maturity ($= 0.533, = 5.415, = 0.001$), indicating a significant impact on performance outcomes. The effect of Digital Transformation on Organizational Performance (0.424, $t = 4.444$, $p < 0.001$) is essential, demonstrating the role of digital activities in the rise in performance. Nevertheless, there is no statistically significant path between Digital Transformation and AI Maturity ($= 0.230$, $t = 1.237$, $p = 0.216$), indicating that digital transformation itself does not have a direct effect on increased AI maturity. In general, the findings were primarily positive, and all hypothesized relations were supported, except for the direct impact of Digital Transformation on AI Maturity.

Table 4.17: Indirect Relations (Group A: Frontline & Operational)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
BM -> AIM -> OP	0.229	0.242	0.101	2.259	0.024	Partial Mediation
DT -> AIM -> OP	0.075	0.083	0.072	1.052	0.293	Full Mediation

The outcomes of the mediation analysis show that AI Maturity plays distinct roles in the associations between the antecedent variables and Organizational Performance. Indirect Improvement of Organizational Performance through AI Maturity within the context of Blockchain Maturity is a positive, statistically significant (2.259, 0.229, p = 0.024) effect, which implies partial mediation. Although this means that Blockchain Maturity directly and indirectly increases Organizational Performance through the advancement of AI Maturity, the significance of AI Maturity as a valuable tool through which blockchain capabilities deliver performance benefits is underscored. On the contrary, CRM Digital Transformation has no significant indirect influence on Organizational Performance through AI Maturity (0.075, t = 1.052, p = 0.293). The role of AI Maturity does not appear to be critical in the relationship between Digital Transformation and Organizational Performance. Thus, the effect of digital transformation on performance is not achieved through AI maturity. In general, the results highlight the mediating significance of AI Maturity in the blockchain performance relationship, yet it did not uphold the mediating significance of AI Maturity in the digital transformation performance association.

Table 4.18: Direct Relations (Group B: Administrative & Support)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
AIM -> OP	0.468	0.472	0.089	5.234	0.000	Supported
BM -> AIM	0.635	0.660	0.173	3.670	0.000	Supported
BM -> OP	0.165	0.185	0.186	0.886	0.376	Not- Supported
DT -> AIM	0.201	0.177	0.179	1.121	0.262	Not-Supported
DT -> OP	0.362	0.337	0.155	2.339	0.019	Supported

The outcomes of the mediation analysis show that AI Maturity plays distinct roles in the associations between the antecedent variables and Organizational Performance. Indirect

Improvement of Organizational Performance through AI Maturity within the context of Blockchain Maturity is a positive, statistically significant (2.259, 0.229, p = 0.024) effect, which implies partial mediation. Although this means that Blockchain Maturity directly and indirectly increases Organizational Performance through the advancement of AI Maturity, the significance of AI Maturity as a valuable tool through which blockchain capabilities deliver performance benefits is underscored. On the contrary, CRM Digital Transformation has no significant indirect influence on Organizational Performance through AI Maturity (0.075, t = 1.052, p = 0.293). It means that the role of AI Maturity does not appear to be critical in the relationship between Digital Transformation and Organizational Performance. Thus, the effect of digital transformation on performance is not achieved through AI maturity. In general, the results highlight the mediating significance of AI Maturity in the blockchain performance relationship, yet it did not uphold the mediating significance of AI Maturity in the digital transformation performance association.

Table 4.19: Indirect Relations (Group B: Administrative & Support)

Relations	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
BM -> AIM -> OP	0.297	0.309	0.094	3.170	0.002	Partial Mediation
DT -> AIM -> OP	0.094	0.087	0.087	1.079	0.281	Full Mediation

The results of this mediation analysis indicate that AI Maturity strongly mediates the correlation between Blockchain Maturity and Organizational Performance. Blockchain Maturity has a positive, statistically significant indirect impact (organizational performance) via AI Maturity (= 0.297, = 3.170, = 0.002), which means partial mediation. This implies that Blockchain Maturity enhances Organizational Performance directly and indirectly by raising AI Maturity, underscoring the significance of AI capabilities as a tool for turning blockchain initiatives into performance improvements.

