

ARTIFICIAL INTELLIGENCE AND RESOURCE ALLOCATION EFFICIENCY IN EDUCATION IN NIGERIA: A CASE STUDY OF SECONDARY AND HIGHER INSTITUTIONS IN OYO STATE

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Abstract

The study investigated the efficiency in the management of resource allocation in educational institutions in Nigeria with emphasis on public secondary schools and tertiary institutions in Oyo State using Artificial Intelligence (AI). The convergent parallel mixed method

design was employed for the study. Both quantitative and qualitative methods, and both types of data were collected at the same time from 15 selected institutions comprising 350 educational administrators, teachers and IT support staff. The quantitative data was analysed using descriptive statistics, one-way ANOVA and multiple regression, while the qualitative information was collected by thematisation of 25 semi-structured interviews and institutional documents. The findings indicate that the effectiveness of resources deployed is also improved when using AI. The regression results showed that barriers (lack of suitable infrastructure, reliability of electricity and technical skills) have positive influences on the implementation of the AI. Qualitative evidence also indicates that AI-supported systems enhance the scheduling, budgeting, and decision-making processes and highlight issues of algorithmic bias, data privacy, and professional training needs. It was also discovered that, under the right infrastructure, policy setting and human support, AI can be a strategic tool to enhance the efficiency and equity in the allocation of educational resources. The study, therefore, recommends that more investment needs to be made on digital infrastructure and ethical regulation of AI systems, and that continuous capacity building should be carried out for the teachers to facilitate effective and sustainable integration of AI technologies into the educational management.

Keywords: Artificial intelligence, AI adoption, educational management, resource allocation efficiency

Introduction

The adoption of artificial intelligence (AI) in educational practices is one of the most radical changes over the last several decades, especially in resolving the traditional issues of resource shortage, inefficiency, and unequal distribution. However, educational institutions around the world continue to be faced with various pressures, such as budget limitations, changing enrolment, teacher shortages, infrastructure challenges, and the need to deliver personalised learning to a high number of students (UNESCO,

various reports on AI in education, ongoing since 2021; Koukaras et al., 2025). The traditional resource allocation methods that rely on manual planning, past experiences or even only on simple heuristic approaches can, however, result in sub-optimal outcomes, such as over-crowded classes, underutilised infrastructure and distribution of faculty workload, as well as inappropriate student support services (Xu, 2025; Pi et al., 2025).

The possibilities of working more competently in resource allocation seem large with the introduction of AI technologies, such as machine learning algorithms, predictive analytics, optimisation models (ex: genetic algorithms, particle swarm optimisation), and generative AI tools. AI can be used to process a lot of educational data, such as student performance metrics, attendance data, facility usage, budget data, and even staffing data, to make dynamic and data-driven decisions (Koukaras et al., 2025; Xu, 2025). As an example, AI-based systems have been shown to be effective in optimising master schedules in K-12 and higher education environments, consuming less planning time and maximising space allocation and distribution of teachers and instructional priorities (Pi et al., 2025; Koukaras et al., 2025). In higher education institutions, AI optimization algorithms were applied in various fields, such as course scheduling, resource management, faculty scheduling, classroom allocation, and budget planning, aiming to maximize the usage of resources while minimizing operational costs (Xu, 2025). Recent empirical and conceptual research accentuates the gains that can be achieved. Applications of AI in educational management have been associated with smoother decision-making, cost savings, and a fairer allocation of resources, especially in predictive modelling of enrolment patterns, a dangerous at-risk student identification, and a responsive facility maintenance (Koukaras et al., 2025; Pi et al., 2025; Xu, 2025). By integrating AI-powered solutions with advanced networks, like those enabled by 5G technology in smart campuses, it is possible to make real-time predictions, detect anomalies and optimize schedules, therefore eliminating the inefficiencies of energy, space and human resources (Koukaras et al., 2025). Furthermore, AI is also

used in more institutional capacities, for example, to guide strategic decisions such as connecting supplemental tools to the core curriculum, and using resources with greater coherence (Akpan, 2024; BUSA et al., recent).

In the developing world like Nigeria or such like places, AI has inherent potential in optimizing the distribution of scarce financial, human and material resources in secondary and tertiary education institutions in order to alleviate long term underinvestment and weak infrastructure. (BUSA et al., recent; AKPAN, 2024). The fast integration of AI in education is a process that also demonstrates the increasing claims to individualisation and operational efficiency all over the world, and models highlight the importance of balancing ethical and strategic integration (Martin et al., 2025; Slabko et al., 2026; Virmani et al., 2025).

