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AI-Driven Supply Chain Management in Healthcare: Evaluating Institutional Readiness from Tertiary Hospitals in Ghana

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Abstract

Healthcare supply chain management (SCM) in sub-Saharan Africa faces a myriad of persistent systemic challenges, fragmented data ecosystems, chronic underfunding, and overreliance on manual, reactive processes. This study assesses the institutional readiness of Ghana's premier public tertiary referral hospitals for Artificial Intelligence (AI)-driven supply chain management and its influence on institutional performance. Anchored in three complementary theoretical frameworks, the Technology- Organization- Environment (TOE) Framework, the Theory of Planned Behavior (TPB), and Dynamic Capabilities Theory (DCT), the study operationalizes institutional readiness across three interdependent dimensions: organizational, economic, and environmental factors. The study adopted a mixed-methods research design. For the quantitative aspect, survey questionnaires were used to collect data from 140 staff members. Additionally, qualitative data were obtained through interviews with 12 key informants, and the data were thematically analyzed. Quantitative data were analyzed using hierarchical multiple regression, including moderation analysis employing mean- centered interaction terms in line with established procedures. Key findings emerged, which are, firstly, AI- driven SCM exerts a positive and statistically significant influence on institutional performance. Secondly, institutional readiness moderates the relationship between AI- driven SCM and institutional performance. The study concludes that while tertiary hospitals demonstrate awareness of AI's transformative potential, critical readiness gaps persist in data governance, technical infrastructure, staff competency, and regulatory alignment. The study recommends a readiness-first implementation strategy encompassing the formation of a multidisciplinary AI taskforce and investment in interoperable cloud infrastructure.

Keywords
Artificial Intelligence, Healthcare Supply Chain, Tertiary Hospitals, TOE framework, Institutional Readiness

1. Introduction
Global Healthcare supply chains face a confluence of systemic pressures: aging infrastructure, escalating drug demand, fragmented data ecosystems, and chronic underfunding. Emerging economies like Ghana, with expanding health sectors, are at a critical juncture where conventional supply chain practices are increasingly inadequate. The tertiary hospital, also known as the country's premier public referral facility, exemplifies both the magnitude of these challenges and the transformative potential of Artificial Intelligence (AI) to address them.
AI-driven Supply Chain Management (SCM) refers to the deployment of machine learning algorithms, predictive analytics, natural language processing, and robotic process automation within supply chain operations to enhance forecasting accuracy, inventory optimization, procurement efficiency, and logistical responsiveness (Chen, 2024). Unlike traditional digitization, AI-driven SCM creates self-improving systems that learn from historical data patterns, enabling healthcare institutions to shift from reactive to proactive supply management. This is particularly consequential in Ghana, where the Ghana Integrated Logistics Management Information System (GhiLMIS) as deployed in 2020, is primarily for retrospective reporting rather than predictive decision making.
Ghana's national AI agenda, articulated in the 2023 National AI Policy Framework, positions healthcare supply chains as a priority sector for AI integration. The Ministry of Health's five-year digital transformation roadmap (2022–2027) mandates that tertiary hospitals achieve Level 3 digital maturity by 2027, including predictive procurement capabilities. Yet, despite these policy imperatives, empirical evidence on tertiary hospitals' institutional readiness to implement AI-driven SCM remains woefully under-researched. This study seeks to fill that empirical gap. The concept of institutional readiness, as operationalized in this study, is grounded in the Technology Organization Environment (TOE) Framework (Tornatzky & Fleischer, 1990) and encompasses three interdependent dimensions: (i) technological infrastructure and data quality, (ii) organizational capacity including human capital and governance structures, and (iii) environmental factors such as regulatory compliance and vendor ecosystem maturity. Readiness is not a binary state but a dynamic, multi-layered process of capability development (Damoah, Ayakwah & Tingbani, 2021). Institutional performance, the study's dependent variable, is conceptualized as the degree to which an organization achieves its operational, financial, and service delivery objectives (Fosso Wamba et al., 2022). In healthcare settings, this encompasses inventory efficiency, procurement cost reduction, stockout prevention, patient care continuity, and stakeholder satisfaction.

Evidence from comparable African contexts confirms that AI integration in healthcare SCM is operationally feasible in sub–Saharan Africa but is contingent upon specific readiness conditions being met (Atadoga et al., 2024). This is not different from the studies on Zipline, Ghana's AI-managed drone delivery network, and Kenya's use of AI in National Hospital Insurance Fund procurement. This study, therefore, assesses those readiness conditions at tertiary hospitals, providing both diagnostic and prescriptive contributions to the field. Despite the fact that the healthcare supply chain benefits from the use of AI technology, the digitalization of the healthcare industry is not widely accepted. The research on the crucial success criteria of healthcare supply chain AI adoption as a whole is lacking in evidence (Boute & Udenio, 2022). Previous studies have also explored the potential uses of artificial intelligence in supply chain management and identified the main obstacles to its deployment in various sectors of industry, including how AI affects the performance of procurement departments (Aishwarya, 2023; Alomar, 2022). However, with regard to components of institutional preparedness for AI-driven supply chain management, limited information in the tertiary hospitals in emerging economies like Ghana exists, hence this study seeks to close this significant gap. Also, so far, discussions have largely focused on AI preparedness within a broad organizational framework, without delving into the nuances of supply chain management (Hao & Demir, 2024; Helo & Hao, 2022). Yet AI adaptation and preparedness are argued to be inherently context-specific, dependent on multiple stakeholders, and difficult to generalize across domains (Dogru & Keskin, 2020; Boute & Udenio, 2021). SCM's intricate data structure, which includes information from numerous external suppliers alongside an abundance of internal data for supply base management, makes it a compelling area for AI readiness (Ahmed et al., 2024). Supply chain management is a highly process-intensive activity with drawn-out, tedious operational procedures that could be automated, allowing focus to shift toward more strategic SCM tasks such as supplier relationships and supply chain designs (Hao & Demir, 2024). Thus, despite numerous studies investigating the managerial influence of AI on supply chain mode selection decisions, identifying the critical success factors for AI adoption, and demonstrating its potential to improve supply chain resilience (Damoah et al., 2021; Cubric, 2020), there remains limited information on the actual use of AI in healthcare supply chain management. Hence, the objective of this research is to assess the institutional readiness for the AI supply chain management of public tertiary hospitals to influence healthcare performance.

