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Project Scheduling, Resource Allocation, and AI-Based Optimization as Drivers of Last-Mile Logistics Efficiency in Nigeria

Godspower Saro Dike
Centre for Logistics and Transport, University of Port Harcourt

Endurance Ikechi Eke
Faculty of Maritime Studies, Admiralty University of Nigeria, IBUSA, Delta State

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Abstract: *This study examines how resource allocation, project scheduling, and AI-based optimization interact to improve last-mile logistics performance in Nigeria's changing supply chain environment. The final mile phase, which makes up the most expensive and operationally challenging part of logistics, is still limited by a lack of infrastructure, manual scheduling, and disjointed data systems. Utilizing survey data from 200 logistics experts in key Nigerian cities, the study employs a quantitative explanatory methodology, drawing on project scheduling theory and combinatorial optimization models. To investigate the proposed correlations and the mediating role of AI optimization, descriptive, regression, and structural equation modeling (SEM) analyses were performed. The findings showed that last-mile performance is significantly predicted by project scheduling (* β *= 0.455, p < 0.001), resource allocation (* β *= 0.298, p = 0.002), and AI optimization (* β *= 0.426, p < 0.001), which together account for 23.9% of the variance in last-mile performance (R2 = 0.239). Excellent fit was demonstrated by the SEM model (CFI = 0.954; RMSEA = 0.046), indicating that scheduling and resource management have an impact on delivery efficiency that is mediated by AI optimization. The results highlight how, in order to attain operational accuracy and environmental balance, Nigeria's logistics industry must integrate data-driven scheduling, intelligent resource deployment, and sustainability-oriented AI technologies.*

Keywords: project scheduling, resource allocation, AI optimization, last-mile logistics, structural equation modeling

INTRODUCTION

The last mile of logistics, representing the crucial final link between distribution hubs and end customers, remains the most cost-intensive, operationally complex, and environmentally sensitive segment of modern supply chains (Bakogianni & Malindretos, 2021; Allen et al., 2018; Arnold et al., 2018). With the rapid growth of urbanization and e-commerce, alongside heightened consumer expectations for fast and reliable deliveries, the last-mile segment has become increasingly strained. In developing economies such as Nigeria, these challenges are compounded by infrastructural inadequacies, inefficient scheduling systems, and weak coordination across logistics actors, leading to delays and inflated operational costs. Globally, last-mile delivery contributes over 50% of total logistics expenses, driven largely by duplicated routes, underutilized vehicle capacity, traffic congestion, and excessive carbon emissions (Badrinarayanan, 2024). These inefficiencies underscore the urgent need for optimized project scheduling and effective resource allocation frameworks to enhance Nigeria’s last-mile logistics performance and competitiveness.

According to research, project timing and resource allocation are crucial for maximizing delivery and transportation performance in situations with fluctuating demand (Dike & Eke 2025; Akunna et . al., 2025; Jackson, 1955; Ponz-Tienda et al., 2013; Vanhoucke, 2013). The efficient allocation of delivery windows and fleet resources within logistics systems is made possible by the Interval Scheduling Problem (ISP) and associated combinatorial optimization frameworks (Papară & Schirliu, 2024), which reduce idle time, overlap, and delays. However, in Nigeria's logistics environment, a dependence on manual scheduling and static routing compromises delivery predictability and timeliness, and a lack of data integration makes it difficult to synchronize distribution and warehousing.

Route planning and scheduling have undergone a global revolution thanks to emerging technologies like artificial intelligence (AI) and machine learning (ML). Predictive models powered by AI improve delivery accuracy, lower energy costs, and allow for dynamic rerouting in unpredictable situations (Vaka, 2024; Badrinarayanan, 2024). Through data-driven fleet orchestration, these solutions have been demonstrated to lower operating costs while increasing scheduling precision by over 30%. However, there are several obstacles to adoption in Nigeria's logistics industry, such as disjointed data systems, expensive implementation, a lack of ICT infrastructure, and a shortage of workers.The optimization problem is further complicated by sustainability. According to Bakogianni and Malindretos (2021), when implemented through public-private partnerships, sustainable last-mile frameworks, which include electric vehicles, cargo lockers, cooperative logistics networks, and urban consolidation centers—can dramatically lower emissions and traffic. However, Nigeria's logistics ecosystem is still disjointed and devoid of multimodal coordination, integrated regulatory mechanisms, and adaptive routing systems, which leads to inefficiencies and environmental stress.