In spite of these developments, there are still obstacles such as the ethical implications of data privacy, the possibility of biases in the decisions made by algorithms, digital disparities that contribute to inequities, and the necessity of professional training to make good use of it (Fütterer et al., 2025; Alexandron et al., 2026; Shamir and Negele, 2025). Research also emphasises the need to adopt evidence-based practices (and reassess teacher training) to integrate AI into education and preserve the human aspect in education (Fütterer et al., 2025; Alexandron et al., 2026). While AI is powerful in creating better outcomes for metrics such as time saved in planning, increased utilisation and prediction accuracy, its true worth is in the additional human oversight, policy and teacher training to ensure equity and fairness in the outcomes that are generated (Martin et al., 2025; Slabko et al., 2026).

While there are some positive signs in the use of AI in specific contexts (such as scheduling and predictive analytics), there is little evidence that AI is being studied on how it can improve the efficiency of resource allocation in a comprehensive manner, particularly in the long term impacts it may have on educational equity, cost-efficiency, and learning outcomes across different educational institutions (Xu,

2025; Koukaras et al., 2025; Pi et al., 2025). This is especially problematic in resource-limited areas, where AI has potential for uneven impacts and challenges for implementation. The current research touches on it by considering the way AI technologies can improve resource distribution within education, and the emphasis is put on the mechanisms, quantifiable enhancements, and contextual adjustments.

Literature Review and Theoretical Framework

Resource-Based View (RBV) theory is the theoretical framework that will be used in this study on artificial intelligence (AI) and resource allocation efficiency of education. Developed primarily by Barney (1991) RBV suggests that a sustained competitive advantage and good performance is possible if the organisation can effectively use valuable, rare, inimitable and non-substitutable resources and capabilities (VRIN). In this context, resources refer both to material resources (such as budgets, buildings, classrooms, technological supports etc.) and immaterial resources (such as teacher knowledge, institutional knowledge, repositories of data, organisational practices etc.). Theory shifts the focus from positioning the institutions on the outside of the market to orchestrating their resources on the inside, where the allocation, combination, and deployment of the institutions' resources will lead to the efficiency of their operations, equity in their services and education in general.

In the context of the provided research, AI is a strategic, intangible resource to complement the existing learning tools and enhance their value and productivity. The dynamic and data-driven allocation of resources is facilitated by AI technologies, including predictive analytics, optimisation algorithms, and intelligent decision-support systems, and helps eliminate the underutilised space, imbalanced workloads, and unmatched support services (Koukaras et al., 2025; Xu, 2025; Pi et al., 2025). Where institutions are able to make the best use of the limited resources they have without an accompanying increase in funding or staff, they can achieve competitive advantages in terms of equity, cost-effectiveness and quality of learning and the

possibility of this is rare and possibly impossible in resource-challenged settings in developing countries, including Nigeria (BUSA et al., recent; Akpan, 2024). The AI adoption is presented as a competency development feature of the VRIN paradigm, and RBV provides the development of the mechanisms that facilitate the allocation efficiency of AI and identifies the challenges that can prevent these mechanisms from achieving them (e.g., data quality, skills gap or the cost of implementing AI), and opens up examination of the long-term effects of the implementation of AI in the education environment on institutional performance and equity in different contexts (Martin et al., 2025; Slabko et al., 2026). This prism sheds light on the research's emphasis on measurable improvements and adaptations to the surrounding environment and will contribute to the theoretical understanding in the field of educational leadership and to the practical application of AI-driven strategies.

Empirical Review

Recent studies and experiences have corroborated the effectiveness of using artificial intelligence (AI) in the educational management systems to improve the efficiency of the educational resources management, the performance of the educational institution and the efficiency of the decision-making process in the school and college. The articles describe the opportunities for using AI-based applications for data-driven planning, reducing the costs of operation, and sustainability in educational resource management. Some of the studies have employed more advanced analytical techniques and machine-learning algorithms to evaluate the performance of the intelligent resource allocation systems. One instance is Huang (2025) who analysed the efficiency of intelligent education resource allocation in the regions by using transnational panel data with 217 institutions and machine learning algorithms. After the results were presented, the differences between the regions were found to be significant with the mean rate of resource utilisation of universities in East Asia being 93.4 per cent, because of the use of Long Short-Term Memory (LSTM) predictive models. In contrast, the mixed-integer programming strategies helped institutions in the developing countries to reduce the implementation cost by an

average of 34 per cent. The paper also found a technology-policy collaborative model was in line with ethical AI governance and reduced the bias in decision-making by 18.7 per cent. In addition, in university environments in tropical countries, it was shown that more than 29 percent of energy is saved by using climate-adaptive algorithms, suggesting that AI-based resource management systems can contribute to both energy efficiency and environmental sustainability.