Conversely, the relationship between Digital Transformation and Organizational Performance through AI maturity is statistically insignificant (0.094, t = 1.079, p = 0.281). This means that AI Maturity is not a significant mediator between Digital Transformation and Organizational Performance. Hence, the effects of Digital Transformation on Organizational Performance take other channels instead of AI maturity. In general, the results indicate that the central mediating

role of AI Maturity in the blockchain-performance relationship is confirmed, although its mediating role in the digital transformation-performance one is not supported.
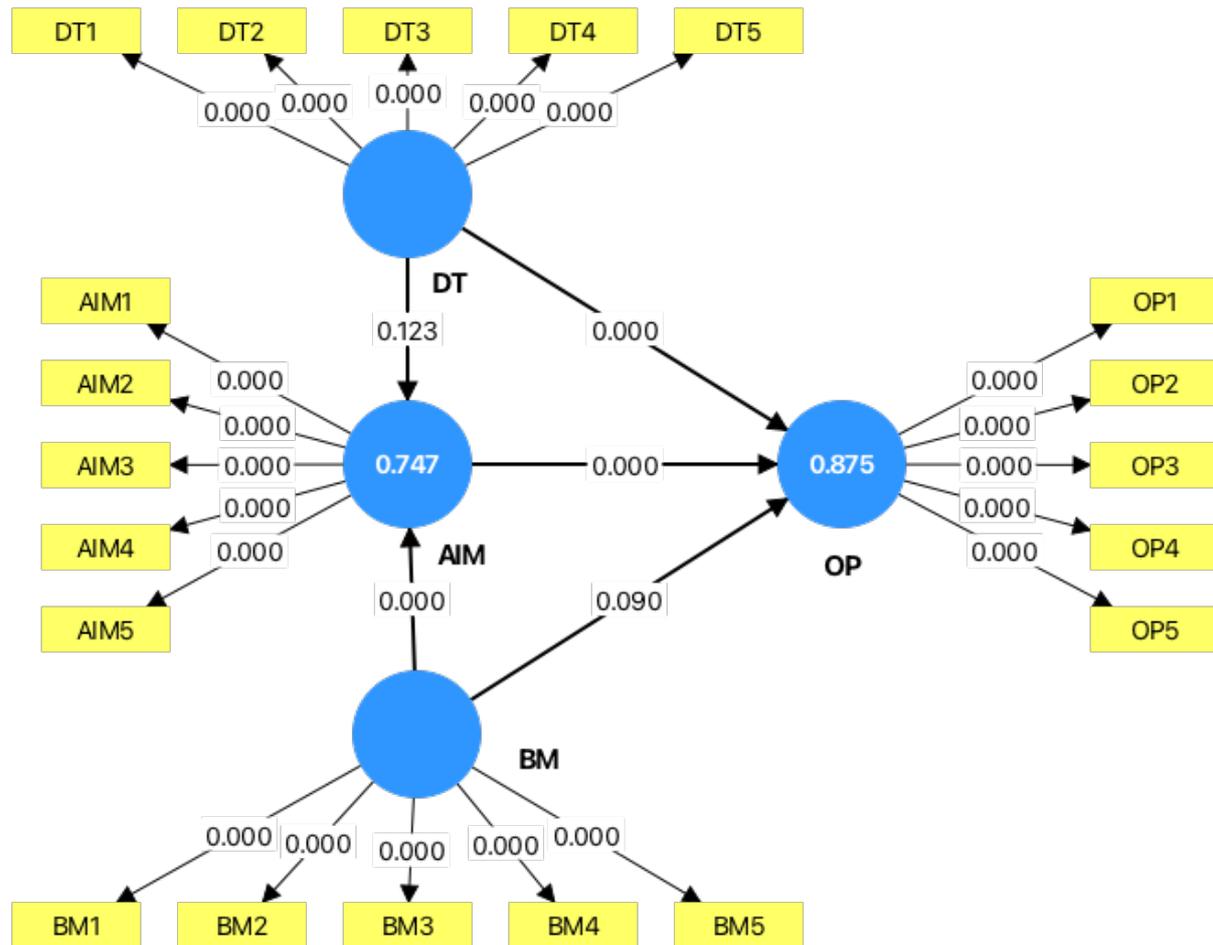

Figure 4.7: P-Values

The figure shows the bootstrapping results for the measurement and structural models, with p-values indicating the statistical significance of the estimated relationships. The p-values for all indicator loadings for Digital Transformation (DT), AI Maturity (AIM), Blockchain Maturity (BM), and Organizational Performance (OP) are 0.000, indicating that all measurement items load significantly on their respective constructs and demonstrating excellent indicator reliability.