2. Literature Review

2.1Artificial intelligence

A definitional consensus on AI is essential to avoid conceptual conflation across this study's constructs. The OECD (2019, p. 7) defines AI as 'a machine-based system that can, for a given set of objectives, make predictions, recommendations, or decisions influencing real or virtual environments.' This definition, adopted by the G20 and referenced in Ghana's National AI Policy (2023), is preferred over older formulations because it emphasizes outcomes (predictions, decisions) rather than processes, making it measurable and policy relevant.

Complementing the OECD definition, Haenlein and Kaplan (2019) distinguish three functional levels of AI: (i) Narrow AI, task-specific systems such as demand-forecasting algorithms or automated reorder triggers deployed in SCM contexts; (ii) General AI, hypothetical systems with cross-domain cognitive ability, not yet commercially deployed; and (iii) Super intelligent AI, speculative future systems. This study's scope is exclusively Narrow AI applications in healthcare SCM, specifically machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and predictive analytics. In the healthcare SCM context, Boute and Udenio (2022) operationalize AI-driven SCM across four functional domains: predictive demand forecasting (using ML regression and neural networks to project medication consumption), intelligent inventory management (AI-triggered automatic replenishment), supplier selection optimization (multi-criteria AI scoring of vendor reliability), and logistics coordination (AI-managed delivery routing and cold chain monitoring). This quadripartite taxonomy informs the study's AI-driven SCM measurement instrument.

2.2 AI-Driven Supply Chain Management

One disruptive force that has emerged to revolutionize supply chain management is Artificial Intelligence (AI) because of its significant solutions to herculean supply chain challenges. The utilization of automation, predictive analytics, and optimization places AI at the forefront of dealing with traditional, manual-oriented systems that derail and hinder progress in supply chain optimization (Atadoga et al.2024). AI facilitates supply chain processes by assisting businesses in processing historical and real-time data to further improve decision-making and accurately forecast. This analytics is based on trends, seasonality, consumer behavior, and economic indicators, amongst others, thereby enhancing the predictive power for better decision making (Damoah et al., 2021; Cubric 2020). These advances secure AI as the cornerstone of modern and emerging supply chains seeking to be as visible as possible. AI could also be utilized to optimize warehouse activities, reduce costs in transport, and facilitate the complexities associated with large data analysis with speed and exceptional precision. As the supply chain spans the entire operations of a firm from production, trade, and logistics, AI capabilities also feature in the entire management as far as the various flows of products, funds, and information are concerned (Aishwarya, 2023; Alomar, 2022). Moreover, from a business entity perspective, AI can enable people management via predictive behaviors, effective and efficient resource utilization, as well as improving the agility of the digital, transformative nature of their supply chains.

2.3 Institutional Readiness for the Adoption of AI

In terms of readiness of the organization, for AI implementation to be successful, organizational preparedness is essential. This entails evaluating the infrastructure, technology, and human resources as they stand right now. Businesses must make the investment to provide the required infrastructure, which includes fast internet, powerful computers, and strong cybersecurity. Additionally, companies must hire and train AI specialists to create a workforce proficient in AI technologies. Adoption of AI may be severely hampered by a lack of adequate infrastructure and qualified staff (Boute & Udenio, 2021). To elevate healthcare service delivery, existing paper-based record-keeping must be phased out. There has to be a reorientation of staff for their new initiative of AI integration. A simplification procedure to meet the information technology competence level audit of staff is imperative. Not just digital literacy is required but strengthening the human capital capabilities in areas such as data analytics, machine learning, amongst others, is critical. The goal is to target the long-term sustainability of the usage of AI, while establishing the ethical concerns that revolve around its usage. This is essential because a scalable digital system, capable of real-time data capture, integrated with healthcare supply chain platforms and cloud collaboration, is an ingredient for building intelligent, responsive AI-supply chain ecosystems. It is worth noting that IT infrastructure alone is insufficient; however, regulatory policies for institutional alignment must follow to harmonize the digitization and digitalization drive. Readiness assessment is also key, as well as assurance of development partners to assist and reinforcement of their effort by embedding AI milestones into their technical assistance projects while linking incentives to AI-supply chain uptake.

2.4 Challenges in the use of AI in Hospital supply chains

There are several technological, societal, and legal obstacles to integrating AI in SCM. In order to properly utilize AI's potential benefits in SCM, these challenges must be resolved.