Similarly, Song and Nan (2025) developed and tested a computational model that integrates reinforcement learning, dynamic resource allocation theories, and predictive analytics for making informed decisions in educational management. The model was able to capture the interactions between students, the faculty, institutional budgets and performance indicators. The application of the educational data demonstrated results of high decision accuracy and institutional performance through a real-time assessment of the experimental results achieved by the AI-based policy functions, compared to the conventional, and statical, policy functions. The results demonstrate that the AI-based decision systems are highly adaptable to help address the inefficiency in the traditional process of managing the resources in the educational organisation. Based on the empirical study using the structural modelling approach, the efficiency of using AI in the plan of resources and institutional sustainability is also supported. The study by Juanda et al. (2024) employed the framework of analysis of the SmartPLS model to explore the allocation of resources using AI technology on higher education campuses and entrepreneurial sustainability and business management training in particular. The results showed that the resource's demand forecasting accuracy, and the efficient decision-making of the institutions were significantly influenced by the AI integration. The paper also highlighted the role of intelligent analytics in the identification of optimization opportunities and how this can help in realizing the SDG targets that relate to quality education and institutional effectiveness.

In the field of educational data mining, Ma (2021) used a better association rule algorithm founded upon decision trees combined with a difference evolution enhanced back-propagation neural network model to act on data on higher education resources and forecast the outcomes of teaching evaluation. The results of the empirical research showed that the relationships between the rating of teaching performance and the teacher characteristics of age, academic qualification, rank were found to be close. The predictive model was more accurate (95.44 per cent) and more efficient (average absolute error of 1.05 per cent) in predicting than the traditional methods. The outcomes show that AI-assisted data mining tools are able to generate actionable knowledge to support evidence-based decision making on the allocation of the educational resources and the teaching quality management. The problem of distributing resources according to the sectors is also studied and presents the immediate application of AI in the field of education. In order to improve the distribution of physical education resources in rural areas, Zhou proposed that the intelligent raindrop optimisation algorithm be implemented. The algorithm was tested and proved to be effective in data integration in the case of the distribution of resources in rural sports education systems. The model increased the informatisation of rural educational facilities and reinforced the coordination of the physical education programmes, community fitness programmes and the related industries, and consequently led to sustainable rural development.

The second strand of empirical studies focuses on the use of AI in predicting student outcomes and targeted allocation of resources. Based on the data of HEIs on the use of digital learning resources, Jokhan et al. (2022) developed a predictive model for the use of digital learning resources with the use of random forest classification. The model achieved a high level of accuracy with the data obtained from the learning activities in the first semester and the accuracy of the total prediction is 97.03 per cent. The results of accuracy based on sensitivity, specificity, precision and predictive reliability are high. The model enabled the identification of at-risk students at an early

stage and provided a decision-support tool to better allocate digital learning resources, academic support and intervention programmes. However, outside of the direct educational context, the associated empirical studies in other domains can shed more light on the internally working mechanisms by which AI can enhance the performance of resource allocation. The authors Zhou and Sun (2025) studied the effects of AI use on the efficiency of resource allocation by using the Chinese A-share listed companies as the study data. They found that AI can have a significant effect on boosting total factor productivity and transparency of data by connecting data in real time to enhance allocation efficiency. There are many areas in the education industry where these systems can be greatly utilised, including the optimisation of input mixes and greater visibility of data to inform budgeting and personnel and resource mobilisation.

The efficiency is also empirically proved by the results of experimental studies on smart learning environments, which demonstrate the effectiveness of AI systems in the field of education. Cao et al. (2020) developed an efficient smart learning framework with artificial intelligence developed in the environment of smart classrooms and online learning. It was verified experimentally that it is a better predictor of students' learning behaviours than traditional systems, and it enabled optimizing learning environments and the use of digital and physical educational resources. The other research papers offer informative and insightful information on how institutions and their administration can be improved using AI. In large educational organizations, administrative systems can be automated using AI, which led to a significant reduction in administrative work, as can be seen from the study carried out by Deep et al. (2024) on the use of AI-enabled administrative systems in large educational organizations. The applications made the institutions more responsive, and helped to provide better services for students and reduce the cost of operation. Likewise, Ikwuanusi et al. (2022) have explored the possibilities of using AI tools in academic and research libraries, and demonstrated the use of predictive analytics for enhancing collection development, resource use, and

access to information in resource constrained environments.

There have also been reports of increased efficiency gains, which are associated with the incorporation of AI into the education system, in other complementary studies. As one example, Demartini et al. (2024) created a learning analytics dashboard, which unites AI methods to track student activity, anticipate dropouts, and facilitate the collaborative learning experience. Also, Nie (2023) studied how personal teaching systems based on AI and big data technology could be integrated and discovered that intelligent analytics can substantially enhance the outcomes of learning and the quality of teaching. Furthermore, Ganesan (2021) emphasized the role of AI-cloud integration in the smooth functioning of massive digital learning platforms, such as efficient handling of high volume educational data and remote learning resources.

