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# AI-Based Scheduling and Performance of Tertiary Hospitals in Onitsha, Anambra State

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ABSTRACT
The study employed a descriptive survey research design to examine the impact of AI-based scheduling on hospital performance in Onitsha, focusing on Federal Medical Center Onitsha and Guinness Eye Clinic Onitsha. A stratified random sampling technique was used to select 60 respondents from doctors, nurses, administrative staff, patients, and security personnel. Data were collected using a four-cluster structured questionnaire rated on a four-point Likert scale. The instrument's validity was ensured through expert review, while reliability yielded Cronbach's alpha values ranging from 0.79 to 0.86. Data collection lasted two weeks, and analysis involved descriptive statistics and ANOVA at a 0.05 significance level. This research found that there was a poor average rate of adoption of AI-based scheduling systems in tertiary hospitals in Onitsha (domain mean: 2.05-2.82 on a scale of 5). Mean of staff training was the highest (2.82) and replacement of manual systems with full replacement of manual systems showed the lowest (2.05). With respect to effect on service delivery, mean values ranged between 2.17 to 2.57 indicating little perceived effects. Some of the top challenges experienced by the participants included, data privacy (3.58), resistance to change (3.20), technical expertise (3.10). Nevertheless, solutions such as government funding (3.68) and staff training (3.50) had high levels of support, the means to increase AI adoption practically in a wide variety of ways. Finally, although the modern implementation and perceived efficiency of the AI-based scheduling of tertiary hospitals in Onitsha are minor, widespread awareness of its positive aspect has been realized. The ability to address highlighted barriers using specific policy interventions and institutional assistance may notably improve performance and efficiency in hospitals.



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## INTRODUCTION

Artificial Intelligence (AI) has become one of the most promising technologies in the health industry specifically to improve efficiencies in operations and service delivery via scheduling systems. AI in scheduling is through the use of machine learning algorithms, predictive analytics, and scheduling optimization models to algorithmically increase the automation of appointment bookings, employee rostering, and functional resource planning. Recent interest in the adoption of these systems by tertiary hospitals has been published in recent literature due to their possibilities in dealing with the complexities of high-volume and specialized healthcare environments. Artificial Intelligence (AI) has many definitions that have been given by scholars and practitioners, this is due to its wide applications and its changes over time. Ogunbodede and Atchrim (2025) defined AI as the study of agents that take percepts of the environment and execute actions, in which the focus was on the intended objective to create systems that would replicate intelligent behavior akin to human beings. Likewise, Vaikosen and Magini (2025), a co-founder of AI, describes it as, among other things, the science and engineering of making intelligent machines, and one of them intelligent computer programs, which happens to have both a scientific and engineering aspect to the perspective of the discipline, as a way of problem-solving.

Operationally, AI in this study is defined as the use of intelligent computer systems in order to streamline organizational processes at the hospital level; namely, the automated scheduling and performance analysis of tertiary healthcare settings. AI-based scheduling is the application of artificial intelligence software and technologies to automate, optimize, and control task assignment, booking, or use of resources in an organization. Khaledian et al (2024) define AI-based scheduling as the use of machine learning and optimization algorithms to dynamically assign resources, schedule, and dynamically accommodate constraints, objectives and priorities. This will promote efficiency, flexibility, and responsiveness within the dynamic environment like healthcare, manufacturing and logistics. Likewise, Lua et al (2022) define AI-based scheduling as a smart procedure, which involves predictive analytics and decision-making algorithms to allocate time slots, staff, and resources, and efficiently minimize delays and maximize productivity. They are concerned with how AI can tackle uncertainty and a multiplicity of variables to better plan and execute plans.

Operationally, in this study AI-based scheduling can be defined as the utilisation of intelligent software systems within tertiary hospitals to organise and allocate clinical appointments, assign staff, and simplify administrative tasks. It is about how AI can be used to enhance efficiency, minimize waiting time, and overall quality of service delivery in hospitals. Recent literature shows that the adoption of AI based scheduling systems in third institutions differs internationally. In well-developed areas, including North America, Western Europe, and some areas in Asia, tertiary hospitals have invested heavily in AI scheduling systems to coordinate patient visits and workflow (Wang et al, 2021). According to research conducted by Dai et al, (2025), large tertium hospitals employ AI-aided scheduling in the provision of outpatient services. Nonetheless, in less developed countries, the level of adoption is low, mainly because of technical infrastructure, the costs of implementation are higher, and healthcare employees are not sufficiently digitally literate (Adedinsewo et al, 2025). In sub-Saharan Africa, most tertiary hospitals continue to use manual scheduling systems though patient volumes are up.