With regard to technical difficulties, Data quality, system integration, and cybersecurity concerns are among the technical difficulties that impede the use of AI in supply chains. Effective AI algorithms require high-quality data, yet many organizations struggle with inconsistent and insufficient data. Furthermore, it might be difficult and expensive to integrate AI technologies with historical systems and current IT infrastructure. Given that AI systems are susceptible to data breaches and cyberattacks, cybersecurity is still another major worry (Boute & Udenio, 2021). There exist cultural challenges as well. Organizational culture must change for AI adoption in SCM to be successful. Common cultural barriers include fear of losing one's career, resistance to change, and ignorance of AI technologies. Workers can be reluctant to embrace new procedures and wary of AI solutions. This opposition can be lessened by offering thorough training programmes, communicating the advantages of AI clearly, and including staff members in the implementation process. To overcome these cultural obstacles and create an atmosphere that is conducive to the adoption of AI, change management is crucial (Boute & Udenio, 2021). Pertaining to regulatory obstacles, AI regulatory frameworks are still developing, which causes ambiguity and compliance issues. Existing legislation does not adequately handle issues like data privacy, intellectual property rights, and accountability for judgments made by AI. To maintain compliance and prevent possible legal ramifications, businesses must manage these legal complications. Because laws varied greatly between nations and regions, the supply networks' global scope adds even another level of complication. To encourage the responsible application of AI in supply chains, proactive legislative frameworks and standardized international norms are required (Alomar, 2022).

A comprehensive strategy is needed to address the technological, cultural, and regulatory obstacles to AI application in SCM. To fully utilize AI's promise to improve supply chain resilience and efficiency, it is imperative to manage organizational transformation, improve data quality, navigate complicated regulatory environments, and ensure organizational readiness.

3. Empirical Review

A critical comparative analysis of existing empirical studies reveals both convergence in findings and important methodological heterogeneity. This review synthesizes some recent studies most directly relevant to the study's objectives, organized by research design and thematic focus.

Fosso Wamba, Queiroz, Guthrie, and Braganza (2022) conducted a multi-country survey ($n = 512$) across manufacturing and healthcare sectors, finding that AI SCM adoption positively influences institutional performance ($\beta = 0.62$, $p < 0.001$). Using Partial Least Squares Structural Equation Modelling (PLS SEM), they demonstrate that operational efficiency mediates 43% of the total AI performance effect. Their study's strength lies in its large, multi-sector sample, but it lacks healthcare-specific analysis and does not measure readiness as a moderator, a gap this study directly addresses. Also, Jackson et al. (2024), studying generative AI in SCM across 15 hospitals in South Africa and Nigeria, find that generative AI capabilities significantly improve procurement decision speed (by 34%) and cost optimization (by 18%), but only in institutions scoring above the 70th percentile on their AI readiness index. This threshold effect provides strong empirical justification for this study's hypothesis that institutional readiness moderates the AI performance relationship (H4). However, their study did not specifically point to only tertiary hospitals, thereby limiting direct applicability in this context.

Damoah, Ayakwah, and Tingbani (2021) provide the most contextually relevant Ghanaian evidence, documenting AI drone deployment in Ghana's health supply chain. While their qualitative case study methodology precludes quantitative generalization, they identify three Ghana-specific readiness barriers absent from Western literature: intermittent electrical power supply disrupting server-based AI operations, regulatory ambiguity around AI automated procurement under Act 663, and limited vendor technical support ecosystems. This study extends Damoah et al.'s (2021) qualitative insights with quantitative measurement in tertiary hospitals. Contrasting with the positive findings above, Hangl et al. (2022) conducted a systematic review of 78 AI SCM studies and found that 62% of reported performance improvements in healthcare settings failed to replicate when assessed 12 months post implementation. They attribute this 'performance decay' to inadequate readiness preparation, specifically, the absence of ongoing staff training and data governance updates. This longitudinal perspective reinforces this study's emphasis on sustainable rather than point-in-time readiness assessment and supports the recommendation for a monitoring and evaluation framework as suggested in this research. Khatua, Khatua, Chi, and Cambria (2021), using SEM on 358 responses from manufacturing and service sector firms, demonstrate that strategic AI SCM adoption, defined as AI deployment aligned with organizational strategic objectives, has a direct beneficial impact on performance ($\beta = 0.54$, $p < 0.01$) that is 2.1 times stronger than tactical or opportunistic AI adoption. Their findings underscore the importance of strategic alignment in this study's governance and leadership dimensions of institutional readiness. However, their sample is exclusively Southeast Asian, limiting cross-cultural applicability.

Additionally, Gao, Gao, Xiao, and Yao (2023) examine AI in vaccine supply chain coordination in China, using qualitative methods to demonstrate that risk-aware AI SCM selection enhances institutional performance. Their finding that institutions with structured risk management protocols achieve 29% better supply continuity during disruptions aligns with H3's proposition that institutional readiness positively affects performance. Critically, their study reveals that AI readiness must include explicit risk governance frameworks, an element this study incorporates into its institutional readiness questionnaire.

Moreover, Atadoga et al. (2024), in the most directly comparable African study, conduct a comparative review of USA and African AI SCM trends, finding that while both contexts show strong associations between AI adoption and performance, African institutions require 40% longer implementation timelines due to infrastructure and skills gaps, and achieve 23% lower performance improvement rates than US counterparts in the first 18 months. This comparative finding contextualizes realistic performance expectations for Ghanaian tertiary hospitals and informs the study's practical recommendations regarding phased implementation timelines.

3.1 Theoretical Review

As developed by Tornatzky and Fleischer (1990), the TOE Framework indicates a foundational structure for examining various factors that influence new technology adoption by firms (Yang et al.2021). Three contextual factors are critically perused, namely, technological factors which look at some features of the technology, such as the relative advantage, compatibility, complexity, amongst others, organizational factors that consider firm size, top management support, HR competence, amongst others, and environmental factors which look at partner pressure, regulator pressures, competitive pressure, amongst others. By addressing these dimensions, the interplay between internal and external influences on innovation adoption becomes apparent in supply chains (Zang et al.2020).