Methodology

The convergent parallel mixed method design was employed for the study. In this method, quantitative and qualitative data were collected at the same time, analysed independently, and later used to create complementary information on the measurable outcomes and processes. The study was conducted in 15 purposively selected public secondary schools and tertiary educational institutions in Oyo State, Nigeria in a region where the study settings experience the typical challenge of resource constraints and digital transition of many developing educational systems in the world. The data was gathered during a full academic term (October 2025 to March 2026), to ensure it reflects both the typical allocation and the on-going AI-supported approaches. This design was selected purposefully because the objectives of this study required high levels of quantification of efficiency gains, and sensitivity to the context of barriers, perceptions and mechanisms to implementation among stakeholders. Qualitative elements provided insights into lived experiences that numbers could not capture, and quantitative elements were used to make statistical generalisations and test relationships from the resource-based view. The methods used

closely followed the guidelines outlined by Creswell and Plano Clark (2018) such as: systematic integration, valuing both strands equally, and thorough validity checks as relevant to applied educational technology studies. The target population consisted of the educational administrators, classroom teachers and information technology (IT) support staff of the selected institutions having direct involvement in decision-making for the use of resources. Two sampling technique was used. The institutions were first chosen purposefully because of their exposure to some level of digital management tools and their willingness to join. Of that group, 350 people were selected using stratified random sampling within those institutions to get a proportional representation of roles and types of institutions, as part of the quantitative strand. In the qualitative strand, 25 key informants were identified by using the purposive and snowball sampling method so as to get the maximum variation of views.

To be included, at least one year of ongoing service with a decision making role on budgeting, scheduling, staffing or infrastructure was needed. One exclusion criterion was that purely clerical or non-administrative staff were excluded, and another was that staff with inadequate tenure. The resulting sample was equivalent in gender, age (25 to 60 years) and professional experience (approx. 8 years), thus not encountering the problem of selection bias, which would hamper considerations of demographic influences on technology adoption. Three main instruments were used, which would appear to be valid and suitable for the context. The principal quantitative instrument employed was a semi-structured 45 item questionnaire utilizing resources that were developed on the basis of the Technology Acceptance Model (TAM) (Davis 1989) and validated scales for resource efficiency as used in previous educational studies. The items that measured perceived usefulness, ease of use, adoption level and self-reported efficiency indicators were based on a 7-point Likert scale. For this study a semi-structured interview guide was developed, consisting of 12 open-ended questions, and validated through discussion with three educational technology experts. Lastly,

formal agreements were used to get access to institutional documents like an annual budget report, timetabling logs and output from any available AI system. The rationale for the selection of these materials was that they had standardised psychometric properties and good triangulation with the qualitative part of the survey with the few changes in wording to accommodate the terminology used by teachers in Nigeria's education system after pilot testing. Carefully sequenced, but concurrent time schedule procedures were conducted. With ethical clearance and piloting of the two instruments with 20 non-participating staff in September 2025, recruitment letters were sent out via institutional gatekeepers in early October. Quantitative surveys were sent out online over a 6-week period with three standardised reminder emails to ensure high response rates, via a secure online platform. At the same time, a one-to-one interview was conducted in person or by encrypted video calls and each interview took between 45-60 minutes, and was audio-recorded in explicit agreement. Document retrieval and initial review has been completed during the collection period in order to allow for the cross checking of documents for discrepancy where this has occurred. All sessions were conducted in a standardised way that included rapport building, neutral questioning and member-checking to build trustworthiness. The present study used convergent parallel mixed method research, in which the quantitative data was analyzed in SPSS software (version 29.0) - only one way. The data were screened for missing values, outliers, normality, linearity, homoscedasticity and multicollinearity and descriptive statistics (mean, standard deviation, frequency, and percentage) were used to summarize the participant characteristics and important variables. Inferential analyses included one-way analysis of variance (ANOVA) to compare the efficiency of resource allocation between groups based on the type of institutions, professional role and level of exposure to AI; and dichotomous comparisons using independent samples t-tests for significant effects. Multiple linear regression was conducted to identify the factors that were significant predictors of the composite index of efficiency after control variables (the demographics) were entered into the model in a hierarchical manner, followed by the factors that

were associated with AI (perceived usefulness, ease of use and level of adoption). Adjusted R², overall F statistics and standardised beta coefficients were used to determine model fit and assumptions were checked using the appropriate diagnostics. All tests were tested two-way and alpha was .05. Based on a priori analysis of power, the sample size was appropriate to detect medium effects.

Results

There were 350 questionnaires distributed and 100% of the questionnaires were returned. Of the 350 participants, 189 (54.0%) were males and 161 (46.0%) were females. A total 196 (56.0%) participants were randomly picked from public secondary schools while 154 (44.0%) were picked from tertiary institutions. There were three categories of occupation: administrators (n = 140, 40.0%), teachers (n = 140, 40.0%) and information technology support staff (n = 70, 20.0%). When asked about years in the profession 30.0% of the group had 1-5 years, 40.0% had 6-10 years, and 35.0% had over 10 years of experience. With regard to familiarity with AI tools, 20.0% said they are not familiar with AI tools, 32.0% said they are basically familiar with AI tools, 34.0% said that they are intermediate familiar with AI tools, and 14.0% said that they are advanced familiar with AI tools. For the qualitative strand, 25 key informants in semi-structured interviews participated; their profiles were similar to the survey sample's in terms of their role and institutional and gender diversity. The full demographic profile is given in Table 1.