The impact of electronic scheduling by AI has been covered extensively. Among the major advantages is decreasing the waiting times and congestion of patients. As Agbeyangi and Lukose (2025) assert, AI tools are more precise when it comes to scheduling because they use past patient records, appointment trends, and peak times, making the appointment time slots optimal, and delays minimal. Such an increase in scheduling results in increased patient satisfaction and improved health outcomes. Moreover, AI-based staff scheduling has enhanced efficient workforce utilization by providing the right numbers of staff at different times during peak and non-peak periods, eliminating employee burnout and improving the level of care (Iheme, 2023). The use of AI in scheduling also enhanced the use of resources in tertiary hospitals. Predictive analytics could help hospitals predict the service demand, including diagnostic tests and surgeries, which can harmonize allocation of operating rooms, medical equipment, and beds (Ogolodom et al, 2023). These efficiencies factor in on cost savings and operations performance.

Nonetheless, there are numerous obstacles to using an AI-based scheduling service in tertiary hospitals in spite of its advantages. One of the greatest challenges lies in data privacy and security because such systems must access sensitive patient information (Sarfo et al, 2024). Also, absence of technical skills in the hospital management teams can easily result in resistance or misuse of the systems. Implementation may also be complicated by interoperability between the AI systems and the hospital information systems that are in place (Nwaomah, 2025). In addition, algorithmic biases in scheduling systems cause concern. By relying on past data, AI models can actually recreate prior inequalities in healthcare, most prominently in prioritizing patients (Xie et al, 2019). This brings up ethical issues and demands clearer and interpretable AI in healthcare. Although papers like the one by Oladipo et al, 2024) outlined the significance of the ongoing staff training, investments into cybersecurity, and system customization when enhanced outcomes of AI schedule optimization are desired, such suggestions are typically made on the basis of experiences in technologically progressive settings, where resources are sufficient. Conversely, the obstacles that hospitals in Onitsha, Anamalra State, must struggle with are relatively different including poor digital infrastructure, poor awareness among medical staff of how AI functions, and funding availability that can affect the implementation and effectiveness of AI-powered scheduling solutions.

Furthermore, no localized studies have been conducted on the organizational, cultural, and infrastructural dynamics that shape the adoption of AI scheduling systems in the setting of Nigerian tertiary hospitals, which is why the study will use a qualitative approach. There is no extensive research study carried out to assess the rate of adoption, operational issues, and overall performance concerns linked to AI-enabled scheduling in tertiary healthcare institutions in Onitsha. The extent of this gap denies hospital administrators and policymakers pertinent data that can inform their decisions with regard to investing in AI technology. This gap necessitates adequate motivation to the present study. The proposed study will seek to provide a context-specific knowledge into the impact of AI-based scheduling systems on the performance of a hospital, especially within the context of service delivery, staff efficiency, and resource utilization. Not only the results will cover research niche suffering the shortage of investigations but also may act as a viable guide to hospital management, governmental bodies, and health tech providers interested in advancing the level of care efficiency with the help of AI-based technology in the context of resource-poor environments. Therefore, the rationale behind the study is viable because it will yield evidence-informed insights that are necessary to make intelligent decisions, guided policies, and strategic action plans to maximize the application of AI-driven scheduling programs in the context of operational realities of tertiary hospitals in Onitsha.

**Statement of the Problem**

Tertiary hospitals, which serve as critical healthcare delivery points for complex and specialized care, are increasingly overwhelmed by a combination of operational inefficiencies and systemic constraints. Key challenges include prolonged patient waiting times, limited availability of medical personnel, and suboptimal allocation of healthcare resources. These issues negatively impact patient satisfaction, clinical outcomes, and the overall effectiveness of hospital services. As the demand for healthcare services continues to rise due to population growth and the increasing burden of chronic diseases, these inefficiencies place unsustainable pressure on healthcare infrastructure. Recent advancements in Artificial Intelligence (AI) have introduced intelligent scheduling systems that can optimize hospital workflows, balance workloads, and enhance the efficiency of service delivery. AI-based scheduling tools have demonstrated the potential to streamline patient appointments, reduce idle time for medical professionals, and make real-time decisions that adapt to changing clinical situations. Despite these advantages, the implementation of such systems remains inconsistent, particularly in resource-constrained settings or regions with limited digital maturity.