The relationship between AI Maturity and Organizational Performance is statistically significant (p = 0.000) in the structural model, which proves the positive influence of AI maturity on an organization. It is also essential that the path between Blockchain Maturity and AI Maturity is significant (p = 0.000), indicating that Blockchain Maturity plays a critical role in the presence of AI Maturity. However, there is no statistical significance between Digital Transformation and AI Maturity (p = 0.123), indicating no direct relationship between the two.

The Direct Relationship between Digital Transformation and Organizational Performance demonstrates the relationship is insignificant (p = 0.090), suggesting a less-influential but possibly meaningful effect at the selected level of significance.

The values of R 2 presented within the endogenous constructs show that their explanatory power levels are very high, with AI Maturity (R 2 = 0.747) and Organizational Performance (R 2 = 0.875) their predictors being adequately explained. In general, the bootstrapping findings prove the strength of the measurement model and give a solid support to the majority of the hypothesized structural relationships, especially to the central role of AI maturity in the driving force of organizational performance and to the mediation of the influence of blockchain maturity.
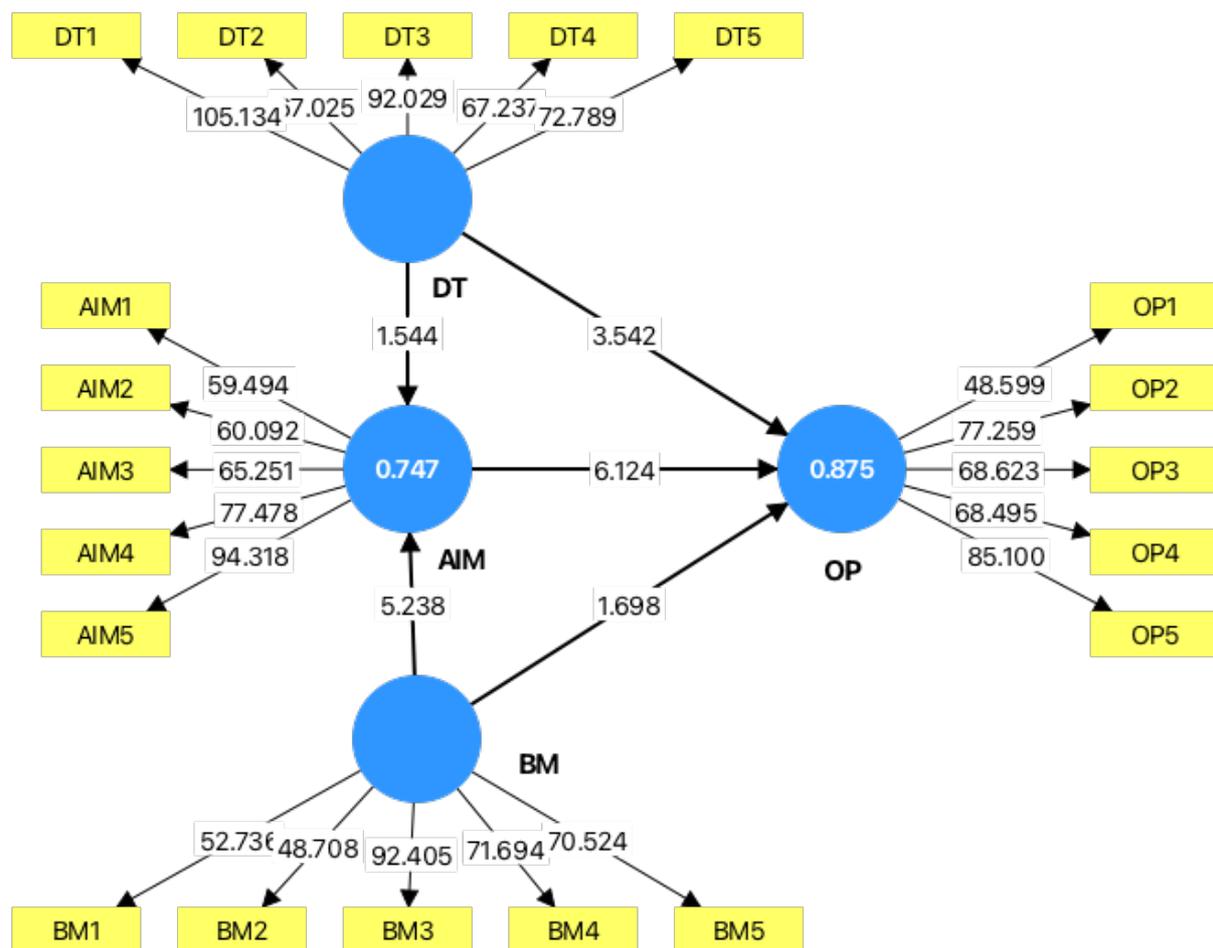
Figure 4.8: T-Values