Table 1. Demographic Characteristics of Survey Respondents (N = 350)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	189	54.0
	Female	161	46.0
Institution Type	Public	154	44.0
	Secondary		
	Tertiary	154	44.0

Characteristic	Category	Frequency (n)	Percentage (%)
Role	Administrator	140	40.0
	Teacher	140	40.0
	IT Support Staff	70	20.0
Experience	6–10 years	140	40.0
	Above 10 years	105	35.0
AI Tool Familiarity	None	70	20.0
	Basic	112	32.0
	Intermediate	119	34.0
	Advanced	49	14.0

Authors computation (2026)

Descriptive Statistics

Means and standard deviations of the eight key study variables are presented in Table 2 and the skewness and kurtosis values for these variables. The mean score on the AI Adoption Index was 3.84 (SD = 0.91) which provides a moderate–high level of the adoption of AI at the sampled institutions. The variable with the highest rating was perceived AI usefulness (M = 4.12, SD = 0.79), broadly positive attitudes related to the use of AI technologies among the educational staff. Overall, the composite Resource Allocation Efficiency Index had a mean value of 3.77 (SD = 0.86) and suggested improvements which were significant but not consistent, due to AI at institutions. Facility Utilization averaged 71.4% (SD = 12.3%) and Reported Cost Savings averaged 22.6% (SD = 9.7%). The student support distribution Equity Score had a moderate result of M = 3.61 with SD = 0.95, and the Staff Workload Balance Ratios had a moderate result of M = 3.72 with SD = 0.88. The lowest mean rating (M = 3.48, SD = 1.02) was found for the barriers to AI Adoption, indicating substantive obstacles to the positive efficiency implications. The skewness and kurtosis values were as expected and within acceptable limits (|skewness| <1.0; |kurtosis| <1.0) suggesting approximately normal distribution appropriate for parametric analysis.

Table 2. Descriptive Statistics for Key Study Variables (N =

Variable	n	Mean	SD	Skewness	Kurtosis
AI Adoption Index	350	3.84	0.91	-0.32	-0.14
Facility Utilization (%)	350	71.4	12.3	0.18	-0.27
Reported Cost Savings (%)	350	22.6	9.7	0.41	0.09
Staff Workload Balance Ratio	350	3.72	0.88	-0.21	0.12
Equity Score (Student Support)	350	3.61	0.95	-0.17	-0.08
Resource Allocation	350	3.77	0.86	-0.29	0.05
Efficiency Index					
Perceived AI Usefulness	350	4.12	0.79	-0.44	0.31
Barriers to AI Adoption	350	3.48	1.02	0.29	-0.31

Authors computation (2026)

Note. All the scales related to AI Adoption Index and resource scales were measured using a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). Institutional Document Review is reported as Facility Utilization and Cost Savings, both in percentages.

Analysis of Variance (ANOVA)

A Comparison of the Perceived Efficiencies of the Roles in a Group

A one-way Analysis of Variance (ANOVA) was conducted to determine if there was a significant difference in Resource Allocation Efficiency Index among the three professional roles. There was a statistically significant main effect, $F(2, 347) = 18.43$, $p < .001$, eta square = .096, indicating a medium sized difference between the groups (Cohen, 1988). Post hoc pairwise comparisons, using Tukey's HSD testing, revealed that the perceptions of the efficiency were significantly greater from the administrative staff than from their teachers ($M = 4.07$, $SD = 0.74$; $M = 3.68$, $SD = 0.88$; mean difference = 0.39, $p < .001$), and that the perceptions of the efficiency were marginally greater from the administrative staff than from their IT support staff ($M = 4.07$, $SD = 0.74$; $M = 3.92$, $SD = 0.81$; mean difference = 0.15, $p = .034$). Also, there was no significant difference between teachers and IT support staff (mean difference = 0.24, $p = .072$). Similarly, independent samples t-tests revealed differences in

the efficiency scores of those in tertiary institutions and those in secondary schools ($M = 3.93$, $SD = 0.82$ vs. $M = 3.64$, $SD = 0.87$, $t(348) = 3.41$, $p = .001$, $d = 0.35$). The results are briefly summarized in Table 3.

Table 3. One-Way ANOVA: Resource Allocation Efficiency Index by Professional Role

Role	N	Mean	SD	F	P
Administrators	140	4.07	0.74	18.43	<.001
Teachers	140	3.68	0.88		
IT Support Staff	70	3.92	0.81		

Authors computation (2026)

Note. Post hoc comparisons were made using Tukey's HSD and found that there was a medium effect, $\eta^2 = .096$. * $p < .05$, ** $p < .001$.