Several barriers contribute to this uneven adoption. Technical hurdles such as lack of interoperability with existing hospital information systems, high initial deployment costs, and inadequate IT infrastructure discourage many hospitals from embracing AI-based solutions. In addition, financial limitations, especially in public tertiary institutions, make it difficult to prioritize investment in digital health innovations. Ethical concerns related to data privacy, security, and algorithmic transparency also create resistance from stakeholders, including hospital administrators, clinicians, and patients. Moreover, the fear of algorithmic bias—where scheduling algorithms may inadvertently prioritize certain patients or procedures over others—raises questions about fairness and equity in care delivery. Another critical factor is the shortage of adequately trained personnel who can manage, interpret, and integrate AI tools into existing workflows. Without proper training and institutional readiness, hospitals may misuse or underutilize these technologies, leading to ineffective outcomes. The absence of clear regulatory policies and standards governing the use of AI in clinical settings further hampers confidence in their adoption.

Consequently, tertiary hospitals risk missing out on the transformative benefits of AI-powered scheduling, potentially exacerbating disparities in healthcare access and quality. There is an urgent need for targeted interventions—such as capacity-building programs, policy frameworks, and pilot initiatives—to address these barriers. Bridging these gaps will be essential to realizing the full potential of AI in enhancing hospital performance and improving patient-centered care.

**Specific Objectives**

1. To assess the level of adoption of AI-based scheduling systems in tertiary hospitals in Onitsha.

2. To determine the influence of AI-based scheduling on service delivery in tertiary hospitals.
3. To identify the challenges associated with implementing AI-based scheduling in tertiary hospitals in Onitsha.
4. To propose strategies for improving the effectiveness of AI-based scheduling systems in tertiary hospital settings.

**Research questions**

1. What is the level of adoption of AI-based scheduling systems in tertiary hospitals in Onitsha?
2. What is the influence of AI-based scheduling on service delivery in tertiary hospitals in Onitsha?
3. What are the challenges associated with implementing AI-based scheduling in tertiary hospitals in Onitsha?
4. What strategies can be used to improve the effectiveness of AI-based scheduling systems in tertiary hospital settings in Onitsha?

**Hypotheses**

1. $Ho_1$: There is no significant difference in the level of adoption of AI-based scheduling systems among tertiary hospitals in Onitsha.
2. $Ho_2$: There is no significant difference in the influence of AI-based scheduling systems on service delivery across tertiary hospitals in Onitsha.
3. $Ho_3$: There is no significant difference in the challenges associated with implementing AI-based scheduling systems among tertiary hospitals in Onitsha.
4. $Ho_4$: There is no significant difference in the perceived effectiveness of proposed strategies for improving AI-based scheduling systems across tertiary hospitals in Onitsha.

**Theoretical framework**

The study was anchored on Technology Acceptance Model (TAM). The Technology Acceptance Model (TAM), developed by Fred Davis in 1989, is a theoretical framework that seeks to explain how users come to accept and use new technologies. Derived from the Theory of Reasoned Action (TRA) by Fishbein and Ajzen, TAM has become one of the most widely used models in the field of information systems and technology adoption. It posits that the acceptance of a technology is primarily determined by two perceptions: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which a person believes that using a particular system will enhance their job performance. In contrast, perceived ease of use is the degree to which a person believes that the technology will be free from effort. These two factors influence the user's attitude toward the technology, which in turn affects their intention to use it, ultimately leading to actual usage. The model underscores the importance of user perceptions in determining whether a technology will be embraced or rejected, especially in organizational settings where system success often depends on widespread user acceptance.

Applying TAM to the use of AI-based scheduling systems in tertiary hospitals in Onitsha, Anambra State, the theory offers a clear lens through which to understand the dynamics of technology adoption among hospital personnel. In these healthcare facilities, operational challenges such as long patient wait times, overcrowding, and inefficient staff deployment are prevalent. AI-based scheduling has the potential to address these issues by automating and optimizing appointment systems, resource allocation, and staff workload balancing. However, the effectiveness of these systems depends significantly on how hospital staff perceive them. If healthcare workers believe that the AI scheduling system can genuinely improve patient flow, reduce waiting times, and make their daily responsibilities more manageable, they are more likely to view it as useful and integrate it into their routine. Conversely, if the system appears complex or difficult to use, particularly in environments with limited digital infrastructure or low computer literacy, the likelihood of rejection increases.

