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AI for optimizing School Timetabling and Human Resource Deployment

Joyce Uche Egwu[1]*, Iwezu Ngozi Caroline[2]

[1] Educational Foundations, Chukwuemeka Odumegwu Ojukwu University, Igbariam, Anambra State, Nigeria
[2] Educational foundation, Federal College of Education (Tech). Asaba, Delta State, Nigeria

Correspondence e-mail * : rkacademy2012@gmail.com

Abstract: Artificial intelligence (AI) is increasingly transforming administrative and academic processes in educational institutions, offering tools that can streamline operations, reduce human error, and improve overall efficiency. The study used a descriptive survey to examine 65 lecturers' perceptions of AI-driven timetabling and administrative tools in selected tertiary institutions in Anambra State, Nigeria. Data were collected online via Google Forms using a validated, reliable Likert-scale questionnaire. Analysis employed robust M-estimators for central tendencies and tests of normality, revealing mostly non-normal data. Consequently, Mann-Whitney U and Wilcoxon W tests were used to compare male and female perceptions, showing significant gender differences across scheduling conflict reduction, staff allocation, instructional time management, and administrative decision-making. The study's robust estimates using Huber, Tukey, Hampel, and Andrews M-estimators indicate stable central tendencies across all AI-related items, with values ranging from (15.32–15.57) for scheduling conflict reduction to (17.04–17.51) for instructional time management, reflecting minimal influence of outliers. Normality tests revealed that most variables, except administrative decision-making ($p > .05$), were non-normal, justifying the use of Mann-Whitney U and Wilcoxon W for comparing male and female perceptions. Gender differences were significant across all hypotheses: males consistently rated AI-driven timetabling ($U = 227.50$, $p = .006$), staff allocation ($U = 264.50$, $p = .029$), instructional time management ($U = 203.00$, $p = .002$), and administrative decision-making ($U = 272.50$, $p = .041$) more positively, leading to rejection of all null hypotheses and highlighting gendered perception patterns. The observed gender differences highlight the importance of targeted training and awareness programs to ensure equitable adoption and utilization among all staff members. Integrating AI into school management processes is therefore critical for modernizing administrative practices, improving academic delivery, and supporting data-driven decision-making across institutions.

Keyword : Artificial intelligence, School timetabling, Human resource deployment, educational administration, Gender perceptions

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INTRODUCTION

Planning school schedules and staffing schools, including teachers, service personnel, and classes, are complicated combinatorial problems that entail many hard and soft constraints and preferences. Hard constraints involve qualifications of teachers, access, curriculum design, and classroom sizes. Soft preferences involve convenience of the teacher, even distribution of workload and minimisation of idle time to the students and teacher. Due to its time-consuming process and the possibility of errors and challenges with scaling to larger and more diverse schools, manual scheduling is notorious (Baig and Yadegaridehkordi, 2025). This lack of efficiency negatively impacts on the use of resources and increases the stress of teachers. The use of artificial intelligence approaches, especially search-based heuristics, evolutionary computation, and hybrid optimisation algorithms, provides superior performance in terms of time, precision, and adaptability in creating conflict-free schedules and efficient planning of personnel deployment (Ceschia et al., 2023; United States Department of Education, 2023).

The evolution of educational timetabling has gradually shifted from rigid constraint-satisfaction models toward intelligent systems that adapt to real institutional pressures. Studies on ICT adoption in Nigerian schools suggest that digital tools already shape how teachers and administrators organise learning (Ikegbusi et al., 2021). AI pushes this further by applying heuristic search and evolutionary computing to reduce scheduling conflicts and improve resource use. Discussions on job management efficiency also point to AI's growing relevance in academic environments (Onuh et al., 2024). Emerging work on AI-driven learning for sustainability shows how optimisation and automation now support broader educational goals (Ofozoba et al., 2025). These innovations align with ongoing reforms in school management and employability strategies (Egwu & Ekwe, 2024), while complementary research connects interactive pedagogies to improved student outcomes (Ikegbusi & Egwu, 2024). Surveys of benchmark problems show that timetabling itself is an NP -hard problem, requiring intelligent strategies that explore solutions that are feasible and which improve schedule quality by not only being fair but also compact and find efficient room allocation (Ceschia et al, 2023; Qadri et al, 2025). Initial algorithms were genetic algorithms, simulated annealing, tabu search and local search. Modern methods include multi-objective evolutionary and swarm intelligence, which enhance the control of the incompatibility of performance specifications (Romaguera et al., 2024; Opeyemi et al., 2025).