Systemic inefficiency is further exacerbated by the lack of intelligent scheduling and adaptive resource-allocation mechanisms. Delivery windows often overlap geographically, and vehicles frequently depart underloaded or unsynchronized. In advanced contexts, AI-enhanced scheduling integrates energy data, traffic analytics, and delivery time windows to achieve multi-objective optimization, simultaneously minimizing cost, emissions, and travel time (Akunna et . al., 2025; Schneider et al., 2014; Hiermann et al., 2016; Vaka, 2024). Moreover, the ethical use of AI in logistics and data governance has become increasingly significant, demanding a balance between technological efficiency and responsible data management (Patel, 2024; Anyanwu et al., 2024; Amoo et al., 2024). In Nigeria, such integrated frameworks are still in their infancy.

Thus, three interconnected shortcomings, poor alignment between project scheduling, routing, and resource-allocation frameworks; slow adoption of AI-enabled optimization tools; and inadequate incorporation of sustainability principles into last-mile logistics design—create a glaring research gap. In order to improve last-mile logistics performance in Nigeria, this study explores how project scheduling and resource allocation, enhanced by AI-based optimization and sustainability-oriented planning, can improve operational efficiency, environmental balance, and service reliability (Tucker-Drob & Salthouse, 2009).

LITERATURE REVIEW

Last-Mile Logistics in the Digital Supply Chain

Connecting distribution hubs to final customers, last-mile logistics (LML) is the last and most complex step in the delivery process. It is usually carried out in crowded metropolitan settings with significant demand unpredictability, restricted access, and traffic congestion (Bakogianni & Malindretos, 2021). According to studies, this segment's operational complexity and fragmentation result in a disproportionate contribution to overall logistics costs, ranging from 28% to 53% (Badrinarayanan, 2024). Inadequate road infrastructure and poor scheduling and dispatch system integration exacerbate inefficiencies in many growing economies, including Nigeria.

The logistics industry is changing globally due to digitalization and smart planning technologies. Adopting technology-driven coordination and sustainable delivery models can save costs, traffic, and carbon emissions (Akunna et . al., 2025; Allen et al., 2018; Arnold et al., 2018). However, fragmented routing, inadequate data systems, and a lack of technological adoption all contribute to Nigeria's ongoing logistical inefficiencies, which impede optimization attempts.

Project Scheduling and Logistics Coordination

In order to maximize total project efficiency, project scheduling theory, which has its roots in operations research, stresses the methodical sequencing of tasks and allocation of time-based dependencies (Vanhoucke, 2013). Jackson (1955) presented time-slot management as a technique for reducing production system delays with his seminal Interval Scheduling Problem (ISP). Since then, this framework has developed into a potent logistics coordination model that aids businesses in more effectively allocating drivers, trucks, and delivery windows (Ponz-Tienda et al., 2013; Papară & Schirliu, 2024). Recent studies extend these models with AI-driven project scheduling and predictive analytics for better accuracy and responsiveness (Nabeel, 2024; Shinde, 2024).

The foundation for coordinating warehouse operations, routing, and delivery frequency in logistics is scheduling. Time-based scheduling reduces overlapping trips, idle fleet hours, and on-time performance when done correctly (Ponz-Tienda et al., 2013). The majority of Nigerian delivery systems, on the other hand, lack systematic scheduling, which leads to inadequate synchronization between distribution and warehousing nodes. Dynamic rescheduling and real-time responsiveness are further improved by including artificial intelligence (AI) into scheduling procedures, which permits ongoing adaptations to variations in demand, traffic, and weather (Badrinarayanan, 2024).

Resource Allocation Optimization in Logistics

Optimising logistics operations requires effective resource allocation. In order to maximize productivity at the lowest possible cost, it involves distributing scarce resources—vehicles, drivers, and time—across several delivery routes. These issues have been resolved in large part by models based on algorithmic optimization and mathematical programming, such as linear and dynamic programming (Ponz-Tienda et al., 2013; Papară & Schirliu, 2024). Electronic Data Interchange (EDI) has emerged as a key technology for attaining end-to-end supply chain visibility (SCV), particularly in transport-intensive scenarios, as a result of the rapidly growing digital transformation of logistics. Digitalization facilitates data-driven decision making, process integration, and real-time information sharing across global supply chains, which enhances customer service, responsiveness, and efficiency (Dike & Eke, 2025). Efficient resource allocation guarantees the best possible use of delivery fleets and the equitable distribution of energy and human resources in sophisticated supply networks. According to Papară and Schirliu (2024), algorithmic scheduling models based on combinatorial optimization can decrease delivery delays and boost truck utilization by up to 35%. However, underutilized fleets, redundant personnel allocation, and low fuel efficiency continue to plague Nigeria's logistics industry. The lack of a coordinated framework for resource allocation that incorporates AI and predictive analytics is reflected in these inefficiencies.

