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Healthcare Workers' Perceptions of The Potential Role of Artificial Intelligence in Enhancing Data Management at Tertiary Hospitals in Yenagoa, Bayelsa State

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ABSTRACT

Healthcare data management in many Nigerian tertiary hospitals continues to rely heavily on paper-based systems and disconnected electronic platforms, resulting in misplaced records, delayed healthcare services, and weak health planning. Although artificial intelligence (AI) has emerged as a promising innovation for strengthening health information systems, its practical implementation in resource-limited settings such as Yenagoa, Bayelsa State, remains extremely limited. This study examined healthcare workers' perceptions of the potential role of AI in improving data management and evaluated the readiness of tertiary hospitals in Yenagoa for its possible introduction. A mixed-methods design was adopted. Quantitative data were collected through a structured survey involving 120 healthcare professionals and health information management staff, while qualitative data were obtained through in-depth interviews with five heads of information technology units across three tertiary hospitals. Descriptive statistics were used to summarise the survey findings, while thematic analysis was employed to analyse the interview transcripts. The findings showed that major data management problems included missing patient folders, duplicate records, and excessive time spent retrieving files. Although awareness of AI was moderate, actual use of AI technologies was absent. Respondents identified automated data capture, duplicate record resolution, and intelligent scheduling as the most valuable potential contributions of AI. Major barriers included unstable electricity supply, poor internet connectivity, inadequate technical expertise, and high implementation costs. The study concludes that although healthcare workers perceive AI as potentially beneficial, significant infrastructural and human capacity limitations

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place the hospitals at a low-readiness stage. The study recommends that hospital administrators prioritise investment in basic digital infrastructure, staff training, and stable power supply before introducing AI-driven systems.

INTRODUCTION

Hospitals rely extensively on accurate and timely information. When a patient arrives at the emergency unit, clinicians require immediate access to previous diagnoses, allergies, and test results. Health administrators also depend on reliable data to plan staffing, procure medications, and report disease outbreaks. In Nigeria's tertiary hospitals, which serve as referral centres for millions of people, the quality of healthcare data management directly influences patient survival and public health outcomes. Unfortunately, many of these institutions still struggle with paper files, fragmented electronic systems, and records that cannot be located when urgently needed. The emergence of artificial intelligence (AI) has generated global discussion regarding how data-driven intelligent systems may help resolve these long-standing problems. However, in places such as Yenagoa, the capital city of Bayelsa State in the Niger Delta region, the discussion remains limited. This study therefore seeks to examine, in a careful and context-sensitive manner, how healthcare workers in Yenagoa perceive the potential role of AI in improving data management and to assess the readiness of their hospitals for such technological innovation.

Bayelsa State is one of Nigeria's youngest states, characterised by a terrain dominated by rivers, creeks, and seasonal flooding. Yenagoa hosts three major tertiary hospitals: the Federal Medical Centre, the Niger Delta University Teaching Hospital, and the Bayelsa State Specialist Hospital. These facilities serve patients from across the state and neighbouring riverine communities. Despite their strategic importance, they operate under substantial constraints. Electricity supply is unstable, broadband internet access is inconsistent, and the number of trained health information managers remains limited. In this environment, healthcare data management frequently involves shelves of paper folders, handwritten ward registers, and multiple parallel electronic systems that lack interoperability. This reality differs considerably from the advanced digital ecosystems commonly described in literature from Europe and North America and therefore requires a locally grounded investigation.

1.1 Statement of the Problem

Healthcare data management in Yenagoa's tertiary hospitals is affected by several persistent challenges. Patient folders are often misplaced, laboratory results may be delayed or attached to the wrong file, and statistical reports required by state and national authorities are frequently incomplete or submitted late. These shortcomings waste clinical time, frustrate patients, and weaken evidence-based decision making. Although the Nigerian healthcare system has made attempts to digitise records, many of these initiatives have struggled because of technical and human-related challenges. At the same time, global advances in AI—such as natural language processing systems capable of interpreting doctors' handwriting and algorithms capable of linking fragmented records to a single patient identity—offer possible solutions. However, no known study has specifically examined how healthcare workers within this context perceive the potential of AI, nor assessed the readiness of these hospitals to adopt such technologies. Without this understanding, hospital managers and policymakers risk either overlooking a potentially valuable tool or introducing systems that are unsuitable for local realities.