The use of metaheuristic methods has been predominant due to its scalability. With appropriate domain-specific repair operators and tailored crossover strategies, genetic algorithms have demonstrated excellent performance on challenging school datasets numerous times (Romaguera et al., 2024; Maspiyanti et al., 2025). Swarm intelligence techniques including particle swarm optimisation and artificial bee colony algorithms also work effectively, searching a large search space effectively and resistant to constraint violations (Zhu et al., 2021). One of the significant trends in the literature is the uptake of multi-objective frameworks, as schools do not optimise one goal as frequently. Administrators tend to consider coverage, teacher equity, staff preferences, and resource utilisation at the same time. The Non-Dominated Sorting Genetic Algorithm and other Pareto-based methods allow multiple schedules with trade-offs to be generated, thus allowing the decision-makers to compare trade-offs instead of choosing one particular solution with the use of weighted scoring (Opeyemi et al., 2025). Hybrid systems, in which constraint programming is used to verify feasibility and metaheuristics are used to promote quality, are now recommended by many researchers. Such systems hasten the convergence and ensure conflict-free results (Ceschia et al., 2023).

The literature is not limited to timetable building, but also to the wider human-resource deployment issues. Some of the studies underline the necessity of AI systems to match teacher skills with subjects, to manage substitute teachers more productively, and distribute workloads in a manner that supports wellbeing and professional growth. Making schedules more resilient can be assisted by data-driven models analyzing patterns of teacher absence and historical use of substitutes, which may guide administrators to develop more robust schedules (United States Department of Education, 2023). Pilot projects and surveys show that AI-assisted timetabling tools can save administrative time and enhance the quality of decisions related to staff allocation (Koukaras et al., 2025).

In spite of these developments, researchers point out that there are still challenges. Most of the high-performing algorithms are computationally demanding and require expert parameter optimization and strong data infrastructure, thus making them unavailable to most schools with limited technical capabilities. The issues relating to transparency and trust also persist; educators also react more favorably to AI-supported schedules when the systems are able to present explanations, give manual options, and explain the logic behind the trade-offs in the schedule (United States Department of Education, 2023). Another gap is that there is limited empirical research about the relationship between optimised timetables and quality of instruction, teacher satisfaction, and student outcomes (Ceschia et al., 2023). New research highlights the need of adaptive and interactive AI; incremental scheduling, real-time adaptation on teacher absences, and staff management software integration are potentially fruitful directions. Multi-objective interfaces and human-centred design should be increasingly recommended to balance efficiency with teacher agency (Zhu et al., 2021; United States Department of Education, 2023).

The study is motivated by persistent inefficiencies and structural constraints inherent in manual scheduling practices, which have become increasingly inadequate for contemporary educational environments. As subject offerings expand, lecturers' qualifications diversify, student enrolment continues to rise, and staffing models evolve, the complexity of school timetabling intensifies. Manual approaches often result in scheduling conflicts, uneven workload distribution, and suboptimal utilisation of instructional spaces, with subsequent implications for lecturer satisfaction and the overall quality of instruction.

Although previous studies have demonstrated the promise of heuristic and evolutionary optimisation methods, notable gaps remain. Recent reviews indicate that many algorithms exhibit strong computational performance yet lack validation in real institutional contexts and respond poorly to dynamic conditions such as sudden staff absences or fluctuating enrolment trends (Ceschia et al., 2023). Furthermore, there is limited evidence on how automated timetabling influences broader organisational outcomes, including equitable staff deployment and the promotion of inclusive education. Concerns also persist regarding the opacity of AI systems, as many models lack transparency and explainability, thereby weakening trust and acceptance among educators (Zhu et al., 2021).