AI-Driven Optimization and Digital Transformation

For supply chain management and logistics, artificial intelligence (AI) and machine learning (ML) have become game-changing technologies. AI-based solutions continuously modify delivery operations to reduce delays and raise customer satisfaction through adaptive scheduling, real-time analytics, and route optimization. According to Badrinarayanan (2024), intelligent fleet orchestration using AI-enabled logistics solutions can save operating costs and increase delivery accuracy by more than 30%. Vaka (2024) also noted that neural-network-based optimization and predictive analytics can cut emissions by 25% and travel distances by up to 22%, highlighting the sustainability advantages of AI implementation. Cost, time, and energy usage can all be decreased at the same time through multi-objective optimization made possible by the incorporation of AI into scheduling and allocation (Schneider et al., 2014; Hiermann et al., 2016). However, data and infrastructure constraints prevent the limited adoption of such systems in underdeveloped economies such as Nigeria.

Sustainability and Urban Logistics Perspectives

Optimization of last-mile logistics increasingly includes sustainability issues. According to Bakogianni and Malindretos (2021), sustainable urban freight systems that are based on electric vehicles, shared transportation infrastructure, and cooperative delivery platforms provide the double advantages of environmental preservation and cost savings. These methods encourage synchronized delivery and reduce urban congestion when combined with AI-enhanced scheduling.Nigerian logistics systems, on the other hand, function independently, with little integration or policy alignment between city planners and transportation providers. This restricts the uptake of coordinated routing systems and clean technology. Systemic efficiency results from coordinated processes that reduce cognitive and operational redundancy, as Tucker-Drob and Salthouse (2009) noted in behavioral performance research. This idea is also relevant to logistics networks looking for adaptive efficiency through integrated systems.

Conceptual Relationships

a.Project Scheduling → Allocation of Resources
The order and time of deliveries are decided by structured scheduling frameworks, which guarantee that the best use of available vehicles and human resources is made. While efficient schedules balance workloads and eliminate redundancies, inadequate scheduling results in idle assets and poor delivery synchronization (Jackson, 1955; Papară & Schirliu, 2024).
b. Allocation of Resources → Logistics Performance at the Last Mile

Effective allocation improves fleet utilization, decreases overlapping trips, and increases route density—all of which are important factors that affect last-mile performance (Ponz-Tienda et al., 2013; Vanhoucke, 2013).
b. The Mediating Role of AI Optimization
By dynamically integrating real-time data, AI-driven systems mediate the interaction between planning and performance, improving scheduling and resource allocation (Badrinarayanan, 2024; Vaka, 2024).
d. The Moderator Role of Sustainability
By encouraging operational balance and environmental stewardship, sustainable logistics techniques like cooperative distribution and energy-efficient routing enhance the impact of AI and planning systems (Bakogianni & Malindretos, 2021; Schneider et al., 2014; Hiermann et al., 2016).

METHODOLOGY

In order to examine the connection between project scheduling, resource allocation, AI-based optimization, and last-mile logistics performance in Nigeria, this study uses a quantitative, explanatory research approach. Using structured survey data, the approach makes it easier to evaluate proposed links and examine the mediating function of AI-driven optimization. In keeping with previous logistics optimization frameworks, the method combines descriptive and inferential studies to explain causal relationships among the important constructs (Ponz-Tienda et al., 2013; Papară & Schirliu, 2024; Vanhoucke, 2013). Professionals working in the logistics, transportation, storage, and supply chain management industries in major Nigerian cities including Lagos, Port Harcourt, Abuja, and Kano make up the study's population.

These responders were selected from distribution service providers, e-commerce companies, transportation agencies, and logistics corporations. A cross-section of operational, technical, and administrative staff directly involved in last-mile delivery and scheduling decisions made up the 200 valid replies that were collected.

A systematic questionnaire based on previously approved logistics and operations management tools was used to gather primary data. Project Scheduling Efficiency, Resource Allocation Practices, AI-Based Optimization, and Last-Mile Logistics Performance were the five areas of the questionnaire. A

4-point Likert scale, with 1 denoting "strongly disagree" and 4 denoting "strongly agree," was used to score each item. To guarantee construct validity, clarity, and reliability, the instrument underwent pre-testing.

Statistical methods for both descriptive and inferential analysis were applied to the data. To summarize respondent characteristics and item responses by organizational type and region, descriptive statistics (mean, standard deviation, and frequency) were employed. While multiple regression analysis looked at the predicted impact of project timing and resource allocation on last-mile logistics performance, reliability analysis using Cronbach's alpha validated the internal consistency of all scales.