According to Helo and Hao (2022), it is regarded as an expansion of the Theory of Reasoned Action (TRA), which was put forth by Ajzen and Fishbein (1980). Intentions capture the motivations behind actions and demonstrate the level of effort and willingness an individual is willing to try to carry out the activity. According to the idea, attitude, perceived behavioral control, and subjective norm are important factors that influence behavioural intention and, consequently, their behavior. Hence, by elucidating how staff members' aggregate intentions and behaviors impact overall preparedness, the Theory of Planned Behavior relates to institutional readiness for AI-driven SCM. Even if an organization is technically prepared for AI, its staff will oppose adoption, and the project will fail if they don't have a positive attitude, don't feel supported by their peers, or think they have little influence over the new technology.

Teece et al. (1997) proposed the Dynamic Capabilities Theory, which was cited by Doru and Keskin (2020). This theory marked a substantial change in our understanding of how businesses gain and preserve a competitive edge in quickly evolving contexts (Cubric, 2020). The ability of an organization and its management to integrate, develop, and reconfigure internal and external competencies to face rapidly changing surroundings is the general definition of DCs, as stated by Teece et al. (1997). Essentially, the Dynamic Capabilities Theory offers a lens to evaluate an institution's innate ability for continuous adaptation, whereas standard readiness models analyze a snapshot of an institution's preparedness. This dynamic capacity is essential for AI-driven SCM in Ghana's healthcare industry to achieve resilience, sustainable efficiency, and better patient care.

3.2 Conceptual Framework and Hypothesis Development

Building on the theoretical frameworks of TOE, TPB, and DCT, and informed by the empirical review, this study's

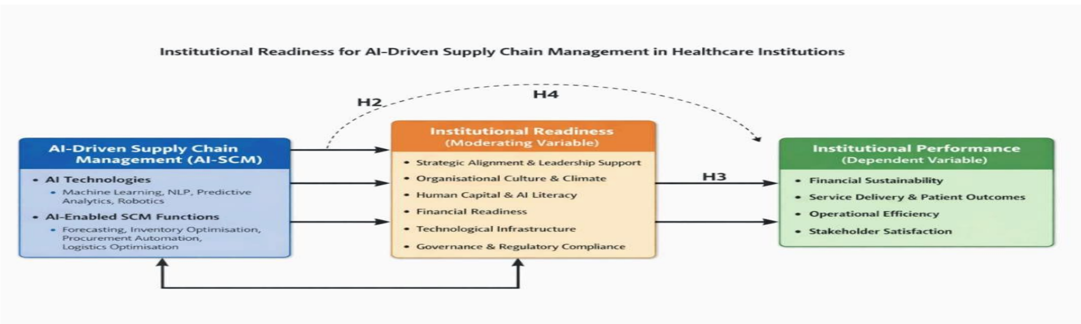

Figure 1. Conceptual Framework

Source: Extension of Framework (Jamil et al. 2025)

conceptual framework posits three pathways (Figure 1). The direct pathway proposes that AI-driven SCM (comprising AI technologies and AI-enabled SCM roles) directly and positively influences institutional performance (operational efficiency, financial sustainability, service delivery quality). The readiness pathway proposes that AI-driven SCM also directly and positively shapes institutional readiness levels (strategic alignment, organizational culture, human capital, operational capability). The moderation pathway, the study's most novel contribution, proposes that institutional readiness moderates the AI SCM performance relationship, such that high readiness amplifies the positive performance impact of AI-driven SCM, while low readiness attenuates it. This moderation hypothesis reflects Teece et al.'s (1997) DCT proposition that technology alone is insufficient without the dynamic capabilities to deploy it effectively.

3.3 AI -Driven supply chain management and institutional Readiness

AI has also been used in healthcare supply chain management to improve demand forecasts. According to research by Chen (2024), AI-driven prediction models could forecast demand for medical services and supplies with accuracy by analyzing a variety of characteristics, such as patient demographics and seasonal trends. Inventory management is a well-known use of AI in healthcare supply chain management. For example, a study by Chen (2024) discovered that AI algorithms can predict inventory demands by utilizing current trends and previous data, which lowers surplus inventory and stockouts. By maintaining ideal inventory levels, healthcare professionals may cut waste and guarantee the availability of necessary goods. Furthermore, ordering can be automated by AI-powered systems, which saves a significant amount of time and money (Alomar, 2022). The use of AI in healthcare has drawn more attention from researchers, who have highlighted how it can increase operational effectiveness, save expenses, and optimize resource allocation (Alomar, 2022). To improve decision-making and expedite processes, key AI technologies, including robotics, machine learning, and natural language processing, have been included in healthcare supply chain management. For instance, for digital integration into tertiary hospitals, Ghana's mature Integrated Logistics Management Information System (GhiLMIS) offers the "big data" basis required for artificial intelligence. Whether or not this data is "AI-ready" (clean, labelled, and available in real-time) determines tertiary hospitals' preparedness. Hospital boards that see AI as a cost-saving tactic to manage limited. Internally Generated Funds (IGF), rather than merely a tool, are the most prepared. In the end, this improves healthcare organizations' responsiveness to patient requirements by empowering them to make well-informed decisions about resource allocation and procurement (Alomar, 2022). Chatbots and other AI-powered assistants can do initial triage, respond to patient enquiries, and give supply chain support, hence increasing access to care, particularly for individuals living in remote places or with low incomes (Tsolakis et al., 2023). Therefore, it is hypothesized that,

H1: AI-Driven supply chain management has a significant positive relationship with institutional readiness.