1.2 objective of the study

The main objective of this study was to assess healthcare workers' perceptions of the potential role of artificial intelligence in improving healthcare data management at tertiary hospitals in Yenagoa, Bayelsa State. The specific objectives were to:

1. Identify the major challenges experienced in managing healthcare data in the selected hospitals.
2. Determine the level of awareness of artificial intelligence and the current adoption status among healthcare and health information management staff.
3. Explore the specific contributions that artificial intelligence is perceived to make in addressing existing data management challenges.
4. Examine the barriers perceived to hinder the introduction of artificial intelligence for healthcare data management in these settings.

1.3 Research Questions

1. What are the major challenges affecting healthcare data management in the tertiary hospitals studied?
2. What is the level of awareness and current adoption of artificial intelligence among staff?
3. In what ways do healthcare workers perceive artificial intelligence could improve healthcare data management?
4. What barriers do staff perceive as likely to hinder the successful introduction of artificial intelligence?

1.4 Significance of the Study

This study is important for several reasons. For hospital administrators in Yenagoa and comparable settings, it provides an evidence-based understanding of the foundational issues that require attention before AI can realistically be considered. For researchers in health informatics, the study contributes a context-specific case study from an under-researched region, thereby enriching the literature on AI adoption in low-resource environments. For state and national health policymakers, the findings may support the development of more practical digital health strategies that acknowledge the realities of electricity supply, internet connectivity, and workforce preparedness.

1.5 Scope and Delimitation

The study focused on the three tertiary hospitals located in Yenagoa, Bayelsa State. It was limited to healthcare data management processes, including record creation, storage, retrieval, sharing, and reporting. The investigation of AI was restricted to its perceived role in improving these processes and did not extend to clinical diagnostic applications. Participants included doctors, nurses, health information officers, and heads of IT units.

2. LITERATURE REVIEW

This section reviews existing literature through the lens of a socio-technical framework, which conceptualises healthcare organisations as systems made up of interacting technical, human, organisational, and environmental components. The reviewed literature provides the foundation for understanding the readiness of Yenagoa's tertiary hospitals for AI-supported healthcare data management.

2.1 Healthcare Data Management in the Modern Hospital

Healthcare data management refers to the systematic collection, storage, processing, and utilisation of patient and administrative information to support healthcare delivery and organisational learning (Shortliffe & Cimino, 2018). In an ideal healthcare system, every patient encounter generates a record that is accurate, complete, accessible to authorised users at the point of care, and protected against unauthorised access. Globally, healthcare systems have increasingly moved toward integrated electronic health records capable of capturing everything from outpatient consultations to radiological imaging. However, this ideal remains largely unattained in many hospitals across sub-Saharan Africa. Existing literature consistently highlights challenges such as fragmented paper records, poor data quality, inadequate infrastructure, and shortages of trained personnel (Akhigbe et al., 2021; Ojo, 2016). These difficulties become more pronounced in specialist referral centres where patient volumes are high and clinical cases are more complex.

2.2 The Emergence of Artificial Intelligence in Healthcare Data Management

Artificial intelligence refers to computer systems capable of performing tasks that ordinarily require human intelligence, including language interpretation, pattern recognition, and decision making (Russell & Norvig, 2021). Within healthcare, AI is increasingly being applied to data management in several important ways. Natural language processing algorithms can interpret unstructured clinical notes and automatically extract diagnoses, medications, and procedural codes, thereby reducing the burden of manual abstraction (Jiang et al., 2017). Machine learning systems can analyse millions of records to identify and merge duplicate patient identities (Rajkomar et al., 2019). Predictive analytics can forecast patient admission trends, enabling hospitals to allocate beds and staff more efficiently (Obermeyer & Emanuel, 2016). In addition, AI-driven tools can automate medical coding and billing processes, reducing human error and improving revenue cycle management (Davenport & Kalakota, 2019). Importantly, much of this innovation has been developed and tested in high-income countries characterised by reliable electricity, stable internet connectivity, and a large pool of technical expertise. Whether these technologies can operate effectively in a setting such as Yenagoa remains an important unanswered question.