In the specific context of Onitsha, where many tertiary hospitals face both resource and technological constraints, TAM highlights the need for proper training, sensitization, and support to influence positive perceptions. By addressing both the usefulness and ease of use through hands-on workshops, user-friendly interfaces, and consistent technical support, administrators can foster greater acceptance and encourage sustained use of AI-based scheduling. This, in turn, can enhance hospital performance by improving efficiency, reducing delays, and elevating the overall quality of healthcare service delivery.

## METHODOLOGY

The methodology adopted for this study was a descriptive survey research design. This design was chosen because it allowed the researcher to gather detailed information from a broad range of respondents within their natural hospital settings. The area of the study was Onitsha, a bustling commercial city in Anambra State, Nigeria. Specifically, the research was conducted at Federal Medical Center Onitsha and Guinness Eye Clinic Onitsha. These two healthcare institutions were selected because of their status as tertiary healthcare providers with diverse patient volumes and administrative structures. Their operational complexity made them suitable for a study centered on scheduling systems and hospital performance.

The population for the study included healthcare workers and patients within the two hospitals. Respondents comprised doctors, nurses, administrative staff, security personnel, and patients who either participated directly in hospital scheduling activities or were affected by them. The total estimated population across the two hospitals was three hundred (300) individuals. To ensure that every relevant group within the population was adequately represented, the researcher employed a stratified random sampling technique. This involved dividing the population into five key categories: doctors, nurses, administrative staff, security personnel, and patients. From these categories, a total sample size of sixty respondents was selected proportionally and randomly. This approach helped to minimize sampling bias and ensured that views from all key stakeholder groups were captured.

Data for the study were collected using a structured questionnaire titled AI-Based Scheduling and Hospital Performance Questionnaire (AISHAPQ). The questionnaire was carefully designed to address the core objectives of the study. It was divided into four major clusters. The first cluster focused on the level of adoption of AI-based scheduling systems.

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The second cluster examined the influence of AI-based scheduling on service delivery. The third cluster assessed the challenges associated with implementing AI scheduling in tertiary hospitals, while the fourth cluster explored strategies for improving the effectiveness of AI-based scheduling systems in Onitsha hospitals. Each item within the questionnaire was measured using a four-point Likert scale. Respondents were asked to indicate their level of agreement by choosing from the options: Strongly Disagree, Disagree, Agree, and Strongly Agree. This scale was selected to encourage respondents to take clear positions on each statement while minimizing neutral answers.

To ensure the validity of the instrument, the draft questionnaire was subjected to expert review. Three specialists in Health Services Management, Information Technology, and Educational Measurement and Evaluation from Nnamdi Azikiwe University, Awka, reviewed the instrument. Their feedback helped refine the questions, improve clarity, and ensure the instrument aligned well with the study's objectives. The reliability of the instrument was tested through a pilot study conducted among fifteen respondents from a tertiary hospital outside Onitsha. This pilot group was selected to reflect the characteristics of the main study population without overlapping with it. The responses from the pilot test were analyzed using the Cronbach's Alpha reliability coefficient. The reliability results for each cluster were as follows: 0.81 for the cluster on the level of adoption of AI-based scheduling systems, 0.84 for the influence on service delivery, 0.79 for the challenges associated with implementation, and 0.86 for strategies for improving effectiveness. These results indicated a high level of internal consistency, confirming that the instrument was reliable and suitable for the main study.

The data collection process lasted for two weeks. The researcher, with the assistance of two trained research assistants, distributed the questionnaires to the selected respondents at Federal Medical Center Onitsha and Guinness Eye Clinic Onitsha using Google survey. Each respondent was assured that their responses would be treated with utmost confidentiality and used solely for academic purposes. Adequate time was given to respondents to complete the questionnaire at their convenience. After collection, all completed questionnaires were properly coded and entered into the Statistical Package for the Social Sciences (SPSS) version 25 for analysis. Descriptive statistics such as mean, standard deviation, variance, skewness, and kurtosis were used to provide answers to the research questions. To test the null hypotheses, Analysis of Variance (ANOVA) was employed at the 0.05 level of significance. This statistical technique helped to determine whether there were significant differences in responses among the different categories of respondents within the hospitals studied.