3.4 AI-Driven Supply Chain Management and Institutional Performance

AI has also been used in healthcare supply chain management to improve demand forecasts. According to research by Chen (2024), AI-driven prediction models could forecast demand for medical services and supplies with accuracy by analyzing a variety of characteristics, such as patient demographics and seasonal trends. In the end, this improves healthcare organizations' responsiveness to patient requirements by empowering them to make well-informed decisions about resource allocation and procurement (Alomar, 2022). As a result, AI has several uses in the healthcare industry, ranging from improving patient care and clinical diagnostics to expediting drug discovery and simplifying administrative duties. Some of the largest issues facing the sector, including ageing populations, growing expenses, and clinician burnout, can be addressed with its capacity to analyze enormous volumes of data (Tsolakis, Schumacher, Dora, & Kumar, 2023). National AI Strategy (2025) shows that Healthcare is given priority as a "high-impact sector" in Ghana's National AI Strategy, which is presently under "Phase 2" execution. The UNESCO RAM Framework also affirms that public hospitals are being audited by Ghana's Ministry of Communications and Digitalization using the Readiness Assessment Methodology (RAM). This gives tertiary hospitals in Ghana a uniform framework to assess their ethical and regulatory compliance before implementing AI in the supply chain. From this review, it is hypothesized that,

H2: There is a positively significant relationship between AI-Driven Supply Chain Management and Institutional Performance

3.5 Institutional Readiness and Institutional Performance

Readiness and preparedness for any change have a significant bearing on the performance of that change. AI-Driven supply changes are no exception. The availability of the requisite technology, coupled with the staff acceptance through effective orientation, early involvement, training, and phased transition, will have a significant

impact on the success or otherwise of any new system. In Ghana, a new presidential directive that went into effect in 2026 mandates that all public sector organizations present a roadmap for the deployment of AI. This national impetus generates a particular combination of institutional opportunities and demands for the tertiary hospitals. Any new project must be in line with the company's overarching strategic objectives as espoused by Naz et al. (2022). Also, flexibility is one important indicator of preparedness as the firm's capacity to make in-house modifications in response to shifting external circumstances is needed (Rajesh, 2020). Moreover, a culture that embraces change, fosters creativity, and grows from mistakes is better able to manage shifts. A firm's success or failure can be attributed to the members' individual and collective views of the necessity of change and its ability to execute it. It is therefore hypothesized that,
H3: Institutional readiness has a significantly positive relationship with institutional performance.

3.6 Moderating Influence of institutional readiness in the relationship between AI -Driven supply chain management and institutional Performance
According to Kaewsaeng (2024), institutional readiness is a function of the successful utilization of a system for effective performance. This is essential because in this context, AI tools and infrastructure will have to be in place before deployment is done for these tertiary hospitals. The organizational factors, which include the staff competence in analytics, big data management, amongst others, require stringent rudiments that must be properly planned with top management support due to extensive resource mobilization requirements. Agyeman-Prempeh (2025) argues that, in terms of technological readiness, a reflection on the firm's capacity to integrate and leverage new technologies is imperative and has a significant effect on the leveraging levels for effective firm performance. This is because it encourages staff to receive regular skill training, which eventually changes the organizational climate as a result of the organizational learning that goes on. Again, an experimental culture emerges eventually, where sharing knowledge now becomes vital for operational efficiency. According to DCT, a firm could achieve a sustained competitive edge if it can adapt, adopt, and reconfigure its resources to match the turbulent and dynamic business environment. Financial and other facilitating conditions from both internal and external stakeholders are vital for any change or adoption process. Indeed, as Sharma et al. (2025) put it, businesses must understand and plan towards changing circumstances in order to deal with future challenges. The association between TOE moderating the relationship between AI-driven supply chain management and institutional performance is a significant one because how effectively a firm can utilize its capacity to willingly adopt new technologies is consequential to the acceptance and usage for performance improvement. Hospitals will better position themselves to embrace new technologies in order to reap the full benefit and quickly curtail difficulties of the digital revolution by understanding firm readiness characteristics, as it potentially influences adoption and performance. Therefore, it is hypothesized that:

H4: Institutional readiness moderates the relationship between AI-Driven supply chain management and institutional performance.

4. Methodology
The research will adopt a descriptive research design. Descriptive studies include a description of the current situation, according to Nind and Lewthwaite (2020). The study utilized a mixed method. Quantitative research is a structured way of collecting and analyzing data from various sources. Its purpose is conclusive, as it seeks to quantify the problem and understand its extent, looking for results that can be projected to a larger population (Patel & Sambasivan, 2021).

The purposive sampling technique was used to select staff in the procurement, logistics, stores, finance, IT, and human resources departments of the tertiary Hospitals. The purposive sampling method was selected because of the knowledge and expertise of the respondents, making them suitable for the study (Joseph & Gupta, 2021) in the qualitative aspect. A semi-structured interview guide comprising 15 open-ended questions was developed to explore readiness perceptions, implementation barriers, and AI SCM aspirations. A pilot study was conducted, and the reliability estimations and clarity assessment. All constructs exceeded the 0.70 threshold recommended by Nunnally (1978) for social science research instruments, confirming acceptable internal consistency before main data collection.

For the quantitative data, survey questionnaires were used. All items used a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) for the operationalization of all study variables, linking each construct to its measurement items.