2.3 Artificial Intelligence and Data Management in Developing Countries

When attention shifts to developing countries, the discourse surrounding AI changes significantly. Scholars have observed that although AI possesses considerable potential, its implementation in low-resource settings must overcome a distinct set of barriers. Wahl et al. (2018) noted that many AI systems are trained using data from Western populations and may therefore perform poorly when applied to local patient demographics and disease patterns. More practically, the hardware, software, and connectivity requirements associated with advanced AI systems are often difficult to meet in settings where even basic internet access remains unstable. Nevertheless, some pilot initiatives have produced encouraging outcomes. In parts of India and Kenya, low-cost AI applications operating on affordable devices have been used to digitise paper records through optical character recognition and identify missing information in health registries (Gulshan et al., 2016; Price & Cohen, 2019). These examples indicate that a context-appropriate and gradual approach to AI implementation may be more realistic than attempting to adopt fully integrated smart hospital systems immediately.

2.4 Healthcare Data Management and AI in Nigeria

Nigeria's healthcare data management environment reflects the broader African experience but also presents unique characteristics. The country has a national health information management policy that promotes the adoption of electronic records, although implementation remains uneven (Federal Ministry of Health Nigeria, 2016). Some teaching hospitals in Lagos, Abuja, and Ibadan have introduced electronic health record platforms, but many have struggled to sustain these systems once donor funding expired. Studies conducted at the University of Nigeria Teaching Hospital and Lagos University Teaching Hospital have documented continuing challenges such as incomplete records, parallel paper and electronic systems, and healthcare workers who regard data entry as an additional burden rather than an essential clinical responsibility (Nwankwo & Nwankwo, 2020; Ibeneme et al., 2021). With regard to AI, the literature remains limited. A few opinion papers and conference presentations have encouraged Nigeria to embrace AI in healthcare, but empirical studies examining the practical use of AI for healthcare data management in Nigerian hospitals remain scarce (Eke et al., 2021; Adebayo et al., 2022). Where AI is discussed, attention is usually directed toward diagnostic imaging or outbreak prediction rather than the routine management of patient records.

2.5 Barriers to AI Adoption: A Socio-Technical Perspective

The global literature identifies several categories of barriers to AI adoption, and these barriers align closely with the socio-technical framework. Technical barriers include the absence of standardised data formats, poor data quality, and insufficient computational infrastructure (Reddy et al., 2019). Organisational barriers include weak leadership commitment, resistance to change among staff, and the absence of clear governance structures for AI implementation (Bates et al., 2014). Human resource barriers relate to the shortage of data scientists, health informaticians, and clinicians capable of effectively engaging with AI outputs (Beam & Kohane, 2018). Financial barriers are also substantial, as AI systems may be expensive to purchase, customise, and maintain. Ethical and legal barriers concern issues such as patient privacy, data security, and accountability when AI systems make errors (Obermeyer et al., 2019). In a setting such as Yenagoa, additional environmental challenges—including frequent power outages, high humidity affecting equipment, and limited access to technical support vendors—create an especially difficult implementation environment.

2.6 Conceptual Framework

This study is anchored on a socio-technical understanding of healthcare organisations. According to this perspective, any technological innovation functions within a system consisting of four interacting dimensions: technical (infrastructure and software), human (skills, perceptions, and fears), organisational (leadership, workflows, and institutional culture), and environmental (electricity supply, climate, and geography). The success of AI in healthcare data management therefore depends not only on the sophistication of the technology itself but also on the degree to which it aligns with these four dimensions simultaneously. The framework informed the design of the data collection instruments, guided the analytical process, and shaped the interpretation of findings. It ensured that the study moved beyond merely listing barriers to examining how these barriers interact to influence overall readiness.