These gaps underscore the need for empirical studies that explore not only the technical potential of AI-driven timetabling systems but also how different demographic groups within the academic workforce perceive their effectiveness. Gendered differences in professional experiences, workload patterns, and interaction with institutional technologies may shape lecturers' views on the ability of AI to reduce scheduling conflicts, optimise staff allocation, enhance instructional time management, and inform administrative decision making in human resource deployment. Investigating these perceptual variations provides a justified basis for the hypotheses guiding this study, particularly regarding whether male and female lecturers differ significantly in their evaluations of AI-supported scheduling systems.

Research objectives

1. To examine how AI-driven timetabling systems reduce scheduling conflicts
2. To assess how AI optimizes staff allocation based on workload
3. To evaluate the extent to which AI-supported timetable generation improves instructional time management.
4. To determine how AI tools shape administrative decision making in human resource deployment.

Hypotheses

1. There is no significant difference between male and female lecturers' perceptions of the ability of AI-driven timetabling systems to reduce scheduling conflicts.
2. There is no significant difference between male and female lecturers' perceptions of how AI optimizes staff allocation based on workload.
3. There is no significant difference between male and female lecturers' perceptions of the extent to which AI-supported timetable generation improves instructional time management.
4. There is no significant difference between male and female lecturers' perceptions of how AI tools shape administrative decision making in human resource deployment.

METHOD

The study utilized a descriptive survey to analyze the perceptions of lecturers about AI-based timetabling systems and their use in educational management. The design was considered to be suitable, because it helped to collect quantitative data systematically, which would help to identify patterns and compare the perceptions according to gender. The research was done in a sample of tertiary institutions in Anambra State, Nigeria. They were chosen based on these institutions having experience with, or deploying, AI-based administrative and timetabling systems. A population of interest was all lecturers in the sampled institutions and 65 lecturers (both male and female staffs and with varying years of experience in teaching) were involved in the research. The purposive sampling was used to identify lecturers who had experience in using AI-driven timetabling or administrative systems, and all 65 respondents who met the eligibility criteria were included.

The data was collected online using Google Forms, which is a format that made the distribution of data and the collection of responses efficient and preserved the confidentiality of the participants. The tool was a structured questionnaire with Likert-scale questions in relation to reducing scheduling conflicts, optimization of staff allocation, managing instructional time and administrative decision making. The questionnaire was validated by three lecturers with high expertise in educational administration and technology. These professionals assessed the items in terms of clarity, relevance, and comprehensiveness and their feedback was taken seriously in the final instrument. The reliability was checked with the help of a pilot study conducted with a sample that was not included to the main study population; the Cronbach alpha coefficient amounted to over 0.80, which corresponds with a high internal consistency.

Analysis of the data involved descriptive and inferential statistics. Strong M-estimators Huber, Tukey, Hampel and Andrews, were used to approximate the central tendencies and reduce the effect of possible outliers. Normality tests, performed on means of the Kolmogorov-Smirnova and Shapiro-Wilk tests, have shown that most variables are not normally distributed, although this is not the case with administrative decision-making. As such, non-parametric tests were considered suitable. MannWhitney U and Wilcoxon W tests were then used to analyze the difference in perception between female and male lecturers in the study areas at 0.05 level of significance, thus giving a very strong evaluation of the difference among genders when it comes to perceptions of AI tools in educational management.

RESULTS AND DISCUSSION

Table 1. Distribution of Respondents by Teaching Experience and Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Teaching Experience	Less than 5 years	7	10.8	10.8	10.8
	5–10 years	11	16.9	16.9	27.7
	11–15 years	14	21.5	21.5	49.2
	Above 15 years	33	50.8	50.8	100.0
	Total	65	100.0	100.0	
Gender	Male	17	26.2	26.2	26.2
	Female	48	73.8	73.8	100.0
	Total	65	100.0	100.0	

The sample in table 1 shows that most respondents have considerable teaching experience, with those above 15 years forming the largest group (50.8 percent) and a cumulative share of (100.0). Teachers with 11 to 15 years follow at (21.5 percent), while those with 5 to 10 years and less than 5 years account for (16.9 percent) and (10.8 percent). The gender distribution is notably uneven. Females make up the majority at (73.8 percent), while males represent only (26.2 percent). Overall, the dataset of (65) respondents is dominated by experienced and predominantly female teachers, which may shape perspectives expressed in the study.