To test the proposed model and the mediating role of AI-based optimization, Structural Equation Modeling (SEM) was also used. Consistent with modern supply chain and logistics modeling methodologies, this method enabled the simultaneous estimate of direct, indirect, and total effects among the research constructs.

RESULTS

Table 1: Reliability Statistics (Cronbach's Alpha)

Construct	Cronbach's Alpha	Reliability Interpretation
Project Scheduling	0.83	High reliability
Resource Allocation	0.81	High reliability
AI Optimization	0.86	Very high reliability
Last-Mile Performance	0.84	High reliability

All constructs have Cronbach's Alpha values over the 0.80 cutoff, according to Table 1's data, which suggests that each scale's items have a strong correlation and consistently measure its corresponding dimensions. In instance, AI Optimization showed the highest reliability ($\alpha = 0.86$), indicating that the products made to capture the data-driven and technical features of logistics optimization are very robust and coherent. Both Resource Allocation ($\alpha = 0.81$) and Project Scheduling ($\alpha = 0.83$) show good dependability, indicating that respondents consistently saw the indications of resource deployment, task coordination, and temporal planning similarly. Similarly, Last-Mile Performance ($\alpha = 0.84$) demonstrates that the dataset accurately reflects metrics including service quality, cost-effectiveness, and delivery timeliness.

The measuring tool's great internal consistency is confirmed by the reliability results, confirming its appropriateness for sophisticated statistical analyses like regression and structural equation modeling (SEM). The next examination of the connections between project scheduling, resource allocation, AI optimization, and last-mile logistics performance is made more confident by this inherent robustness.

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Table 2: Descriptive Statistics by Organization Type

Organization Type	Project Scheduling (Mean)	Resource Allocation (Mean)	AI Optimization (Mean)	Last-Mile Performance (Mean)
Courier Firms	3.44	3.39	3.49	3.52
E-commerce Firms	3.38	3.31	3.46	3.47
Transport Firms	3.23	3.18	3.29	3.32
Warehousing Firms	3.18	3.12	3.20	3.23

Table 2's descriptive results show considerable organizational differences in the uptake and effectiveness of AI-driven logistics optimization, resource allocation, and project scheduling. Across all categories, courier firms had the highest mean values, especially in AI Optimization (M = 3.49) and Last-Mile Performance (M = 3.52). Their direct involvement in time-sensitive delivery operations necessitates effective scheduling, adaptive routing, and real-time optimization systems, as seen by this result. According to Badrinarayanan (2024) and Vaka (2024), who found AI-enabled delivery optimization to be a crucial competitive differentiator in logistics networks, the high mean values also imply that courier companies have attained comparatively advanced levels of digital integration.

With high means across all structures, e-commerce companies trail closely behind, highlighting the significance of coordinated scheduling and wise resource allocation in online retail delivery operations. The technological frameworks found in international studies of digital last-mile logistics are consistent with their dependence on order forecasting, data analytics, and third-party logistics support (Bakogianni & Malindretos, 2021; Papară & Schirliu, 2024).

The relatively lower mean values recorded by transportation and warehousing companies, on the other hand, suggest more conventional operating structures and a limited uptake of AI-based optimization techniques. Project scheduling and last-mile coordination are less integrated in these organizations since they frequently place a higher priority on line-haul operations and asset utilization than on dynamic delivery optimization (Ponz-Tienda et al., 2013; Vanhoucke, 2013).

Additionally, the data consistently demonstrates that better last-mile performance across all organization types is correlated with higher levels of project scheduling and resource coordination. The conceptual framework of the study, which views resource allocation and project scheduling as important predictors of logistics efficiency with AI optimization acting as a mediating factor, is supported by this (Schneider et al., 2014; Hiermann et al., 2016).

Table 3: Descriptive Statistics by Region

Region	Project Scheduling (Mean)	Resource Allocation (Mean)	AI Optimization (Mean)	Last-Mile Performance (Mean)
Lagos	3.42	3.36	3.48	3.51
Abuja	3.35	3.31	3.45	3.46
Port Harcourt	3.28	3.23	3.36	3.39
Kano	3.17	3.09	3.14	3.19
Kaduna	3.12	3.05	3.11	3.14

Table 3's findings show geographical differences in the efficiency of AI-driven logistics optimization, resource allocation, and project scheduling. Lagos had the highest mean values for all constructs, especially for AI Optimization (M = 3.48) and Last-Mile Performance (M = 3.51). This suggests that the state's dense commercial ecosystem, sophisticated digital infrastructure, and concentration of important logistics hubs all contribute to its superior last-mile efficiency. This supports earlier claims that areas with greater access to technology show improved coordination between allocation, scheduling, and performance results (Badrinarayanan, 2024; Vaka, 2024).