2.7 Summary of Literature and Gap

The reviewed literature confirms that healthcare data management remains a major challenge in Nigeria and that AI presents plausible solutions. However, no study has examined healthcare workers' perceptions of AI's potential role or assessed readiness for AI implementation within the specific infrastructural and socio-technical conditions of tertiary hospitals in Yenagoa, Bayelsa State. This study addresses that gap by providing a localised and perception-based investigation that foregrounds the perspectives of the staff who would ultimately become the users of any future AI system.

3. METHODOLOGY

3.1 Research Design

A descriptive mixed-methods design was adopted for this study. The quantitative component enabled the measurement of healthcare data management challenges, awareness of AI, and perceived roles of AI across a reasonably large sample of respondents. The qualitative component provided deeper insight into the organisational, human, and environmental factors influencing readiness for AI adoption. The integration of both approaches was considered most suitable for capturing both the breadth and depth of the phenomenon under investigation.

3.2 Study Area

The study was conducted in Yenagoa, the capital city of Bayelsa State, situated in the Niger Delta region of Nigeria. The area is characterised by low-lying terrain, a tropical monsoon climate, and an economy largely dependent on public service and small-scale commercial activities. Healthcare infrastructure in the city includes both public and private institutions, with the three tertiary hospitals serving as the highest referral centres within the state.

3.3 Population of the Study

The target population consisted of healthcare professionals and health information management personnel working at the Federal Medical Centre Yenagoa, Niger Delta University Teaching Hospital Okolobiri, and the Bayelsa State Specialist Hospital Yenagoa. At the time of the study, the estimated combined professional workforce across the three hospitals was approximately 450 individuals, including doctors, nurses, pharmacists, laboratory scientists, and health information officers.

3.4 Sample Size and Sampling Technique

A sample size of 120 respondents was selected for the quantitative survey. This figure was determined after considering the accessible population of approximately 450 staff members, an anticipated response rate of 85–90% based on previous survey experience in comparable Nigerian hospital environments, and the need to obtain a sample large enough for descriptive subgroup analysis without excessively disrupting busy clinical schedules. A non-probability purposive sampling technique was employed, selecting only staff directly involved in the creation, retrieval, or management of patient information. Although this sampling method limits statistical generalisation, it ensured that all participants possessed practical experience relevant to the issues under study. For the qualitative component, five heads of health information management and IT units were purposively selected because of their supervisory responsibilities within hospital data systems.

3.5 Data Collection Instruments and Framework Operationalisation

Two instruments were utilised for data collection. The first was a structured questionnaire developed for the quantitative component of the study. It consisted of four sections: demographic characteristics, challenges of healthcare data management, awareness and adoption of AI, and perceived roles and barriers of AI. The second instrument was a semi-structured interview guide used for the qualitative component. Both instruments were developed in alignment with the socio-technical conceptual framework guiding the study. Survey items and interview prompts explored data management challenges, perceived AI contributions, and barriers across the technical, human, organisational, and environmental dimensions of the framework. For instance, the interview guide contained questions such as, "Can you explain how the physical environment and electricity supply affect your present data systems?" (environmental/technical) and "How do you think staff would respond to an AI system that automates some routine responsibilities?" (human/organisational). The instruments were examined by two specialists in health informatics and public health to establish face and content validity. A pilot study involving 15 staff members from a non-tertiary hospital in Yenagoa produced a Cronbach's alpha coefficient of 0.81, indicating good internal consistency. Minor revisions were subsequently made to improve clarity and comprehension.

3.6 Data Collection Procedure

Ethical approval was obtained from the Bayelsa State Ministry of Health as well as the research ethics committees of the participating hospitals. Copies of the questionnaire were distributed manually and retrieved within a two-week period. Participants were assured of anonymity and provided written informed consent before participation. The interviews were conducted in participants' offices, audio-recorded with their permission, and later transcribed verbatim for analysis.

3.7 Data Analysis

Quantitative data were entered into Microsoft Excel and analysed using the Statistical Package for Social Sciences version 25. Descriptive statistical tools, primarily frequencies and percentages, were generated and presented in tables. Qualitative data were analysed using thematic analysis. The analysis began with open coding of the interview transcripts in order to identify initial categories inductively. These categories were subsequently examined in relation to the dimensions of the socio-technical framework, allowing themes to be refined through both data-driven and framework-guided interpretation. This analytical approach ensured that the findings remained grounded in participants' perspectives while also addressing the conceptual concerns of the study.