T-values in this model indicate whether the relationships (path coefficients or indicator loadings) are statistically significant. The t-value is the estimated coefficient divided by the estimated standard error; it means the distance of the estimate from zero in units of standard

errors. Generally speaking, t-values of 1.96, 2.58, and 3.29 are critical values that indicate significance at 5-percent, 1-percent, and 0.1-percent probabilities, respectively.

In your diagram, the t-values next to the structural paths (e.g., 3.542, 6.124, 5.238) are large, exceeding 1.96, indicating that these relationships are statistically significant and could not have occurred by chance. This justifies the finding that there is a tangible impact on the corresponding constructs. Concisely, t-values that have been reported in your model are statistically significant in terms of the strength and reliability of the hypothesized relationships.

Chapter 05
Discussion and Conclusion

5.1 Introduction

This chapter places the empirical results from Chapter 04 in the context of the general theory and practice of digital transformation, the maturity of emerging technologies, and organizational performance. The chapter also summarizes the pertinent findings, concludes based on the research objectives and hypotheses, and expounds on the practical and theoretical implications of the research. It also acknowledges the study's limitations and offers recommendations for future research directions. Combined, these parts show that this study contributes to knowledge and practice at the point of convergence between digital transformation, artificial intelligence (AI), blockchain technology, and organizational performance.

5.2 Discussion of Key Findings

Digital Transformation and Organizational Performance

The findings show that Digital Transformation (DT) and Organizational Performance (OP) have a significant, positive relationship not only in the combined sample but also in each of the two subgroups. This observation validates the claim that initiatives related to digital transformation, including the digitization of processes, the use of digital infrastructure, and technology-based decision-making, have a direct impact on the positive organizational results. It aligns with previous literature that has pegged digital transformation as a strategic opportunity that augments efficiency, responsiveness, and competitiveness.

Yet, the relationship between Digital Transformation and AI Maturity (AIM) was not statistically significant in all models. The theoretical significance of this finding is that digital transformation does not necessarily lead to a high level of AI sophistication. Instead, the maturity of AI demands increased investment in data governance, analytics capabilities, algorithmic skills, and organizational preparedness, rather than generic digital efforts. This conclusion contradicts the widespread belief that AI potential is an inevitable outcome of the digital transformation and demonstrates that AI should be approached deliberately with AI-specific measures.

Blockchain Maturity as a Driver of AI Maturity

Among the most robust and stable aspects of the study, one can mention the substantial positive impact of Blockchain Maturity (BM) on AI Maturity. In both groups and in the combined sample, blockchain maturity was found to be a limiting factor in AI maturity. It implies that blockchain technologies, with their data characteristics of integrity, transparency, traceability, and decentralized trust, provide a trustworthy database that enhances the effectiveness and scalability of AI systems.

The finding extends the existing technology synergy literature by empirically demonstrating that blockchain and AI need not be treated as independent technologies, but rather as complementary capabilities. The maturity of blockchain improves the quality and reliability of the data used to train and deploy AI models. In this way, companies that are investing in blockchain maturity are better positioned to develop their AI capabilities.

AI Maturity and Organizational Performance

The study confirms that AI Maturity plays a positive and significant role in Organizational Performance across all models. This result indicates AI's maturity as a strategic asset for enhancing decision-making, predictive analytics, automation, and innovation. The more advanced an organization is in AI, the more likely it is to use data-driven insights to maximize its operations and create value.