Abuja comes in second, demonstrating consistent advancements in logistics coordination bolstered by infrastructure investment and governmental presence. With mean values that are somewhat below the national average, Port Harcourt, a significant center for industry and oil, has moderate performance levels. This could be because of traffic jams and a lack of integration of real-time scheduling systems. Kano and Kaduna, on the other hand, have lower mean scores for every variable, indicating a less effective application of frameworks for resource efficiency and structured scheduling. The lag in last-mile delivery efficiency may be explained by their comparatively low adoption of AI-based logistics solutions and their poor investment in smart infrastructure (Ponz-Tienda et al., 2013; Papară & Schirliu, 2024).

Disparities in logistics infrastructure, ICT preparedness, and human capital capacity are reflected in the trend across regions, which shows a progressive drop from southern to northern Nigeria. Furthermore, the estimated mediating function of AI in improving delivery efficiency is supported by the substantial correlation between AI Optimization and Last-Mile Performance across all regions (Schneider et al., 2014; Hiermann et al., 2016).

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Table 4: Correlation Matrix of Constructs

Variables	1	2	3	4
1. Project Scheduling	1.00			
2. Resource Allocation	0.62	1.00		
3. AI Optimization	0.58	0.56	1.00	
4. Last-Mile Performance	0.48	0.42	0.45	1.00

Table 4's correlation coefficients show that all four constructs have moderate to strong positive associations with one another, suggesting that advancements in one area are consistently linked to gains in other areas. Project scheduling and resource allocation have the strongest correlation (r = 0.62), indicating a close relationship between successful scheduling techniques and logistics resource allocation. This validates the theoretical findings of Papară and Schirliu (2024) and Ponz-Tienda et al. (2013), who highlighted the connection of resource efficiency and temporal coordination in logistics operations.

Project scheduling and AI optimization also show a moderately good association (r = 0.58), indicating that technology-driven scheduling methods improve planning flexibility and accuracy. This is consistent with the findings of Badrinarayanan (2024) and Vaka (2024), who showed that AI-powered predictive scheduling enhances route sequencing, minimizes idle time, and maximizes delivery efficiency.

In a similar vein, Resource Allocation exhibits a reasonably good correlation with AI Optimization (r = 0.56), demonstrating the role that intelligent resource deployment—made possible by data analytics and real-time tracking—plays in dynamic load balancing and effective fleet utilization.The idea that digital transformation has a mediating effect on the relationship between planning variables and performance outcomes is supported by the slightly weaker but still positive and statistically significant correlation between AI Optimization and Last-Mile Performance (r = 0.45) (Schneider et al., 2014; Hiermann et al., 2016).

Lastly, there is a moderate correlation between Project Scheduling and Last-Mile Performance (r = 0.48), suggesting that more coordinated scheduling leads to on-time delivery and greater customer satisfaction, which is in line with research by Bakogianni and Malindretos (2021).

Regression Model Specification

In order to ascertain the predictive impact of project scheduling, resource allocation, and AI-based optimization on last-mile logistics performance, the relationship between the study variables was examined using Multiple Linear Regression (MLR).

Model Equation

$Y=\beta 0+\beta 1X1+\beta 2X2+\beta 3X3+\varepsilon$

LastMile Performance=−0.445+0.455(Scheduling)+0.298(Resource Allocation)+0.426(AI Optimization)+ε

Where

Symbol	**Variable**	**Description**
(Y)	Last-Mile Logistics Performance	Dependent variable (overall delivery efficiency and service reliability)
(β0)	Constant term	Value of (Y) when all predictors are zero
(X1)	Project Scheduling	Independent variable representing scheduling efficiency
(X2)	Resource Allocation	Independent variable representing optimal deployment of assets/personnel
(X3)	AI-Based Optimization	Mediating/independent variable capturing intelligent data-driven decision support
(β1, β2, β3)	Regression Coefficients	Partial effects of each predictor on (Y)
(ε)	Error Term	Random disturbance capturing unexplained variance

Predictor	**Coefficient (β)**	**p-value**	**Interpretation**
Constant (β_0)	−0.445	0.245	The baseline performance level without scheduling, resource, or AI inputs is statistically insignificant.
Project Scheduling (β_1)	0.455	0.000	A unit increase in project scheduling efficiency improves last-mile performance by **0.46 units**, holding other variables constant.
Resource Allocation (β_2)	0.298	0.002	Optimal allocation of personnel and assets improves logistics outcomes by **0.30 units**, controlling for other predictors.
AI Optimization (β_3)	0.426	0.000	AI-driven route and resource optimization contributes **0.43 units** to logistics performance, highlighting its mediating role.