4.1 Sampling and Data Collection
Primary quantitative data were collected over a four-week period (October–November 2025) through self-administered questionnaires distributed in hard copy across GARH's six target departments. Primary qualitative

data were collected through 12 in-depth semi-structured interviews conducted individually with key informants, each lasting between 45 and 75 minutes. Interviews were conducted in a private office to ensure confidentiality. With participants' consent, all interviews were audio recorded and subsequently transcribed verbatim. Member checking, sharing interview summaries with participants for accuracy confirmation, was conducted with nine of the 12 interviewees, enhancing the qualitative strand's credibility.

4.2 Response rate

140 of the 150 sampled respondents responded, yielding a 93 percent response rate. In business management research, a response rate of more than 50% should be regarded as good, according to Kirsten and Schmid (2020). As a result, the study's reported 93% response rate provided a solid foundation for conclusions. However, because the observed sample size was smaller than initially desired, the 7% non-response rate may introduce bias into the estimates and increase the total variance of the estimates. Each person contacted was assigned a weighting factor by the sample weighting procedure, which was then used to multiply the corresponding data to correct the bias (Barbrook-Johnson & Carrick, 2021). Because the impact of missing data was removed, this guaranteed that the regression coefficients would be estimated consistently (Table 1).

Table 1. Demographic Table

Variables	**Frequency**	**Percentage %**
Gender		
Male	77	55
Female	63	45
Total	**140**	**100**
Age		
18 – 25	32	23
26 - 35	67	48
36 - 45	23	16
46 years +	18	13
Total	**140**	**100**
Educational background		
SHS	9	6
Ordinary level	11	8
Advanced level	18	13
Diploma	34	24
First degree	43	31
Master’s degree	15	11
PhD	10	7
Total	140	100
Working experience		
Less than 6 years	22	16
6 years to 10 years	33	24
11 years to 15 years	51	36
16 years +	34	24
Total	140	100

32 respondents, or 23% of the sample, were between the ages of 18 and 25; 67 respondents, or 48%, were between the ages of 26 and 35; 23 respondents, or 16% of the sample, were between the ages of 36 and 45; and 18 respondents, or 13% of the sample, were 46 years + of age or older (Table 1). The majority of respondents were between the ages of 26 and 35, according to the results of the age demographic characteristics of the respondents. Young generation respondents are more likely to embrace emerging technology.

4.3 Inferential statistics

This research engaged inferential statistics (regression analysis) for the analysis of the data gathered from the responders to address the hypotheses of the study. This subdivision looked at correlation coefficients and regression analysis.

4.4. Correlation coefficient

H1: AI-driven SCM has a positive and substantial influence on institutional performance.

Table 6 depicts the Pearson correlation between the variables. Data as presented implies that the Pearson correlation of AI-driven SCM and institutional performance at Greater Accra Regional Hospital was disclosed to be substantially positive statistically ($B = 0.577$, $p < 0.049$). Thus, H1 is accepted. This implies that there is a substantial positive relationship between AI-driven SCM and institutional performance at Greater Accra Regional Hospital.

H2: AI-driven SCM has an affirmative and considerable impact on institutional readiness.

Similarly, the outcome revealed that there is a substantial positive correlation between AI-driven SCM and institutional readiness at Greater Accra Regional Hospital ($P = 0.292$) ($B = 0.512$) and consequently, H2 is accepted. This infers that there is a substantial positive correlation between AI-driven SCM and institutional readiness at Greater Accra Regional Hospital.

H3: Institutional readiness has an optimistic and significant effect on institutional performance.

Likewise, at $P = 0.011$ and $B = 0.501$, this indicates a substantial positive association between institutional readiness and institutional performance at Greater Accra Regional Hospital; thus, H3 is accepted.

H4: Institutional readiness moderates the relationship between AI-driven SCM and institutional performance.

Finally, the question of whether the link between AI-driven SCM and institutional performance at Greater Accra Regional Hospital is moderated by institutional readiness. H4 is approved because the indirect path's point estimate of 0.509 ($t = 2.650$, $p = 0.012$), bias-corrected lower limit of 0.203, and upper limit of 0.492 support the existence of a moderating effect (Table 2).

Table 2. Pearson correlation

Variable	1. ASCM	2. IR	3. IP
1. AI driven SCM (ASCM)	1.000		
2. Institutional Readiness (IR)	0.612**	1.000	
3. Institutional Performance (IP)	0.589**	0.541**	1.000
Mean	3.67	3.55	3.61
SD	0.82	1.02	0.93

a. Dependent Variable: Institutional performance

Source: Field data, 2026

4.5 Multiple regression examination

Hierarchical multiple regression was employed to test H1 and H3 simultaneously, determine the incremental contribution of institutional readiness beyond AI-driven SCM, and provide standardized coefficients for direct variable level interpretation. Three models were estimated sequentially, with IP as the dependent variable in all models. Multicollinearity diagnostics (VIF and Tolerance) confirmed acceptable levels (VIF range: 1.22–2.87, all below 5.0 threshold; Tolerance range: 0.35–0.82, all above 0.10 threshold). The Durbin Watson statistic (DW =

1.94) falls within the acceptable range of 1.5–2.5, indicating no problematic autocorrelation in residuals (Table 3).