It is also intriguing to note that AI maturity has a high explanatory power, as indicated by the high R2 for organizational performance. This fact suggests that AI maturity is not merely a technological product but an organizational skill that directly influences performance outcomes.

Mediating Role of AI Maturity

The mediation analysis provides detailed information on how technological capabilities can be applied to performance outcomes. It was found that AI Maturity partially mediated the correlation between Blockchain Maturity and Organizational Performance, indicating that Blockchain Maturity positively influences performance both directly and indirectly by increasing AI Maturity. It highlights AI maturity as a crucial mechanism that drives organizational value from blockchain investments.

Compared with AI Maturity, AI Maturity failed to mediate the relationship between Digital Transformation and Organizational Performance. It implies that digital transformation

influences performance by other avenues, including process automation, digital customer engagement, or business flexibility, but not AI maturity in particular. This distinction contributes to understanding the interaction among various technological capabilities within organizations.

Group-Based Differences

The multigroup analysis indicates significant differences between Frontline & Operational Functions (Group A) and Administrative & Support Functions (Group B). Although the general structural patterns are broadly similar, the direct impact of Blockchain Maturity on Organizational Performance was low in Group B as compare to Group A, suggesting that while frontline staff may involvement speedy functioning benefits from blockchain (e.g., supply chain tracking, patient data reliability), administrative departments trust more comprehensively on AI maturity to interpret blockchain data into actionable performance improvements. In Group B, blockchain affects performance indirectly rather than directly, as it is influenced by AI maturity.

The findings indicate that the effects of emerging technologies on performance might be influenced by organizational context, technological readiness, strategic orientation, and the need for digital strategies in the context.

5.3 Conclusion

This study aimed to analyze the correlations among Digital Transformation, AI Maturity, Blockchain Maturity, and Organizational Performance using Partial Least Squares Structural Equation Modelling (PLS-SEM). In response to the growing academic and managerial interest in the joint effects of emerging digital technologies on organizational performance, the study formulated and empirically tested an integrated model that captures the direct and indirect impacts of these constructs. The results provide strong empirical evidence that digital transformation efforts, AI maturity, and blockchain maturity may significantly improve organizational performance, though through different and heterogeneous processes.

In general, the findings validate the hypothesis that a one-dimensional adoption of technology does not drive organizational performance in the digital age, but rather a progression of mature, complementary technological capabilities that are strategically aligned with organizational goals. The strong explanatory variables of the model, and the significant R^2 values for both AI Maturity and Organizational performance, indicate that the proposed model accounts for a substantial percentage of the variance in the key output. It highlights the

conceptual framework's strengths and demonstrates its applicability to existing research on how modern organizations generate value through digital technologies.

One of the main findings of this paper is that AI maturity is a critical and strategic factor in converting technological investments into performance. In the combined sample and sub-group analyses, AI maturity had a substantial positive impact on organizational performance. This finding confirms the notion that AI maturity is not just a technical milestone but an organizational aspect encompassing data readiness, analytical functionality, algorithmic integration, and decision support. Companies with greater AI maturity are better able to leverage data-driven insights, automate complex operations, improve predictability, and facilitate strategic decision-making, all of which are directly linked to better performance.

Notably, the research shows that digital transformation, though a requirement, is not enough in itself to develop AI maturity. Though digital transformation was found to have a noteworthy direct effect on organizational performance, its influence on AI maturity is not statistically significant. There are important conceptual and practical implications of this distinction. It postulates that the digital transformation programs: the digitization of workflows, the use of enterprise systems, or the increase in digital connectivity can produce immediate performance improvements in the form of efficiency advantages and better coordination. Nevertheless, such efforts will not inevitably lead to more advanced AI capabilities unless well-considered investments in data governance, advanced analytics, AI talent, and organizational learning follow. In this way, the research warns against generalizing the processes of digitalization and the maturity of AI and emphasizes that specific AI strategies are required.