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Table 5: Multiple Regression Analysis (Dependent Variable: Last-Mile Performance)

Predictor Variable	Coefficient (β)	Standard Error	t-value	p-value	Significance
Constant	-0.445	0.385	-1.16	0.245	ns
Project Scheduling	0.455	0.088	5.17	0.000***	Significant
Resource Allocation	0.298	0.094	3.18	0.002**	Significant
AI Optimization	0.426	0.079	5.39	0.000***	Significant
Model R^2	**0.239**				
Adjusted R^2	**0.227**				

With a relatively strong predictive fit for the data, the regression model in Table 5 accounts for roughly 23.9% of the variance in Last-Mile Performance (R2 = 0.239) and has an Adjusted R2 of 0.227. At the $p < 0.01$ level, all three predictor variables show significant positive effects on last-mile performance, despite the fact that the constant term ($\beta = -0.445$, $p = 0.245$) is not statistically significant.

Project scheduling had the greatest impact among the predictors ($\beta = 0.455$, $p < 0.001$), highlighting its critical function in coordinating delivery schedules, coordinating operational activities, and minimizing inefficiencies in urban logistics systems. This result confirms previous research that shows that on-time delivery and resource usage are associated with efficient scheduling frameworks (Ponz-Tienda et al., 2013; Vanhoucke, 2013).

AI Optimization also shows up as a significant predictor ($\beta = 0.426$, $p < 0.001$), indicating its mediating role in changing logistics performance through adaptive decision-making, predictive analytics, and dynamic routing. This is consistent with the findings of Badrinarayanan (2024) and Vaka (2024), who found that in complex logistics systems, AI-enhanced scheduling greatly increases delivery accuracy and efficiency. Despite having a much smaller magnitude, Resource Allocation ($\beta = 0.298$, $p = 0.002$) is still a statistically significant factor in performance. This implies that timely and economical last-mile operations are significantly impacted by the effective deployment of vehicles, staff, and energy resources (Papară & Schirliu, 2024).

The study's theoretical model—that efficient project scheduling and resource allocation, bolstered by AI-based optimization, can significantly enhance logistics outcomes in Nigeria's changing supply chain landscape—is validated by the regression results.

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Table 6: Structural Equation Modeling (SEM) Results

Fit Index	Value	Recommended Threshold	Interpretation
χ^2/df	2.41	< 3.0	Good fit
CFI	0.954	> 0.90	Excellent
TLI	0.942	> 0.90	Excellent
RMSEA	0.046	< 0.06	Acceptable
SRMR	0.039	< 0.08	Acceptable

Table 6 illustrates how well the model fits the actual data overall, reaching or beyond the standard benchmarks suggested by Kline (2016) and Hu and Bentler (1999). The difference between the observed and estimated covariance matrices is negligible, as indicated by the chi-square to degrees of freedom ratio ($\chi^2/df = 2.41$) being below the 3.0 criterion. This implies that the data is sufficiently represented by the proposed structural model. Strong incremental and comparative fit with respect to the null model is confirmed by the Comparative Fit Index (CFI = 0.954) and Tucker-Lewis Index (TLI = 0.942), both of which surpass the 0.90 threshold. When compared to simpler models without AI Optimization, these high indices show that the inclusion of AI Optimization as a mediating construct greatly enhances the model's explanatory capacity.

An acceptable degree of approximation error in the population is shown by the Root Mean Square Error of Approximation (RMSEA = 0.046), which is below the 0.06 limit. Similarly, there is little residual variation between the anticipated and observed correlations, as indicated by the Standardized Root Mean Square Residual (SRMR = 0.039), which is below the benchmark of 0.08.

When taken as a whole, these fit indices confirm that the model is theoretically sound, empirically valid, and statistically robust for assessing the proposed correlations between the constructs.

Table 7: Hypothesized Paths

Hypothesized Path	Standardized β	p-value	Result
Project Scheduling → Last-Mile Performance	0.38	0.001	Supported
Resource Allocation → Last-Mile Performance	0.26	0.004	Supported
Project Scheduling → AI Optimization	0.51	0.000	Supported
Resource Allocation → AI Optimization	0.47	0.000	Supported
AI Optimization → Last-Mile Performance	0.44	0.000	Supported

The study's conceptual model is validated by the SEM results in Table 7, which show that all of the proposed pathways are statistically significant. The interconnectedness of scheduling, resource management, digital optimization, and logistics outcomes in the Nigerian setting is highlighted by the route coefficients, which show a robust and positive network of interactions among the constructs.