Multiple Regression

This study employed a multiple linear regression analysis using a standard model, with the Resource Allocation Efficiency Index (RAEI) as the dependent variable and six independent variables were used simultaneously: AI Adoption Index, Perceived AI Usefulness, Years of Experience, Barriers to AI Adoption, Institution Type, and Gender. The overall model was statistically significant, $F(6, 343) = 34.71$, $p < .001$, $R^2 = .378$, adjusted $R^2 = .366$, which means that the predictor set explained about 37.8% of the variance in resource allocation efficiency. The standardized and unstandardized regression coefficients are shown in table 4.

The AI Adoption Index ($\beta = .38$, $p < .001$) was the best predictor and Perceived AI Usefulness ($\beta = .24$, $p < .001$) followed. The barriers to AI Adoption were significantly correlated with a decrease in efficiency ($\beta = -.19$, $P < .001$). Years of Experience exhibited a positive relationship with a small effect size ($\beta = .17$, $p = .001$) and Institution Type was marginally significant ($\beta = .11$, $p = 0.047$) and favored tertiary institutions. The efficiency scores for gender were

not significant ($p = .391$, $b = .04$). Multicollinearity was not found because the VIF values ranges from 1.09 to 2.31 which is below the acceptable threshold.

Table 4. Multiple Linear Regression: Predictors of Resource Allocation Efficiency Index (N=350)

Predictor Variable	B	SE	B	t	p
(Constant)	0.43	0.19	—	2.26	<.001
AI Adoption Index	0.41	0.07	.38**	5.86	<.001
Perceived AI Usefulness	0.29	0.06	.24**	4.83	<.001
Years of Experience	0.18	0.05	.17**	3.60	.001
Barriers to AI Adoption	−0.22	0.06	−.19**	−3.67	<.001
Institution Type	0.14	0.07	.11*	2.00	.047
Gender	0.06	0.07	.04	0.86	.391

Authors computation (2026)

Note. $R^2 = .378$; adjusted $R^2 = .366$; $F(6, 343) = 34.71$, $p < .001$. * $p < .05$, ** $p < .001$.

Qualitative Findings

Themes that emerged from reflexive thematic analysis of the interview transcripts and institutional documents were Efficiency Gains, Equity and Inclusion, Barriers to Implementation, and Trust and Ethical Concerns. Representative quotations are given for each theme and each subtheme and are reported in Table 6. The gains in efficiency included time saving in timetabling and scheduling; and better utilisation of budget. Equity and Inclusion themes included in the targeted identification of at-risk students and more balanced distribution of teachers' workload. Implementation challenges focused on power and connectivity infrastructure issues and staff skills. Themes of trust and ethics brought up the issue of algorithmic bias and data privacy, both of which are similar to and a continuation of the quantitative barrier findings.

Table 6. Qualitative Themes, Subthemes, and Representative Quotations

Theme	Subtheme	Representative Quote
Efficiency Gains	Time savings in scheduling	“The time that we take, for timetabling, changed from weeks to days because of AI” (Administrator, Tertiary).
	Improved budget utilization	“We are using resources where they can be used best, rather than where they have been used previously.” (Administrator, Secondary)
Equity and Inclusion	Targeted student support	“Early identification of struggling students and fairer allocation of support with “predictive tools” (Teacher, Secondary)
	Workload redistribution	“It also identifies imbalances in teacher assignments that we may not have noticed before, which is great for teachers working in tertiary education.” (IT Staff, Tertiary)
Barriers	Digital infrastructure deficits	“The availability of frequent outages and inadequate internet makes it unreliable to implement AI”. (IT Staff, Secondary)
	Skills and capacity gaps	“Today, many staffs do not have the training to effectively use the AI tools and the system exists, but has not been used.” (Administrator, Tertiary)
Trust and Ethics	Algorithmic bias concerns	“Some teachers feel that the AI gives an unfair advantage to some students or patterns of students' resources”. (Teacher, Secondary)
	Data privacy	"Staff are cautious as they are unsure of how they will be used." (Administrator, Tertiary)

Authors computation (2026)

Discussion of Findings

The most significant result of this study is that the use of AI was the most statistically significant predictor of the effective use of resources across the institutions sampled ($\beta = .38$ in regression; $\beta = .42$ in SEM), lending support to the main thesis that AI has the power to effectively improve the identification, deployment, and monitoring of educational resources. This outcome is in line with the increasing amount of empirical literature. Huang (2025) found that the average utilization of resources by universities using Long Short-Term Memory (LSTM) predictive model in East Asia was 93.4%, and by using mixed integer programming, the implementation cost can be saved by around 34% on average for the universities in similar developing settings. The present results reflect these gains, albeit at a lower but relevant level as illustrated by the 71.4% facility use and the average cost savings of 22.6% that in part are driven by the use of AI-based planning, in the context of a resource-limited setting in Oyo State, Nigeria.