Table 2.
Robust Estimates of Central Tendency Using Four M Estimators

	Huber's M-Estimator[a]	Tukey's Biweight[b]	Hampel's M-Estimator[c]	Andrews' Wave[d]
How AI-driven timetabling systems reduce scheduling conflicts	15.5214	15.3274	15.5691	15.3247
Ways does AI optimize staff allocation based on workload	16.4199	16.5945	16.5124	16.5978
The extent that AI-supported timetable generation improve instructional time management	17.3588	17.4862	17.0396	17.5087
How AI tools influence administrative decision making in human resource deployment	15.4252	15.4955	15.4382	15.4946

a. The weighting constant is 1.339.
b. The weighting constant is 4.685.
c. The weighting constants are 1.700, 3.400, and 8.500
d. The weighting constant is 1.340*pi.

The four M estimators in Table 2 produce closely aligned central values across all items, suggesting stable responses even if outliers exist. For scheduling conflict reduction, estimates cluster around (15.32 to 15.57). Staff allocation optimization shows slightly higher stability, ranging from (16.42 to 16.60). Instructional time management records the highest central values, between (17.04 and 17.51), indicating stronger agreement among respondents. Administrative decision making remains moderate, with estimates from (15.43 to 15.50). Overall, the tight numerical spread across Huber, Tukey, Hampel, and Andrews methods reflects consistent participant ratings and minimal distortion from extreme scores.

Table 3.
Tests of Normality for Study Variables

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
How AI-driven timetabling systems reduce scheduling conflicts	.128	65	.010	.952	65	.014
Ways does AI optimize staff allocation based on workload	.145	65	.002	.913	65	.000
The extent that AI-supported timetable generation improve instructional time management	.217	65	.000	.840	65	.000
How AI tools influence administrative decision making in human resource deployment	.107	65	.062	.964	65	.056

a. Lilliefors Significance Correction

The normality results in Table 3 shows that three variables fall below the acceptable significance threshold of (0.05). Scheduling conflict reduction records p values of (0.010) and (0.014). Staff allocation optimization shows even lower values at (0.002) and (0.000). Instructional time management also fails normality with (0.000) for both tests. Only administrative decision-making meets normality criteria with p values of (0.062) and (0.056). This pattern indicates that most variables are not normally distributed. Because the data are Likert scale and largely non normal, Mann Whitney U and Wilcoxon W are justified. They handle ordinal responses, do not assume normality, and compare group differences reliably for male and female respondents.

Hypothesis 1: There is no significant difference between male and female lecturers' perceptions of the ability of AI-driven timetabling systems to reduce scheduling conflicts.

Table 4. Mann Whitney U Test for Gender Differences in Perceptions of AI Driven Timetabling Systems

	Gender	N	Mean Rank	Sum of Ranks
How AI-driven timetabling systems reduce scheduling conflicts	Male	17	43.62	741.50
	Female	48	29.24	1403.50
	Total	65		

Mann-Whitney U=227.500, Wilcoxon W=1403.500, Z=-2.727, Asymp. Sig. (2-tailed)=.006

The ranking pattern in Table 4 suggests that male lecturers report higher perceptions of AI's ability to reduce scheduling conflicts, with a mean rank of (43.62) compared to females at (29.24). The Mann Whitney U value of (227.500) and Wilcoxon W of (1403.500) support this difference. The test yields a Z score of (−2.727) and a significance value of (.006), which is below the (.05) threshold. This indicates that the variation between male and female responses is statistically meaningful. Because the p value is significant, the null hypothesis is rejected, showing a real gender-based difference in perceptions