Table 3. Hierarchical Multiple Regression Results Dependent Variable: Institutional Performance (n = 140)

Predictor	Model 1 B (SE)	Model 1 β	Model 1 p	Model 2 B (SE)	Model 2 β	Model 2 p
Constant	1.842 (0.391)		< 0.001	1.127 (0.412)		0.007
AI driven SCM (ASCM)	0.613 (0.104)	0.540	< 0.001	0.441 (0.118)	0.389	< 0.001
Institutional Readiness (IR)				0.312 (0.089)	0.342	0.001
R^2	0.347			0.453		
Adjusted R^2	0.342			0.445		
F	73.81 (1, 138)		< 0.001	56.97 (2, 137)		< 0.001
ΔR^2				0.106		
ΔF				26.54		< 0.001

Model 1 demonstrates that AI-driven SCM alone explains 34.7% of the variance in institutional performance (R^2 = 0.347, F(1,138) = 73.81, p < 0.001), with a standardized coefficient of β = 0.540 (p < 0.001). This provides strong support for H1: AI-driven SCM has a statistically significant and positive influence on institutional performance at GARH. For everyone, the standard deviation increase in ASCM composite scores, IP increases by 0.540 standard deviations a substantively meaningful effect size by Cohen's (1988) conventions (large effect: β > 0.50).

4.6 Moderation Analysis (H4)

To test H4 that institutional readiness moderates the relationship between AI-driven SCM and institutional performance, a third regression model (Model 3) was estimated following Aiken and West's (1991) mean-centering procedures. ASCM and IR were first mean centered (ASCM_c = ASCM − ASCM_mean; IR_c = IR − IR_mean), and an interaction term (ASCM_c × IR_c) was computed. Model 3 entered all three predictors: ASCM_c, IR_c, and the interaction term (Table 4).

Table 4. Moderation Analysis Dependent Variable: Institutional Performance (n = 140)

Predictor	B	SE	β	t	p	95% CI
Constant	3.612	0.069		52.35	< 0.001	[3.476, 3.748]
ASCM_c (AI SCM centred)	0.441	0.107	0.389	4.12	< 0.001	[0.230, 0.653]

Predictor	B	SE	β	t	p	95% CI

IR_c (Readiness centred)	0.312	0.084	0.342	3.71	0.001	[0.146, 0.478]
ASCM_c × IR_c (Interaction)	0.187	0.063	0.214	2.97	0.003	[0.063, 0.311]
$R^2 = 0.497$	Adjusted $R^2 = 0.486$				$F(3,136) = 44.73$, $p < 0.001$	

The interaction term (ASCM_c × IR_c) is statistically significant ($\beta = 0.214$, $t = 2.97$, $p = 0.003$), confirming that institutional readiness significantly moderates the relationship between AI-driven SCM and institutional performance. H4 is therefore supported. The positive interaction coefficient indicates that the positive effect of ASCM on IP is stronger when IR is high, operationalizing the DCT proposition that AI technology yields superior performance outcomes when deployed in organizations with strong dynamic capabilities.

Simple slopes analysis at ±1 SD of IR reveals that the ASCM IP relationship is significant and positive for both high-readiness institutions ($\beta = 0.603$, $p < 0.001$) and low-readiness institutions ($\beta = 0.268$, $p = 0.041$), but the effect is 125% stronger in high-readiness conditions. This implies that even low-readiness institutions gain some performance benefit from AI-driven SCM, but high-readiness institutions more than double the performance return on AI investment, a critical finding for resource allocation decisions at the tertiary hospitals (Table 5).

Table 5. ANOVA Table Full Model (Model 3)

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	18.742	3	6.247	44.73	< 0.001
Residual	18.994	136	0.140		
Total	37.736	139			

4.7 Qualitative Analysis

Qualitative interview data were analyzed using reflexive Thematic Analysis (Braun & Clarke, 2022) (Table 6).

Table 6. Summary of Qualitative Contributions

Theme	Key Contribution
Tertiary hospital AI-Driven supply chain Mgt	• Digital transformation adequately saved lives during Covid -19 pandemic. • Data driven Supply chain decisions influenced by current system by leveraging the power of technology. • Evident based advantages and validation. • Seamless flow of information assuring harmony is hospitals supply chain
Perceived barriers and enablers of AI-Driven SCM	• Resistance by staff over poor implementation plan • Long term sustainability poorly elucidated • Full adoption timelines extensions • Requisite continuous capacity building imperative

GhiLMIS as a Backbone of Tertiary Hospital Supply Chain	• Crucial incorporation of AI oriented system absolutely useful • Hospital to realize financial sustainability when phased deployment is employed dwindling value (economic, environmental, • Active involvement of staff from the outset a relative advantage
Firm readiness for AI adoption	• Tertiary Hospitals coerced to utilize digital platforms. • Stringent standards applied for compliance to assure improved performance. • Top management support with requisite resources for effective usage despite unforeseen setbacks.

4.6 Discussion of Findings

The confirmation of H1 ($\beta = 0.389$, $p < 0.001$ in the full model) is consistent with Fosso Wamba et al.'s (2022) multi country finding ($\beta = 0.62$, $p < 0.001$) and Khatua et al.'s (2021) SEM results ($\beta = 0.54$, $p < 0.01$), though GARH's effect size is smaller, potentially reflecting the early-stage AI adoption context at GARH where AI driven SCM is inspirationally oriented rather than fully operationalized. The qualitative data elaborates this quantitative finding: key informants from procurement and logistics departments consistently identified GhiLMIS's retrospective reporting limitations as a primary barrier to realizing AI's performance potential. One department head noted: 'We know the data is there in GhiLMIS, but we are not getting predictive outputs from it it tells us what happened last month, not what we should order next week.' This finding aligns with Atadoga et al.'s (2024) comparative observation that African healthcare institutions experience a 23% performance gap relative to US counterparts in early AI adoption phases, attributable to data utilization rather than data availability gaps.