3.8 Ethical Considerations

In addition to obtaining institutional approvals, the study ensured confidentiality by using identification codes instead of participants' names and storing all data in password-protected files. Participation was entirely voluntary, and no form of inducement capable of coercing participation was provided.

4. RESULTS OF FINDINGS

A total of 112 questionnaires were correctly completed and returned, resulting in a response rate of 93%. In addition, all five heads of IT units participated successfully in the interview sessions.

4.1 Demographic Characteristics of Respondents

Among the 112 respondents, 58 were female while 54 were male. Nurses constituted the largest professional category (38%), followed by health information officers (25%), doctors (20%), and laboratory scientists (17%). Most respondents (68%) had worked in their respective hospitals for more than five years, indicating substantial familiarity with the healthcare data management systems currently in operation.

4.2 Healthcare Data Management Challenges

Table 1 presents the frequency and percentage distribution of respondents who reported experiencing each listed challenge regularly. Respondents were permitted to select more than one challenge based on their daily experiences.

Table 1: Major Healthcare Data Management Challenges (N=112)

Challenge	Frequency (n)	Percentage (%)
Time wasted searching for patient records	102	91.1
Missing patient folders	97	86.6
Incomplete data in registers and forms	91	81.3
Duplicate patient records	87	77.7
Delay in monthly report preparation	84	75.0
Illegible handwriting in clinical notes	79	70.5
Fragmented systems without integration	73	65.2
Misfiled laboratory results	68	60.7

Note: Percentages exceed 100% because respondents were allowed to select all challenges they regularly encountered in their daily duties. The percentages therefore represent the proportion of respondents reporting each individual challenge rather than mutually exclusive responses.

As indicated in the table, excessive time spent searching for patient records and missing patient folders were the most frequently reported challenges, affecting more than 85% of respondents. These were followed by incomplete data and duplicate patient records. One nurse expressed the situation in the following words: "Sometimes you will spend 30 minutes just looking for one folder. The patient is waiting, you are sweating, and the folder is nowhere."

4.3 Awareness and Adoption of AI

A majority of respondents (62.5%) stated that they had heard about artificial intelligence through news platforms, social media, or professional workshops. However, only 8% indicated that they could clearly explain what AI is and how it functions. When respondents were asked whether their hospitals currently used any AI-powered system for healthcare data management, all 112 respondents answered in the negative. This was further confirmed during the interviews with the IT heads. One participant remarked, "We have an electronic health record that was introduced two years ago, but it is not AI. It is simply a digital filing cabinet. There is no intelligence behind it."

4.4 Perceived Roles of AI and Qualitative Themes

When respondents were presented with a list of possible AI applications and asked which they believed could be beneficial, several areas were identified. The five most highly rated applications were automated extraction of information from doctors' notes (78%), detection and merging of duplicate patient records (74%), predictive reminders for follow-up appointments (68%), automated generation of monthly statistical reports

(65%), and intelligent scheduling aimed at reducing patient waiting time (61%).

The qualitative data were analysed thematically. Table 2 summarises the major themes, sub-themes, and illustrative quotations mapped across the dimensions of the socio-technical framework.

Table 2: Thematic Map of Qualitative Findings with Illustrative Quotes

Dimension	Theme	Sub-theme	Illustrative Quote
Technical	Perceived AI utility	Automated note extraction	"If a system can read my notes and organise the information automatically, it will reduce stress." (Doctor)
		Duplicate record merging	"Sometimes one patient has three different numbers. AI can clean that." (Health information officer)
	Infrastructure deficit	Unreliable power supply	"Our priority is always clinical services, not server systems." (IT head)
		Poor internet connectivity	"Internet comes and goes; a cloud AI cannot work here." (IT head)
Human	Awareness versus deep understanding	Surface-level familiarity	"I have heard of AI on the news, but I cannot say I understand how it works." (Nurse)
	Workforce anxiety	Fear of redundancy	"Some senior records officers believe AI will replace their jobs." (IT head)
	Skill limitations	Lack of data science expertise	"We do not have anyone trained to manage intelligent systems here." (IT head)
Organisational	Resistance to change	Attachment to paper systems	"They are used to paper and pen, and any change is viewed as a problem." (IT head)
	Leadership priorities	Data systems viewed as secondary	"Management focuses on clinical equipment, not data infrastructure." (Doctor)
Environmental	Physical conditions	Humidity and flooding	"During the rainy season, our server room becomes damp; equipment begins to rust." (IT head)