## RESULTS

**Table 1:** Distribution of Respondents by Role

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Nurse | 12 | 20.0 | 20.0 | 20.0 |
| | Doctor | 16 | 26.7 | 26.7 | 46.7 |
| | Admin | 14 | 23.3 | 23.3 | 70.0 |

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| Patient | 12 | 20.0 | 20.0 | 90.0 |
| Security | 6 | 10.0 | 10.0 | 100.0 |
| Total | 60 | 100.0 | 100.0 | |

Table 1 shows the distribution of respondents across five roles in the study (N=60). Doctors represent the largest group with 16 respondents (26.7%), followed by administrative staff at 14 (23.3%). Nurses and patients each account for 12 participants (20.0% each). Security personnel form the smallest category with 6 respondents (10.0%). The cumulative percentage reveals that by including administrative staff, up to 70.0% of respondents were covered. Including patients brings the total to 90.0%, and all five groups together sum up to 100.0%. This spread indicates a fairly balanced representation from both healthcare providers and service recipients within the study population.

**Table 2**: Gender Distribution of Respondents

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Male | 21 | 35.0 | 35.0 | 35.0 |
| | Female | 39 | 65.0 | 65.0 | 100.0 |
| | Total | 60 | 100.0 | 100.0 | |

Table 2 presents the gender breakdown of the 60 respondents involved in the study. A larger portion of the participants were female, making up 39 individuals (65.0%), while males were 21 (35.0%). This clearly shows that women formed nearly two-thirds of the study population. The cumulative percentage highlights that after accounting for the males (35.0%), the females completed the remaining percentage, bringing the total to 100.0%. This gender spread suggests that females were more available or more willing to participate in the study.

**Research question 1:** What is the level of adoption of AI-based scheduling systems in tertiary hospitals in Onitsha?

**Table 3:** Descriptive Statistics on the Level of Adoption of AI-Based Scheduling Systems in Tertiary Hospitals in Onitsha

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| AI-based scheduling systems are currently in use in my hospital. | 2.43 | 1.280 | 1.640 | -.072 | .309 | -1.736 | .608 |
| My hospital has invested in training staff to use AI-based scheduling systems. | 2.82 | 1.112 | 1.237 | -.465 | .309 | -1.130 | .608 |
| The adoption of AI-based scheduling is supported through | 2.28 | 1.180 | 1.393 | .062 | .309 | -1.607 | .608 |

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| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| hospital management decisions. | | | | | | | |
| AI-based scheduling tools are integrated into daily hospital operations. | 2.28 | 1.106 | 1.223 | .107 | .309 | -1.398 | .608 |
| AI scheduling has replaced traditional manual scheduling methods in my hospital. | 2.05 | 1.241 | 1.540 | .563 | .309 | -1.407 | .608 |
| Valid N (listwise) | | | | | | | |

Table 3 reveal a generally low level of adoption of AI-based scheduling systems in tertiary hospitals within Onitsha. Mean scores range from 2.05 to 2.82 on a 5-point scale, indicating that most respondents lean towards disagreement or uncertainty about AI adoption. The statement on staff training recorded the highest mean (2.82), suggesting some level of investment in capacity building. However, the lowest mean (2.05) was on replacing manual scheduling, implying limited transition. Standard deviations (1.106–1.280) show moderate variability in responses. Negative kurtosis across items (-1.130 to -1.736) reflects a relatively flat distribution, while skewness values suggest a slight tilt towards disagreement.

**Research question 2:** What is the influence of AI-based scheduling on service delivery in tertiary hospitals in Onitsha?

**Table 4**: *Descriptive Statistics on the Influence of AI-Based Scheduling on Service Delivery in Tertiary Hospitals in Onitsha*

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| AI-based scheduling has reduced patient waiting time. | 2.30 | 1.239 | 1.536 | .118 | .309 | -1.669 | .608 |
| The use of AI scheduling has improved staff efficiency. | 2.43 | 1.320 | 1.741 | .012 | .309 | -1.788 | .608 |
| AI scheduling has enhanced | 2.57 | 1.267 | 1.606 | -.207 | .309 | -1.648 | .608 |

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| coordination among hospital departments. | | | | | | | |
| AI scheduling helps optimize the use of hospital equipment and facilities. | 2.43 | 1.280 | 1.640 | -.022 | .309 | -1.725 | .608 |
| Patient satisfaction has improved as a result of AI-based scheduling. | 2.17 | 1.355 | 1.836 | .406 | .309 | -1.726 | .608 |
| Valid N (listwise) | | | | | | | |

The findings in Table 4 suggest that AI-based scheduling has had a limited influence on service delivery in tertiary hospitals in Onitsha. Mean scores range from 2.17 to 2.57 on a 5-point scale, showing general disagreement or neutrality among respondents. The highest mean (2.57) relates to improved coordination among departments, while the lowest (2.17) concerns patient satisfaction, indicating perceived minimal impact on patients. Standard deviations (1.239–1.355) reflect moderate response variability. The negative kurtosis values (-1.648 to -1.788) suggest flat response distributions. Skewness figures, mostly close to zero, indicate fairly symmetrical opinions, with a slight tilt towards disagreement on improved satisfaction and reduced waiting time.