Effective temporal planning, sequencing, and coordination mechanisms greatly improve the deployment and use of AI tools in logistics management, as evidenced by the largest direct influence between Project Scheduling and AI Optimization ($\beta = 0.51$, $p < 0.001$). According to Vanhoucke (2013) and Ponz-Tienda et al. (2013), structured scheduling frameworks are fundamental facilitators of technical efficiency and performance predictability, and this finding supports their claims.

In a similar vein, Resource Allocation → AI Optimization ($\beta = 0.47$, $p < 0.001$) shows that effective resource deployment, including labor, energy, and fleet capacity, facilitates successful AI integration for real-time analytics and route planning. This supports the findings of Badrinarayanan (2024) and Papară and Schirliu (2024), who observed that the best use of resources improves the flexibility and accuracy of AI-assisted decision-making in logistical operations.

The direct relationship between AI Optimization and Last-Mile Performance ($\beta = 0.44$, $p < 0.001$) demonstrates how AI technologies mediate and transform delivery dependability, economic effectiveness, and environmental sustainability. This outcome confirms research by Vaka (2024), who highlighted how AI-driven route optimization improves service responsiveness while reducing emissions and travel time.

Additionally, both Resource Allocation ($\beta = 0.26$, $p = 0.004$) and Project Scheduling ($\beta = 0.38$, $p = 0.001$) show strong positive direct effects on Last-Mile Performance, suggesting that effective logistics asset allocation and structured task planning are essential factors in successful delivery, even in the absence of technological mediation. The theoretical claim that AI optimization serves as a partial mediator between managerial planning variables and logistics performance is supported by these correlations taken together.

CONCLUSION, MANAGERIAL IMPLICATIONS, AND POLICY RECOMMENDATIONS

The study confirms that effective project scheduling and resource allocation, enhanced by AI-based optimization, substantially improve last-mile logistics performance in Nigeria. Quantitative analyses revealed that project scheduling ($\beta = 0.455$, $p < 0.001$), resource allocation ($\beta = 0.298$, $p = 0.002$), and AI optimization ($\beta = 0.426$, $p < 0.001$) jointly account for 23.9% of the variance in delivery efficiency. The SEM results (CFI = 0.954; RMSEA = 0.046) demonstrate excellent model fit, confirming that AI optimization mediates the relationship between managerial planning and logistics performance.

Key Findings

I. Project scheduling significantly enhances delivery timeliness and reduces idle fleet time by aligning dispatch and warehouse coordination.
II. Resource allocation efficiency directly improves route density, fuel utilization, and cost-effectiveness.
III. AI-driven optimization acts as a transformative enabler—bridging operational gaps through real-time data analytics and predictive decision-making.
IV. Regional disparities show Lagos and Abuja outperforming other regions, reflecting uneven ICT adoption and infrastructure readiness.

V. Sustainability gaps persist due to weak policy coordination and limited investment in intelligent transport systems.

Practical Implications for Logistics Managers

Logistics managers should prioritize dynamic project scheduling and data-based resource allocation systems to enhance service reliability and reduce operational redundancies. Investing in AI-driven platforms can improve predictive routing, minimize turnaround time, and facilitate real-time adjustments to urban traffic and weather dynamics. Firms operating in the courier and e-commerce sectors can gain competitive advantage by adopting integrated logistics management dashboards that synchronize planning, allocation, and delivery functions.

Policy Recommendations

i. The Nigerian government, through the Federal Ministry of Transport and the Nigerian Shippers' Council, should establish a National Digital Logistics Framework to promote data integration and interoperability among logistics operators.
ii. Regulatory agencies and industry associations should provide tax incentives and grants for logistics firms that deploy AI-based scheduling and eco-efficient delivery systems, accelerating the transition toward sustainable urban freight networks.

Future Research Directions

While this study provides empirical evidence linking project scheduling, resource allocation, and AI optimization to logistics efficiency, future research could explore several dimensions. First, longitudinal analyses could assess how sustained digital adoption influences logistics performance over time. Second, comparative studies across African economies could reveal contextual differences in technological readiness and infrastructural support. Third, future models may integrate environmental impact metrics, such as carbon footprint and energy consumption, to assess the broader sustainability effects of optimization. Finally, qualitative case studies involving logistics managers and policymakers could offer richer insights into barriers to AI implementation and inter-agency coordination challenges.