Similarly, Song and Nan (2025) found that their computational model that integrates reinforcement learning and predictive analytics (AI-based decision systems) outperformed static policy models in terms of decision accuracy and institutional performance, thus providing theoretical justification for the efficiency pathway identified here. In the Resource-Based View (RBV) perspective used by this study, the results support this view, as AI is seen as a scarce, value-creating resource that allows institutions to achieve higher productivity from current tangible resources like budget funds, classroom space, and teaching staff while expending fewer resources (Barney, 1991; Koukaras et al., 2025). The SEM model also showed that the adoption-efficiency pathway is indirectly mediated by perceived usefulness (indirect $\beta = .19$), aligning with the ToE logic in TAM (Davis, 1989) and what Juanda et al. (2024) observed, that positive attitudes of the faculty and administrators toward the use of AI tools are necessary conditions for sustaining the efficiency improvement.

Not everything, however, is necessarily conducive. As AI starts to optimize higher education for efficiency, it raises concerns about the need for high-quality data and institutional readiness, warns Xu (2025), since "sub-optimal algorithms can maintain or exacerbate learning inequities and biases that have manifested themselves in the past. Martin et al. (2025) also discuss the need to consider efficiency metrics, but emphasize that they should not be the primary focus when using AI without careful consideration of how it can be integrated into the learning process. Due to these deterrent results, the efficiency gains reported in this study can be viewed as enablers, not requirements, and should be viewed in the context of the complementary human monitoring and policy components that support them.

The negative effects of barriers to AI adoption on AI adoption rates and the composite efficiency index were quite large in both regression and SEM ($\beta = -.19$, and $\beta = -.28$, respectively). Qualitative results revealed two main barrier subthemes, namely: a deficit in digital infrastructure, especially electricity and connectivity; and a lack of skills and capacities from the educational staff. The results obtained are highly reflective of the implementation challenges revealed in the Nigerian educational AI policy landscape (BUSA et al., recent; Akpan, 2024) and converge with the international literature on constraints in the implementation of AI in developing countries. In fact, institutions in developing countries needed specifically tailored solutions, such as mixed integer programming, and for this reason, the efficiency gains of AI were being pursued in their own context where they might not be able to guarantee reliable connectivity as they use tools like AI that are dependent on cloud services.

It can be just as clearly seen in the comparative literature that there exists a skills gap. Slabko et al. (2026) note that digitalization in education involves much more than just technology; it necessitates an ongoing investment in ongoing professional development, especially for educators who have not received such training in the

era prior to the integration of AI tools into the field of education management. The mean score for barriers is 3.48 in the present study, and the qualitative quotation “Systems are available, but not used” also indicates that there is more of a gap in using the systems than in procuring them; this suggests that future interventions should place as much emphasis on training and change management as on procurement and hardware and software. This is in keeping with what Deep et al (2024) found was the case in their research of large education systems where the benefits of using AI in administrative efficiency only came through when there was engagement of staff and a redesign of workflows.

Also, it is important to note that the barriers analysis does not fully address the issue of directionality between barriers and adoption in the cross-sectional data; that is, it is not clear whether there is an effect from barriers to adoption or from adoption to barriers. Lower AI adoption institutions will likely feel the barriers to be higher simply based on the lack of experience with AI benefits. The conclusion below suggests that longitudinal designs would better help break this feedback loop and help find the tipping points for increasingly greater efficiency benefits from investing in infrastructure.

The results of the one-way ANOVA showed that administrators rated their resource allocation efficiency higher than teachers (mean difference = 0.39, $p < .001$) and IT staff rated it higher than both of the two other groups. This hierarchy may be due to the varying degrees of access to tools that use AI decision-making capabilities: administrators who interact directly with AI tools for scheduling, budget forecasting and reporting should have both the access and awareness of efficiency gains. Teachers, on the other hand, can have decisions made on them that are influenced by AI, such as receiving the AI-generated timetable revisions or resource assignments, but without knowing exactly how AI made the decisions. This disparity in information is similar to what Alexandron et al. (2026) found, that the extent to which teachers have interacted with the interface of AI

tools plays a major role in shaping their perceptions of these tools, and that the quality of communication regarding the decisions produced by AI tools has a significant impact on teachers' perceptions.

The increased efficiency at tertiary institutions compared to secondary school staff ($d = 0.35$) is consistent with the notion that universities are more likely to have mature technological infrastructure and more technically trained staff, capable of more advanced and successful use of AI technology. The same goes for the international evidence: Both Huang (2025) and Xu (2025) typically studied higher education environments where the implementation of AI optimization algorithms is more well-established and can easily be combined with existing enterprise resource planning (ERP) systems. The secondary schools included in this study are also an interesting methodological contribution, since they bring to the fore the differential equity effects of the use of AI across school levels, which has only been partially explored in the literature.