**Research question 3:** What are the challenges associated with implementing AI-based scheduling in tertiary hospitals in Onitsha?

**Table 5:** Descriptive Statistics on Challenges Associated with Implementing AI-Based Scheduling in Tertiary Hospitals in Onitsha

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| Lack of technical expertise is a major challenge in adopting AI scheduling. | 3.10 | 1.145 | 1.312 | -.972 | .309 | -.557 | .608 |

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| The high cost of AI-based systems limits their implementation. | 2.57 | 1.395 | 1.945 | -.026 | .309 | -1.910 | .608 |
| Resistance to change among staff affects AI scheduling adoption. | 3.20 | 1.176 | 1.383 | -1.115 | .309 | -.421 | .608 |
| There are frequent technical failures in AI scheduling systems. | 2.37 | 1.426 | 2.033 | .152 | .309 | -1.936 | .608 |
| Data privacy concerns limit the use of AI-based scheduling systems. | 3.58 | .591 | .349 | -1.100 | .309 | .264 | .608 |
| Valid N (listwise) | | | | | | | |

The data in Table 5 highlights several challenges limiting the implementation of AI-based scheduling in tertiary hospitals in Onitsha. The highest concern is data privacy (Mean=3.58), suggesting widespread agreement that privacy issues hinder AI adoption. Resistance to change (Mean=3.20) and lack of technical expertise (Mean=3.10) also scored high, showing that human factors are significant barriers. Cost-related challenges showed a moderate mean (2.57), while frequent technical failures had the lowest mean (2.37), indicating less perceived concern in that area. Skewness values, mostly negative (-0.972 to -1.115), suggest a tendency toward agreement on these challenges. Kurtosis values reflect a relatively flat spread of responses.

**Research question 4:** What strategies can be used to improve the effectiveness of AI-based scheduling systems in tertiary hospital settings in Onitsha?

**Table 6:** Descriptive Statistics on Strategies for Improving the Effectiveness of AI-Based Scheduling Systems in Tertiary Hospitals in Onitsha

| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| Regular staff training will improve the use of AI-based scheduling. | 3.50 | .597 | .356 | -.743 | .309 | -.382 | .608 |

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| | Mean | Std. Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| Providing adequate technical support will enhance AI scheduling performance. | 3.37 | 1.008 | 1.016 | -1.522 | .309 | 1.077 | .608 |
| Developing clear policies can promote better use of AI scheduling systems. | 3.47 | .929 | .863 | -1.736 | .309 | 1.948 | .608 |
| Engaging staff in the selection and design of AI scheduling tools will improve effectiveness. | 3.32 | 1.142 | 1.305 | -1.365 | .309 | .181 | .608 |
| Government support and funding will enhance AI-based scheduling adoption in hospitals. | 3.68 | .567 | .322 | -1.639 | .309 | 1.801 | .608 |
| Valid N (listwise) | | | | | | | |

The results in Table 6 indicate strong agreement among respondents on key strategies for improving AI-based scheduling systems in tertiary hospitals in Onitsha. Government support and funding had the highest mean score (3.68), highlighting the perceived importance of external support. Regular staff training (Mean=3.50), clear policy development (Mean=3.47), and providing technical support (Mean=3.37) also emerged as important strategies. Engaging staff in the design process (Mean=3.32) was similarly rated high. The negative skewness values (-0.743 to -1.736) suggest that most respondents agreed with these strategies. Positive kurtosis for some items indicates peaked distributions, reflecting consensus among respondents on the need for these improvements.

**Hypothesis 1:** There is no significant difference in the level of adoption of AI-based scheduling systems among tertiary hospitals in Onitsha.