Conversely, blockchain maturity became one of the essential enablers of AI maturity, with a powerful and coherent positive impact across all models. The given finding gives strong empirical evidence of a complementary relationship between blockchain and AI technologies. The maturity of blockchain enhances the reliability, transparency, and integrity of organizational data, thereby addressing the inherent problems of data quality and trust that limit AI's work. Blockchain technologies create favorable conditions for the successful development and implementation of AI systems by providing a secure, verifiable data infrastructure. Therefore, organizations that invest in blockchain maturity are better positioned to accelerate their AI maturity and, through this channel, enhance organizational performance.

The mediation analysis also supports this conclusion, showing that AI maturity partially mediates the relationship between blockchain maturity and organizational performance. It

implies that blockchain maturity has a direct and indirect impact on performance, as it affects AI maturity. In practice, blockchain investments deliver performance benefits through process efficiencies and transaction security, as well as AI-driven capabilities that support higher-value applications such as predictive analytics, intelligent automation, and advanced decision support.

On the other hand, the lack of a mediating role for AI maturity in the relationship between digital transformation and organizational performance may indicate that digital transformation has other performance-enhancing routes. These can be better operational agility, better customer experience, quicker information flows, or loosening organizational structures. This observation deepens insights into digital transformation by showing that its logic of value creation is multidimensional and not merely pegged to AI-related outcomes.

The multi-group analysis also provides even greater detail on the inferences that arise from the study, showing that there are contextual differences in technological capabilities and their role in performance. Although the general pattern of relations was similar across groups, there were variations in the intensity and importance of some paths, especially the direct impact of blockchain maturity on organizational performance. Such differences indicate that the context of the organization, whether in terms of technological preparedness, the nature of the industry, or strategic focus, is a factor that significantly contributes to the achievement of technology-based value. In this regard, the study concludes that there is no standard channel to digital success; instead, the organization should tailor its technology solutions to their unique contextual factors.

Collectively, the results lead to the general finding that effective performance in the digital age is about outgrowing generic digitalization toward the intentional creation of sophisticated technological maturity. The digital transformation provides the underlying infrastructure and instant performance outcomes; blockchain maturity provides a trusted data environment. AI maturity offers a strategic capability for transforming these technological contributions into sustained performance benefits.

To sum up, the current study makes a significant contribution by empirically showing that organizations' performance can best be explained by integrated digital capabilities, rather than technological efforts in isolation. Explaining the unique and complementary functions of digital transformation, the maturity of blockchain, and the maturity of AI, the study provides a refined, holistic approach to creating digital value. Such conclusions not only contribute to

academic knowledge but also provide an excellent basis for managers to make decisions in more complex digital environments.

5.4   Managerial Implications

The results of this work have several valuable implications for managers and organizational leaders who are willing to enhance performance through digital technologies. To begin with, managers need to understand that digital transformation is a strategic requirement, not a goal. Although digital transformation initiatives directly improve organizational performance, they do not necessarily result in higher AI levels. Thus, leaders should go beyond overall digitalization initiatives and ensure that digital initiatives are strategically aligned with organizational objectives, process redesign, and performance measures. It is crucial to view digital transformation as a long-term strategic process rather than a single technological upgrade to sustain performance improvements.

Second, the findings demonstrate the need to deliberately and structurally invest in AI maturity. The managers are encouraged to view AI maturity as a multi-dimensional capability of the organization, encompassing quality data, analytical infrastructure, human resources, and governance systems. The use of AI tools without organizational preparedness could limit their efficiency. Since the maturity of AI directly and significantly affects organizational performance, executives ought to focus on developing internal AI capabilities, promoting data-oriented cultures, and integrating AI knowledge into core decision-making.

Third, the research focuses on the strategic importance of blockchain maturity as an enabler of AI maturity. Managers cannot think of blockchain as a transactional or security technology, but rather as a fundamental infrastructure that improves data integrity, transparency, and trust. Organizations can overcome significant data barriers that generally limit the use of AI by investing in blockchain maturity, which may include data reliability and traceability. This combined strategy will enable companies to fully leverage the synergies of blockchain and AI to improve their performance outcomes.

Lastly, the differences observed across the groups indicate that the technology strategy should be context-dependent. Before adopting digital, AI, and blockchain projects, managers must be keen to evaluate their organization's technological readiness, industry dynamics, and regulatory environment. A one-size-fits-all model might not yield the best outcomes across different organizational settings. Instead, leaders should embrace flexible, adaptive approaches that align technological investments with organizational capacity and strategic priorities,

enabling digital projects to be effectively transformed into long-lasting performance improvements.