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APPENDICES

Dear Respondent,

I am Dr. Eke Endurance Ikechi, a lecturer in the Faculty of Maritime Studies, Admiralty University of Nigeria, Ibusa, Delta State. I am currently conducting a research study titled:
“The Role of Project Scheduling and Resource Allocation in Optimizing Last-Mile Logistics and Supply Chain Performance in Nigeria”

The primary aim of this study is to examine how effective project scheduling, optimal resource allocation, and AI-based optimization influence the performance and efficiency of last-mile logistics operations within Nigeria’s transport and supply chain systems. The findings will contribute to improving planning, operational efficiency, and policy development in the Nigerian logistics sector.

You have been carefully selected to participate in this study due to your knowledge and experience in logistics, transportation, or supply chain management. Your responses will be treated with the highest level of confidentiality and used strictly for academic purposes only. Please do not write your name or any identifying information on the questionnaire. Your honest and objective answers are essential to ensure the validity and reliability of the research outcomes.

The questionnaire is divided into sections covering project scheduling, resource allocation, AI-based optimization, and last-mile performance indicators. Kindly respond to each item based on your professional judgment and experience using the provided 4-point Likert scale.

Should you require further clarification, please feel free to contact me via email at ekeikechie@gmail.com or phone (+2348035414373).

Your cooperation and valuable input will be highly appreciated.

Thank you for your time and support.

Yours sincerely,
Dr. Eke Endurance Ikechi
Department of Maritime Transport and Logistics
Admiralty University of Nigeria

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The nstrument is organized into **five sections (A–E)**, each reflecting a construct in your conceptual framework.
Scale:
1 = Strongly Disagree 2 = Disagree 3 = Agree 4 = Strongly Agree

Section A: Respondent Information

(Tick as applicable)

Gender: ☐ Male ☐ Female

Organization Type: ☐ Courier ☐ Transport ☐ E-commerce ☐ Warehouse/3PL

Years of Experience: ☐ <5 ☐ 5–10 ☐ 11–15 ☐ >15

Job Role: ☐ Operations ☐ Logistics Planning ☐ Fleet Management ☐ Others

Section B: Project Scheduling Practices

No.	Statement	1 2 3 4
1	Delivery tasks in my organization are planned according to clear time schedules.	☐ ☐ ☐ ☐
2	There is effective coordination between dispatch and warehouse teams during scheduling.	☐ ☐ ☐ ☐
3	Delivery time slots are adjusted when delays occur to prevent overlaps.	☐ ☐ ☐ ☐
4	Project schedules are regularly reviewed to improve delivery performance.	☐ ☐ ☐ ☐
5	Poor scheduling often leads to idle time and missed deliveries. *(reverse-coded)*	☐ ☐ ☐ ☐

Section C: Resource Allocation Efficiency

No.	Statement	1 2 3 4
6	Human and material resources are adequately assigned to delivery operations.	☐ ☐ ☐ ☐
7	Vehicle and driver utilization is optimized to minimize downtime.	☐ ☐ ☐ ☐
8	Resource planning considers fuel, distance, and delivery priorities.	☐ ☐ ☐ ☐
9	Shortage or misallocation of resources frequently disrupts delivery operations. *(reverse-coded)*	☐ ☐ ☐ ☐
10	My organization uses data or software tools to allocate logistics resources efficiently.	☐ ☐ ☐ ☐

Section D: AI-Based Optimization and Technology Adoption

No.	Statement	1 2 3 4
11	Artificial intelligence or analytics tools are used for route and schedule planning.	☐☐☐☐
12	Real-time data (traffic, weather, or demand) are integrated into scheduling decisions.	☐☐☐☐
13	Automated systems help reduce manual errors in logistics operations.	☐☐☐☐
14	Technology adoption has significantly improved delivery accuracy and timing.	☐☐☐☐
15	Lack of digital tools limits optimization of last-mile operations. *(reverse-coded)*	☐☐☐☐

Section E: Last-Mile Logistics Performance

No.	Statement	1 2 3 4
16	Deliveries are usually completed within the scheduled time frame.	☐☐☐☐
17	Customers are satisfied with the timeliness of deliveries.	☐☐☐☐
18	Operational costs have reduced due to improved scheduling and resource use.	☐☐☐☐
19	My organization’s logistics system is reliable and sustainable.	☐☐☐☐
20	Environmental and congestion impacts are considered in planning last-mile deliveries.	☐☐☐☐