The significant positive bivariate correlation between ASCM and IR ($r = 0.612$, $p < 0.01$) supports H2, indicating that institutions demonstrating higher AI-driven SCM engagement also report higher readiness levels. This bidirectional relationship, where AI adoption both requires and builds readiness, aligns with DCT's conceptualization of readiness as a dynamic capability that evolves through practice. Qualitative evidence suggests that tertiary hospitals' partial GhiLMIS digitalization, while limited, has increased staff comfort with data-driven decision-making, incrementally building the organizational readiness foundation needed for more advanced AI tools. This is consistent with Damoah et al.'s (2021) finding that exposure to digital supply chain tools in Ghanaian health facilities generates readiness 'spillover effects' that accelerate subsequent technology adoption.

The significant effect of IR on IP in the multiple regression model ($\beta = 0.342$, $p = 0.001$) confirms H3 and is consistent with Hangl et al.'s (2022) meta-analytic finding that organizational readiness factors are stronger predictors of long-term AI SCM performance than technical factors. The qualitative data provides specific texture: the readiness dimension showing the greatest quantitative variability, staff AI self-efficacy (IR 11, $M = 3.11$, $SD = 1.40$) was also the most consistently cited barrier in interviews. Six of the 12 key informants identified AI skill gaps as the primary internal barrier to performance improvement, with the IT Systems Manager noting that 'the hospital's IT department currently has zero staff formally trained in machine learning or AI system administration.' This human capital gap, predicted by TPB's perceived behavioral control construct, has direct implications for the hospital's procurement practices in AI-literate staff.

The confirmed moderation effect ($\beta\_interaction = 0.214$, $p = 0.003$) represents this study's most theoretically novel contribution. The finding that institutional readiness more than doubles the performance impact of AI-driven SCM (simple slope at +1 SD IR vs. 1 SD IR: 0.603 vs. 0.268) has direct implications for resource prioritization at the tertiary hospitals. The conventional public health investment logic, 'acquire the technology, performance will follow,' is contradicted by these findings. Instead, the data support a 'readiness first' investment sequencing, consistent with Jackson et al.'s (2024) threshold effect finding (significant AI performance gains only above the 70th readiness percentile). Tertiary Hospital's current overall IR mean of 3.55 ($SD = 1.02$) on a 5-point scale suggests it is approaching but has not yet reached the high readiness threshold, making readiness investments a priority over additional AI tools for procurement and other analytical procedures.

5. Conclusion

The study revealed that there is a positive and substantial relationship between AI-driven SCM and institutional performance at tertiary hospitals. Furthermore, the study revealed that there is a substantial positive correlation between AI-driven SCM and institutional readiness at these hospitals. In terms of the effect of institutional readiness on institutional performance, the study revealed that there is a substantial positive association between institutional readiness and institutional performance. Again, regarding the moderating role of institutional readiness on the relationship between AI-driven SCM and institutional performance, it was also found that institutional readiness significantly moderates their relationship.

Recommendation

- Form a Multidisciplinary AI Taskforce: To match the hospital's strategic goal with AI deployment, form a specialized group of IT experts, SCM officers, and clinical leaders.
- Create Institutional AI Ethics Guidelines: To guarantee adherence to Ghana's Data Protection Act and the Public Health Act of 2012, establish explicit internal procedures for data utilization and automated decision-making.
- Phased Roadmap Implementation: To demonstrate return on investment before expanding, start with a pilot programme for predictive demand forecasting in the pharmacy department rather than a facility-wide makeover.
- A structured monitoring and evaluation (M&E) framework is imperative to track progress, enable adaptive management, and generate evidence for future AI SCM investment decisions

Theoretical, Practical, and Policy Implications

This study makes significant theoretical contributions. First, it provides one of the foremost empirical validations of institutional readiness as a moderator of the AI SCM performance relationship in a West African public healthcare context, extending Jackson et al.'s (2024) threshold effect hypothesis with a specific interaction coefficient estimate ($\beta = 0.214$). Moreover, the study demonstrates the practical utility of the TOE framework for diagnosing AI readiness in resource-constrained health systems, adding three Ghana-specific TOE sub-dimensions (power reliability, procurement regulatory clarity, data trust) to the framework's established dimensions, a theoretical extension with implications for AI readiness assessment across comparable sub-Saharan African institutional settings. By applying DCT to frame readiness as a dynamic capability rather than a static assessment, the study reframes the practical challenge: Tertiary Hospitals' readiness development is not a one-time organizational preparation exercise but an ongoing capability-building process that must continuously evolve alongside AI technology development. The study advocates for the establishment of a dedicated AI SCM Data Governance Unit within Tertiary Hospitals, to retrospectively clean GhiLMIS data and implement real-time data entry protocols. Policies geared towards ensuring infusing AI capability assessment should be incorporated into tertiary hospitals' strategic plan. Targeted partnerships can be built with other international bodies to enhance interdisciplinary knowledge sharing. Policy makers could also encourage various health regulators to ensure that compliance with respect to AI deployment is assiduously followed ethically.

Future Studies

Future studies should compare the AI readiness of district or teaching hospitals, such as Korle-Bu, with that of regional hospitals. This would determine whether "readiness" reflects the Ghana Health Service's (GHS) broader systemic resources or facility-level leadership. Although institutional preparedness is the main focus of this study, a follow-up could examine how the Tertiary Hospital's AI integration affects last-mile distribution to satellite clinics. This would establish a direct link between community health outcomes and institutional SCM efficiency. A long-term study is required to compare perceived and actual return on investment when AI tools are implemented. To evaluate the theoretical frameworks used in the readiness assessment, researchers could track metrics such as reductions in "stock-out days" and procurement lead times over 24 months.

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