**Table 7:** ANOVA Summary for the Level of Adoption of AI-Based Scheduling Systems Among Tertiary Hospitals in Onitsha

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 78.816 | 1 | 78.816 | 4.490 | .038 |
| Within Groups | 1018.117 | 58 | 17.554 | | |

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| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Total | 1096.933 | 59 | | | |

The ANOVA result in Table 7 shows a statistically significant difference in the level of adoption of AI-based scheduling systems among tertiary hospitals in Onitsha. The calculated F-value is 4.490 with a significance level (p-value) of 0.038, which is less than the 0.05 threshold. This indicates that the null hypothesis ($Ho_1$) stating there is no significant difference is rejected. The between-groups sum of squares is 78.816 with 1 degree of freedom (df), while the within-groups sum of squares is 1018.117 with 58 degrees of freedom. This result suggests that the adoption levels of AI-based scheduling systems vary significantly between the hospitals studied.

**Hypothesis 2:** There is no significant difference in the influence of AI-based scheduling systems on service delivery across tertiary hospitals in Onitsha.

**Table 8:** ANOVA Summary for the Influence of AI-Based Scheduling Systems on Service Delivery Across Tertiary Hospitals in Onitsha

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 26.726 | 1 | 26.726 | .806 | .373 |
| Within Groups | 1922.674 | 58 | 33.150 | | |
| Total | 1949.400 | 59 | | | |

The ANOVA result in Table 8 shows no significant difference in the influence of AI-based scheduling systems on service delivery across tertiary hospitals in Onitsha. The F-value is 0.806 with a significance level (p-value) of 0.373, which is greater than the 0.05 threshold. This means the null hypothesis ($Ho_2$), which states there is no significant difference, is retained. The between-groups sum of squares is 26.726 with 1 degree of freedom (df), while the within-groups sum of squares is 1922.674 with 58 degrees of freedom. This suggests that perceived influence on service delivery is relatively similar across the hospitals studied.

**Hypothesis 3:** There is no significant difference in the challenges associated with implementing AI-based scheduling systems among tertiary hospitals in Onitsha.

**Table 9:** ANOVA Summary for Challenges Associated with Implementing AI-Based Scheduling Systems Among Tertiary Hospitals in Onitsha

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 335.951 | 4 | 83.988 | 5.173 | .001 |
| Within Groups | 893.033 | 55 | 16.237 | | |
| Total | 1228.983 | 59 | | | |

The ANOVA result in Table 9 indicates a significant difference in the challenges associated with implementing AI-based scheduling systems among tertiary hospitals in Onitsha. The F-value is 5.173 with a significance level (p-value) of 0.001, which is less than 0.05. This leads to the rejection of the null hypothesis ($Ho_3$), meaning that the challenges vary significantly across hospitals. The between-groups sum of squares is 335.951 with 4 degrees of freedom (df), while the within-groups sum of squares is 893.033 with 55 degrees of freedom. This suggests that factors such as technical expertise, cost, resistance to change, technical failures, and privacy concerns differ meaningfully between hospital settings.

**Hypothesis 4:** There is no significant difference in the perceived effectiveness of proposed strategies for improving AI-based scheduling systems across tertiary hospitals in Onitsha.

**Table 10:** ANOVA Summary for Perceived Effectiveness of Proposed Strategies for Improving AI-Based Scheduling Systems Across Tertiary Hospitals in Onitsha

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Between Groups | 76.432 | 4 | 19.108 | 1.709 | .161 |
| Within Groups | 614.902 | 55 | 11.180 | | |
| Total | 691.333 | 59 | | | |

The ANOVA result Table 10 shows no significant difference in the perceived effectiveness of proposed strategies for improving AI-based scheduling systems across tertiary hospitals in Onitsha. The F-value is 1.709 with a significance level (p-value) of 0.161, which is greater than 0.05. This leads to the retention of the null hypothesis ($Ho_4$), indicating that respondents from different hospitals had similar views regarding the suggested strategies. The between-groups sum of squares is 76.432 with 4 degrees of freedom (df), while the within-groups sum of squares is 614.902 with 55 degrees of freedom. This suggests overall agreement on the proposed improvement measures.

**Discussion**

The findings of this study provide important understanding into the adoption, influence, challenges, and improvement strategies for AI-based scheduling systems in tertiary hospitals in Onitsha. For Research Question 1, the descriptive statistics revealed a generally low level of adoption of AI-based scheduling systems, with mean scores ranging between 2.05 and 2.82 on a 5-point scale. This contrasts with the findings of Wang et al, (2021), who reported higher adoption levels in Chinese urban hospitals due to strong government AI policies. Similarly, a study by Kumar et al, (2025) in Saudi Arabia found that AI scheduling tools were already integrated into over 60% of hospital operations. However, in a related study, Adedinsewo et al, (2025) observed low adoption rates in Nigerian public hospitals, largely due to infrastructural limitations. Supporting this, Morah and Brown (2024) emphasized that Nigerian hospitals are still in early AI adoption stages, mainly using basic digital tools rather than full AI integration. The ANOVA result further confirmed significant differences in adoption levels across hospitals in Onitsha (F=4.490, p=0.038).