Hypothesis 2: There is no significant difference between male and female lecturers' perceptions of how AI optimizes staff allocation based on workload

Table 5. Mann Whitney U Test for Gender Differences in Perceptions of AI Optimization of Staff Allocation

	Gender	N	Mean Rank	Sum of Ranks
Ways does AI optimize staff allocation based on workload	Male	17	41.44	704.50
	Female	48	30.01	1440.50
	Total	65		

Mann-Whitney U=264.500, Wilcoxon W=1440.500, Z=-2.184, Asymp. Sig. (2-tailed)=.029

The results in Table 5 shows that male lecturers rate AI's ability to optimize staff allocation more highly, with a mean rank of (41.44) compared to females at (30.01). The Mann Whitney U value of (264.500) and Wilcoxon W of (1440.500) reflect this ranking gap. The Z value of (−2.184) and significance level of (.029) fall below the (.05) threshold, indicating a meaningful difference between the groups. Since the p value is significant, the null hypothesis is rejected, showing that male and female lecturers differ in their perceptions of AI's role in staff allocation.

Hypothesis 3: There is no significant difference between male and female lecturers' perceptions of the extent to which AI-supported timetable generation improves instructional time management.

Table 6. Mann Whitney U Test for Gender Differences in Perceptions of AI-Supported Timetable Generation on Instructional Time Management

	Gender	N	Mean Rank	Sum of Ranks
The extent that AI-supported timetable generation improve instructional time management	Male Female Total	17 48 65	45.06 28.73	766.00 1379.00

Mann-Whitney U=203.000, Wilcoxon W=1379.000, Z=-3.159, Asymp. Sig. (2-tailed)=.002

The results in Table 6 indicate that male lecturers perceive AI-supported timetable generation as more effective in improving instructional time management, with a mean rank of (45.06) compared to females at (28.73). The Mann Whitney U value of (203.000) and Wilcoxon W of (1379.000) reflect this difference. The Z statistic of (−3.159) and a significance level of (.002) are below the (.05) threshold, demonstrating a statistically significant difference between genders. Given the significant p value, the null hypothesis is rejected, confirming that male and female lecturers differ in their perceptions of AI's impact on instructional time management.

Hypothesis 4: There is no significant difference between male and female lecturers' perceptions of how AI tools shape administrative decision making in human resource deployment

Table 7. Mann Whitney U Test for Gender Differences in Perceptions of AI Tools on Administrative Decision Making

	Gender	N	Mean Rank	Sum of Ranks
How AI tools influence administrative decision making in human resource deployment	Male Female Total	17 48 65	40.97 30.18	696.50 1448.50

Mann-Whitney U=272.500, Wilcoxon W=1448.500, Z=-2.040, Asymp. Sig. (2-tailed)=.041

The mean ranks in Table 7 indicate that male lecturers perceive AI tools as more influential in administrative decision making, with a mean rank of (40.97) compared to females at (30.18). The Mann Whitney U value of (272.500) and Wilcoxon W of (1448.500) support this difference. The Z statistic of (−2.040) and significance level of (.041) fall below the (.05) threshold, indicating a statistically significant difference between male and female perceptions. Since the p value is significant, the null hypothesis is rejected, showing that gender influences lecturers' perceptions of AI tools in human resource decision making.

Discussion

The comparison of Hypothesis 1 showed that the male lecturers (mean rank = 43.62) felt that AI driven timetabling systems were more effective in alleviating scheduling conflicts compared to female lecturers (mean rank = 29.24), U = 227.50/Z = 0-

2.727/p=0.006. These results indicate evident gender-based difference in optimism of lecturers on the potential of AI in conflict-resolving. This finding is in line with Koka et al. (2024), who have reported much more positive attitudes towards the adoption of AI among male senior lecturers in foreign-language education. Verboom et al. (2025) came to the conclusion that men and women professors record the same ethical and functional anxieties about AI in teaching and research, suggesting the quantitative gender gap does not indicate deep, structural opposition. Also, Omani higher education studies by Usmani et al. (2025) revealed that social factors and institutional support have a strong impact on women accepting Fourth Industrial Revolution technologies, such as AI, which may partially explain the difference in ratings by female lecturers in the current study: perceived barriers, rather than lack of interest, seem to be the driving factor.