5.5 Theoretical Implications

The present research makes several valuable theoretical contributions to the literature on digital transformation, emerging technologies, and organizational performance. To begin with, it contributes to the theory of digital transformation by showing that it is not to be conceived of as a homogeneous or smooth precursor to high-tech functionality. The lack of a significant relationship between digital transformation and AI maturity supports the assumption that, as a result of digitalization, AI preference levels increase. Instead, the results indicate that digital transformation and AI maturity are distinct yet complementary concepts that require distinct theoretical considerations. Such narrowing helps better understand that digital transformation is an enabling factor rather than a clear determinant of high-order AI maturity.

Second, the research paper is essential to the growing literature on technology complementarities and co-evolution by empirically determining the maturity of blockchain as a key factor in AI maturity. The discovery extends previous theories of technological synergy by demonstrating how one new technology can augment the effectiveness and maturity of another through enhanced data integrity, transparency, and trust. In theory, this champions a systems-based perspective on digital technologies, where value is created through the interplay among more than two technological capabilities, rather than through solitary adoption. In this regard, the research contributes to the conceptualization of the digital ecosystem in organizations.

Third, the resource-based and dynamic capability perspectives are further strengthened by the significant addition of maturing AI as a crucial mediating capability. By demonstrating the mediating role of AI maturity in the relationship between blockchain maturity and organizational performance, the study establishes AI maturity as a higher-order dynamic capability that facilitates organizations in reorganizing technology resources into performance-enhancing outputs. This theoretical point leaves behind the conservative perceptions of IT resources as fixed assets. It emphasizes the contribution of AI maturity in the sensing, seizing, and transforming opportunities in digitally intensive organizational settings.

Lastly, the multi-group analysis contributes to contingency and contextual theories by showing that the impact of digital transformation, blockchain maturity, and AI maturity on organizational performance is not universal. The identified differences in path significance and

strength led to the conclusion that the organization, institution, or environment preconditions the translation of technological capabilities into performance outcomes. The finding also prompts future conceptualizations to include contextual moderators, such as industry features, the regulatory environment, and organizational culture, to explain digital value creation. All these theoretical implications enrich and increase the available conceptual frameworks, providing more integrative and contextualized insights into how new digital technologies propel organizational performance.

5.6   Research Limitations

Although this study has made its contribution, it is subject to several limitations. To begin with, the study follows a cross-sectional design, which limits the power to draw firm causal conclusions about the relationships among digital transformation, AI maturity, blockchain maturity, and organizational performance, as these concepts can change over time. Second, the data were collected via self-report, which can introduce standard-method bias and subjective perception, although reliability and validity measures indicate the measurement's validity. Third, the research project focuses on a particular organizational and contextual environment, which could limit the study's external validity to other industries, nations, or institutional contexts. Lastly, the model focuses on the chosen emerging technologies, i.e., AI and blockchain, and fails to include other applicable digital capabilities, i.e., those that can also affect the performance of the organization, including big data analytics, cloud computing, or Internet of Things (IoT).

5.7   Future Research Directions

Based on the findings and limitations of this research, several directions for future research are suggested. First, future research must employ longitudinal designs to capture the dynamic and evolutionary characteristics of digital transformation, AI maturity, and blockchain maturity, thereby enabling more compelling causal inferences and deeper insight into how these capabilities develop over time. Second, the researchers could expand the model to include a variety of other digital technologies, such as big data analytics, cloud computing, the Internet of Things (IoT), and cybersecurity maturity, to create a more holistic model of digital capability ecosystems and their effects on organizational performance. Third, mixed-methods or qualitative research methods, including case studies or in-depth interviews, can be used in future research to understand the underlying mechanisms, organizational processes, and managerial practices by which AI and blockchain maturity are realized and translated into

performance results. Lastly, the researchers are urged to consider moderating and contextual factors, such as organizational culture, style of leadership, regulatory settings, and industry-specificities, and perform cross-country or cross-industry comparative analyses, to gain a better insight into the contingent conditions under which digital, AI, and blockchain capabilities can generate sustained organizational value.

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