Regarding Research Question 2, the study found that the influence of AI-based scheduling on service delivery in tertiary hospitals in Onitsha was limited. The mean scores obtained ranged from 2.17 to 2.57 on a five-point scale, suggesting that respondents perceived only a minimal impact of AI systems on improving healthcare delivery outcomes such as patient flow, appointment management, and resource utilization. This finding is in sharp contrast to the report by Dai et al. (2025), who documented a 35% reduction in patient waiting times following the implementation of AI scheduling systems in several Chinese hospitals. Similarly, a study by Agbeyangi and Lukose (2025) revealed that AI adoption led to significant improvements in staff efficiency and workload management in South African tertiary hospitals, indicating a much more positive impact than observed in

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the current research. In contrast, the present study aligns more closely with Iheme (2023), who found that many Nigerian hospitals still rely heavily on manual scheduling methods, which inherently limit the potential gains in operational efficiency and service quality that AI systems can offer. Additionally, ANOVA results (F = 0.806, p = 0.373) indicated no significant difference in service delivery perceptions across the hospitals surveyed, a result that supports Ogolodom et al. (2023), who reported a generally uniform but low perception of AI's impact on healthcare delivery within the Nigerian context.

For Research Question 3, challenges such as data privacy concerns (Mean=3.58), staff resistance to change (Mean=3.20), and lack of technical expertise (Mean=3.10) were prominent. This finding agreed with a study by Sarfo et al, (2024), which identified data security as a top barrier to AI adoption in Nigerian hospitals. In a related study, Nwaomah (2025) reported that staff fear of job loss and lack of trust in AI systems were major factors contributing to resistance. Similarly, findings by Oladipo et al, (2024) revealed that cost and frequent technical failures were common barriers to AI integration in low-resource settings. The ANOVA result revealed a significant difference in perceived challenges across hospitals (F=5.173, p=0.001), supporting observations by Xie et al, (2019) that hospital size and ownership structure often influence the nature and intensity of implementation challenges.

For Research Question 4, strategies for improving AI scheduling effectiveness received high ratings. Government support and funding (Mean=3.68), regular staff training (Mean=3.50), and clear policy development (Mean=3.47) emerged as key suggestions. This finding agreed with Sun and Medaglia (2019), who found that targeted government funding improved AI adoption in public health facilities. In contrast, a study by Fahlevi et al, (2022) stressed that internal hospital leadership and management-driven initiatives were more effective than external funding. Additionally, Suleiman et al, (2024) reported that active staff engagement in the design and rollout of AI systems enhanced their effectiveness in selected hospitals in Nigeria. The ANOVA result showed no significant difference in views across hospitals (F=1.709, p=0.161), suggesting that respondents from various hospitals largely agreed on the needed strategies. This aligns with findings from Ogolodom et al, (2023), who also observed consensus among Nigerian healthcare workers on improvement measures for AI adoption.

## CONCLUSION

The study on AI-Based Scheduling and Performance of Tertiary Hospitals in Onitsha, Anambra State, has provided valuable understanding into the current state, influence, challenges, and improvement strategies surrounding AI scheduling systems in the healthcare sector. The findings reveal that the level of adoption of AI-based scheduling systems remains relatively low across tertiary hospitals in the area. Although some investment in staff training was observed, full integration of AI tools into hospital operations is still limited. The influence of AI scheduling on service delivery, especially in reducing patient waiting time and improving staff efficiency, was also found to be minimal. Furthermore, the study identified key challenges such as lack of technical expertise, resistance to change, high system costs, technical failures, and data privacy concerns as significant barriers hindering effective AI implementation. However, respondents strongly agreed on strategic measures that could improve adoption and performance. These include enhanced government support, regular staff training, clear policy development, adequate technical support, and engaging hospital staff in the design and selection of AI tools. While AI-based scheduling holds great potential for transforming hospital performance in Onitsha, addressing technical, financial, organizational, and policy-related barriers remains essential for its successful adoption and impact on healthcare service delivery.

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