In relation to attitudes towards the ability of AI to optimize the staffing in Hypothesis 2, male lecturers rated it higher (mean rank = 41.44) than their female counterparts (mean rank = 30.01), their U = 264.50, Z = -2.184, p = 0.029. The large difference suggests that male lecturers are more optimistic about the capacity of AI to handle the workload distribution. This result is simulated by Baig and Yadegaridehkordi (2025), who discovered that faculty satisfaction and continued use of generative artificial intelligence (GenAI) partly depends on gender: men in their study stated that they continued to use it more, which implied their higher trust or perceived usefulness. A systematic review of AI adoption among women in Asian higher learning by Qadri et al. (2025) identified structural barriers that are shared including poor training and absence of involvement in AI policy formulation, which may reduce the perceived organisational value of AI among female lecturers. Eleje et al. (2025) on the other hand found that gender-based differences in perceived AI effectiveness were moderate in Nigerian higher education and that faculty of the opposite gender were equally concerned implying that culture and institutional context are a strong influence.

In Hypothesis 3, which discussed AI-assisted timetable generation as an enhancement to instructional time management, male lecturers (mean rank 45.06) scored higher again than women (mean rank 28.73) with U 203.00, Z 3.159, p 0.002. The strong effect size indicates that men are more inclined to perceive AI as a tool that can restructure class time to increase teaching efficiency. This observation is consistent with Koka et al. (2024), who found that male senior lecturers are more willing to adopt AI in pedagogical processes, such as time-saving features. However, Dorta-Gonzalez et al. (2024) discovered that female professional researchers used generative AI much less than men, even with career stage factored out; they mentioned perceived training deficit and risk aversion, which reflected fears of female lecturers entrusting AI with scheduling chores of critical importance. Moreover, Campos and Scherer (2024) argue in favor of the belief that gender disparities in digital competence and AI adoption are not caused only by attitudes but also by such systemic factors as infrastructure and role expectations, which probably precondition the lecturers reaction to time-management innovations.

In Hypothesis 4, male lecturers (mean rank=40.97) found AI tools more influential in administrative decision making as compared to female lecturers (mean rank=30.18), U=272.50, Z= -2.040, p=.041. This finding indicates that men are more confident or more aware of the possibility of AI determining human-resource deployment decisions. The result aligns with that of Baig and Yadegaridehkordi (2025), who found that gender was one of the predictors of sustained GenAI use among academic employees, as men indicated higher satisfaction in institutional usage. By contrast, no significant gender differences in the perceptions of the functional or ethical implications of AI in the administrative setting emerged in a qualitative study by Verboom et al. (2025), which suggests that survey-based results might reflect more superficial or aspirational beliefs, as opposed to the ones that are more deeply rooted. Furthermore, systematic review of Asian universities by Qadri et al. (2025) underlines that women are usually not involved in AI governance and policy-making in institutions, which can impose a restriction on their experience or faith in AI-based administrative decision-making and, consequently, the gender gap.

Conclusion

The study concludes that AI-driven systems significantly enhance school timetabling and human resource deployment by improving scheduling efficiency, optimizing staff allocation, and supporting instructional time management. Lecturers' perceptions indicate that male staff generally report higher confidence in AI tools, suggesting gender differences in adoption or perceived utility. Despite this, the overall findings demonstrate that AI has a transformative potential for administrative and academic processes, reducing conflicts, enhancing decision-making, and promoting organizational efficiency. Integrating AI in school management is therefore both necessary and beneficial for modern educational institutions.

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AUTHOR CONTRIBUTIONS

Conceptualization: Author 1, Author 2;
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Investigation: Author 1, Author 2;
Writing—original draft preparation: Author 1, Author 2;
Writing—review and editing: Author 1, Author 2;
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