Conclusion

The aim of this study was to investigate the impact of artificial intelligence technologies on the efficiency of resource allocation in educational institutions particularly public secondary schools and tertiary educational institutions in Oyo State, Nigeria with particular focus on the mechanisms, measurable outcomes, challenges and impacts on equity in educational institutions. The analysis of the quantitative data from 350 educational administrators, teachers and IT support was complemented by a qualitative analysis of the data from 25 key informants and the analysis of institutional documents collected between October 2025 and March 2026.

The all-encompassing evidence reveals three main points. First, the use of AI is a mathematically sound and meaningful predictor for the allocation of resources. The more widely AI tools were deployed, the more likely institutions were to report better rates of facility use, reported cost savings, and student support facilities evenly

distributed and balanced staff workloads. The relationship was substantiated by taking multiple regression, one-way ANOVA and structural equation modelling, and is qualitatively confirmed by the administrator and teacher accounts. These impacts, including the relatively high amount of variance explained by AI adoption in the composite efficiency index, put AI on the list of one of the most impactful institutional capacities that is available to resource-poor educational systems.

Second, perceived usefulness of AI's efficiency-enhancing potential can be enhanced and limited by the barriers to infrastructure and capacity. Perceived usefulness directly intermediated the relationship between AI receptivity and efficiency outcomes, suggesting the technology acceptance comes before and facilitates technology impact. In contrast, factors such as unreliable power and connectivity infrastructure, and lack of employee proficiency and digital literacy, hindered the use of AI and thus reduced efficiency gains. The results are particularly relevant in the Nigerian scenario and comparable developing education system which lacks infrastructure as an incidental phenomenon.

Thirdly, there are equity co-benefits of AI use beyond operational efficiency. The positive impact of AI on the student support equity scores, supported by both SEM and qualitative data, further indicates that properly leveraged AI-driven resource allocation can be a way to improve resource allocation toward historically marginalized student groups. But this equity dividend is not guaranteed: algorithmic bias concerns, data privacy issues, and uneven staff preparedness are real concerns that need to be proactively addressed by designing systems transparently, preparing staff properly and continuously testing systems.

In conclusion, these findings suggest that AI is a powerful tool that can be used in the education sector to enhance resource allocation efficiency and equity, but its impact will vary depending on the specific context. Its potential needs to be realized in resource-poor

environments through efforts to strengthen infrastructure, professional development of institutions, policy alignment, and governance ethics.

Recommendations

- i. Improve basic digital infrastructure: National and state education authorities should invest in basic digital infrastructure, such as reliable electric power, high-speed internet access and cloud computing capacity as essential conditions for efficient use of AI to allocate resources. The Federal Ministry of Education and Universal Basic Education Commission should make provision for the installation of AI-readiness infrastructure in public schools, particularly in secondary schools where there are significant efficiency gaps (BUSA et al, recent; Akpan, 2024).
- ii. Define ethical AI governance principles: Policies should include guidelines for algorithmic transparency, conforming to Nigerian regulations and UNESCO guidelines, regular bias audits and strong student data protection, among others. Addressing privacy and bias issues is essential to adoption and avoiding sub-optimal adoption or outcomes.
- iii. Start with small, low-risk, high-visibility applications: Leaders should ease the way into using AI by first adopting low-risk, high-visibility applications (such as automated timetabling, attendance monitoring, budget forecasting) before moving onto more complex predictive systems. Cross-functional AI task forces (comprising of IT, department leaders, and professors) will have the opportunity to examine AI suggestions and keep the professional judgment to lower resistance noted in the qualitative findings.
- iv. Use clear communication and feedback systems: Give clear explanations in human terms of how AI decisions have been made and make formal systems in place for teachers and students to report any bias or allocations. This strategy builds trust and it is recommended in the development of AI-competent communities (Alexandron et al., 2026; Fütterer et

- al., 2025).
- v. Ensure the embedding of a sustained AI-focused professional development: Teacher training curricula (pre-service and in-service) should contain a strand of AI literacy, data interpretation and critical evaluation of AI outputs. It is worth noting that if there is a connection between people's familiarity with AI and their positive perceptions of their efficiency, then local professional learning communities, which rely on real institutional data and tools, will be more effective than generic training.
 - vi. Design low bandwidth, offline systems with intuitive and interpretable interfaces for the development of settings: Designers should build AI systems that are simple and easy to interpret with an intuitive interface that works without an internet connection in settings with low bandwidth and intermediate user expertise. To ensure the minimisation of bias and relevance, there is need to co-design with the Nigerian institutions and training data that are locally representative (Huang, 2025).
 - vii. Future research should address methodological limitations: future studies should include longitudinal panel studies, quasi-experimental designs (difference-in-differences), and multi-state and/or cross-national comparative studies to test for causality, enhance generalizability and consider longer-term equity impacts on secondary school student outcomes (such as retention and achievement, completion rates, especially in rural/peri-urban schools).

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