4.5 Perceived Barriers to AI Adoption

Barriers to AI adoption were examined through both the questionnaire and interview sessions. The most frequently identified barriers included unstable electricity supply (94%), high cost of AI software and hardware (89%), poor internet connectivity (85%), shortage of trained personnel capable of managing AI systems (82%), resistance to change among staff (71%), and concerns regarding data privacy and security (65%). The thematic analysis further revealed that these barriers are interconnected rather than isolated. For example, unstable electricity undermines technical feasibility, while inadequate technical expertise and resistance to change create additional organisational and human challenges even where infrastructure improvements exist.

5. DISCUSSION OF FINDINGS

The discussion of findings is organised according to the four dimensions of the socio-technical framework in order to demonstrate how readiness for AI adoption is shaped through the interaction of technical, human, organisational, and environmental factors.

5.1 Technical Dimension: Infrastructure as the Major Constraint

The widespread reporting of electricity and internet connectivity problems corresponds closely with the technical dimension of the socio-technical framework. Even the most advanced AI application cannot function effectively without stable power supply and reliable internet access. The qualitative findings clearly indicate that hospital administrators currently prioritise electricity for immediate clinical services over investment in data infrastructure. This finding reframes the discussion on AI readiness by suggesting that unless power solutions are intentionally designed to support healthcare data systems, AI implementation will remain largely theoretical. Offline-capable systems, edge-computing technologies, and solar-powered server infrastructure therefore emerge as essential technical considerations within this context. The issue of high implementation cost further reinforces the technical challenge, as even relatively affordable AI tools may remain inaccessible without sustainable financing mechanisms.

5.2 Human Dimension: Awareness without Practical Capacity

The gap observed between superficial awareness and deeper technical understanding reflects the human dimension of the framework. Healthcare workers are not necessarily opposed to AI technologies; rather, many lack practical exposure to functioning AI systems. This suggests that readiness-building initiatives should begin with practical demonstrations and digital literacy programmes instead of purely theoretical training sessions. The fear of redundancy expressed by some experienced records officers also requires careful management through inclusive change strategies that present AI as a supportive tool rather than a replacement for human labour. As suggested by the socio-technical framework, human factors cannot be separated from organisational culture because workers who feel threatened are more likely to resist even well-designed innovations.

5.3 Organisational Dimension: Leadership and Institutional Priorities

The perception that hospital management places greater importance on clinical equipment than on data infrastructure reflects an organisational culture in which healthcare data management is regarded as a secondary administrative function instead of a critical patient safety issue. According to the socio-technical framework, the absence of leadership commitment can undermine even technically feasible innovations. Repositioning healthcare data management as an essential component of patient safety may therefore help reshape institutional priorities. The qualitative observation that “management focuses on clinical equipment, not data infrastructure” highlights the need for advocacy and policy engagement at the highest levels of hospital administration.

5.4 Environmental Dimension: Technology and Local Context

The humid, riverine, and flood-prone environment of Yenagoa is not merely a background condition; it directly influences the sustainability of healthcare technologies. The socio-technical perspective emphasises that technology must be adapted to local environmental realities rather than assuming universal operating conditions. This finding points to the need for collaboration with technology developers in order to design rugged, low-energy systems capable of functioning effectively within the local environment. Ignoring environmental realities could result in the rapid deterioration of costly technological equipment, as reflected in the interview reports concerning rust and dampness within server rooms.

5.5 Interaction of Dimensions and Overall Readiness

The findings demonstrate that the four dimensions of the socio-technical framework do not operate independently. Unstable electricity supply (technical factor) interacts with shortages of skilled personnel (human factor) to create a situation in which even a purchased AI system may be poorly maintained and rendered ineffective by repeated power interruptions. Organisational resistance to change further complicates staff training efforts, while environmental conditions contribute to equipment degradation, thereby increasing costs and reinforcing managerial reluctance to invest. This interconnectedness suggests that readiness for AI adoption must be developed across all dimensions simultaneously, as isolated interventions are unlikely to produce sustainable outcomes.

5.6 Implications for Policy and Practice

The findings indicate that AI should not be viewed as an immediate solution to healthcare data management problems. Instead, tertiary hospitals in Yenagoa require a phased readiness-building strategy. The first stage should involve strengthening digital infrastructure and stabilising power supply. The second stage should focus on staff development, digital literacy, and organisational change management. The final stage should involve the gradual introduction of simple, offline-capable AI tools designed to address clearly defined challenges such as duplicate record detection and automated reporting. Policymakers should therefore avoid premature investment in expensive AI systems and instead prioritise the foundational conditions identified by the socio-technical framework.

5.7 Limitations of the Study

This study relied largely on self-reported information, which may be influenced by recall bias and social desirability bias. The use of non-probability sampling also limits the extent to which the findings can be generalised to other settings. Furthermore, because none of the hospitals had implemented an operational AI system, the findings reflect perceived opportunities and barriers rather than observed performance outcomes. Future implementation-based studies are therefore necessary to determine how these perceptions translate into actual adoption, acceptance, and practical impact. In addition, although the sample size was adequate for descriptive analysis, it did not support advanced inferential statistical testing capable of revealing possible relationships between demographic variables and readiness perceptions.

6. CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

This study examined healthcare workers' perceptions of the potential role of artificial intelligence in improving healthcare data management within tertiary hospitals in Yenagoa, Bayelsa State. The major finding is that although healthcare workers acknowledge the potential of AI to reduce administrative burdens and improve efficiency, the hospitals currently remain at a low-readiness stage for meaningful AI implementation. Significant barriers across the technical, human, organisational, and environmental dimensions interact to create conditions under which even well-intentioned AI initiatives are likely to struggle. The study therefore concludes that readiness-building efforts, beginning with basic infrastructure development and workforce capacity strengthening, are necessary prerequisites for successful AI adoption in this setting.

6.2 Recommendations

The recommendations of the work are ordered according to the magnitudes of the socio-technical framework.

1. Hospital management should establish dedicated solar-powered server rooms with climate-control systems to protect hardware from humidity and unstable electricity supply.
2. Any AI solution introduced should possess offline operational capability in order to minimise dependence on unreliable internet connectivity.
3. Continuous professional development programmes in digital literacy and health informatics should be organised for all personnel involved in healthcare data management.
4. Change management initiatives should actively involve long-serving records officers and present AI as a supportive system rather than a threat to employment.
5. Hospital leadership should formally recognise healthcare data management as a patient safety issue and allocate dedicated budgetary provisions for digital infrastructure development.
6. The Bayelsa State Ministry of Health should formulate a phased digital health strategy that prioritises foundational infrastructure improvements before large-scale AI implementation.
7. Partnerships should be established with technology developers to design rugged, low-energy AI systems suitable for humid and flood-prone riverine environments.
8. Future studies should pilot selected AI tools within one of the tertiary hospitals and assess their practical effects on data quality, efficiency, and staff workload through longitudinal research designs.

6.3 Final Reflection

Healthcare workers in Yenagoa's tertiary hospitals continue to perform their responsibilities under difficult conditions and with limited technological support. Their primary concern is not the pursuit of sophisticated innovations for their own sake, but the need for systems that make patient records easier to retrieve, improve continuity of care, and support timely clinical decision making. Artificial intelligence, when stripped of exaggerated expectations, represents a collection of practical tools that may help address these everyday challenges. This study has demonstrated that readiness for AI adoption is not simply about acquiring modern technology; it involves developing the technical, human, organisational, and environmental conditions necessary for that technology to function effectively and meaningfully serve those who depend on it most.

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