Japan Bilingual Publishing Co.

Transportation Development Research
https://ojs.bilpub.com/index.php/tdr

ARTICLE

Last-Mile Logistics Optimization in West Africa: A Machine Learning-Driven Case Study of Ghana and Burkina Faso

Eugene Ansah Owusu Ampaw [1,2], ***Qin Jin*** [1]*, ***Maxwell Ako Owusu-Ampaw*** [2], ***Isaac Richard Malan*** [3]

[1] *School of Traffic & Transportation Engineering, Central South University, Changsha 410083, China*

[2] *Department of Theory and History of International Relations, Peoples' Friendship University of Russia, Moscow 117198, Russia*

[3] *School of Computer Science and Engineering, Central South University, Changsha 410083, China*

ABSTRACT

In Sub-Saharan Africa, the emergence of e-commerce and the rising population of cities is placing novel strain on logistics systems. The efficiency of last-mile delivery (LMD) is an important factor for improving the economic output and sustainable development of cities, particularly in fast urban development areas. This study investigates LMD efficiency in urbanizing Accra, Ghana, and Ouagadougou, Burkina Faso for the effects of urbanisation. It also explores the various urban problems such as persistent mass traffic jams, woefully inadequate infrastructure, and a growing number of informal settlements characterized by a lack of addressing systems that collectively impede the operation of LMD. The mixed methods approach integrates Geographic Information System (GIS) analysis with stakeholder surveys and statistical modelling to uncover that unmanaged traffic conditions, coupled with poor road quality, are leading contributors to inefficiency. It increases delivery times, increases operating costs due to fuel use and vehicle degradation, and aggravates environmental damage through the emission of greenhouse gases. Furthermore, informal economies and a lack of formal addressing aggravate these logistical problems within the research, the researchers highlight. An important contribution of this research is the development and empirical validation of a contextualised Automatic Machine Learn

* CORRESPONDING AUTHOR:
Qin Jin, School of Traffic & Transportation Engineering, Central South University, Changsha 410083, China; Email: qinjin@csu.edu.cn

ARTICLE INFO
Received: 13 May 2025 | Revised: 3 October 2025 | Accepted: 13 October 2025 | Published Online: 21 October 2025
DOI: https://doi.org/10.55121/tdr.v3i2.435

CITATION
Ampaw, E.A.O., Jin, Q., Owusu-Ampaw, M.A., et al., 2025. Last-Mile Logistics Optimization in West Africa: A Machine Learning-Driven Case Study of Ghana and Burkina Faso. Transportation Development Research. 3(2): 40–51. DOI: https://doi.org/10.55121/tdr.v3i2.435

ing (AutoML) framework. The results revealed in a systematic case study simulation showed that routes optimized with AutoML achieved a 28% reduction in total delivery time, an estimated 22% reduction in travel distance, and a predicted reduction in fuel consumption by 22.1% compared to routing using regular routing approaches. This paper suggests specific policy recommendations to cities in Sub-Saharan Africa.

Keywords: Last-Mile Logistics; Automatic Machine Learning (AutoML); Route Optimization; Delivery Time Estimation; Sustainable Transport

1. Introduction

Last-mile logistics (LML), representing the final and most critical segment of the supply chain where goods are delivered to the end consumer, has evolved into a cornerstone of economic competitiveness and urban service quality [1]. This phase is particularly salient in the era of a global surge in e-commerce, which has elevated consumer expectations for speed, reliability, and transparency. While technologically advanced economies have leveraged digitalization, robotics, and sophisticated algorithms to streamline last-mile operations, the scenario in developing regions presents a stark contrast characterized by unique and magnified complexities [2–5]. In West Africa, a region experiencing some of the world's fastest urban growth rates, last-mile delivery is fraught with a confluence of infrastructural deficits, regulatory heterogeneity, and profound socio-economic diversity. These factors collectively magnify operational costs, impede service reliability, and constrain the potential benefits of digital commerce [6].

The logistical corridor between Ghana, a historically significant coastal trade hub with ports like Tema and Takoradi, and Burkina Faso, a landlocked nation dependent on transnational corridors for maritime access, epitomizes these regional challenges and opportunities. This corridor functions as a critical artery for regional commerce, facilitating the flow of imported goods inland and the export of agricultural and mineral resources. The efficiency of this flow is severely tested at the last mile within the major urban centers that act as consumption nodes. Cities like Accra and Ouagadougou are characterized by rapid, often unplanned expansion, leading to severe traffic congestion, inadequate road networks, and sprawling informal settlements lacking formal addressing systems [7,8].

For logistics operators, this translates into unpredictable delivery times, excessive fuel consumption, vehicle deterioration, and elevated costs that are often passed on to consumers, thereby stifling economic activity. Extant literature has extensively documented the broad operational and economic challenges of last-mile delivery in emerging markets, highlighting issues such as high-cost shares, infrastructure gaps, and the impact of informal sectors [9,10]. Concurrently, a robust stream of research in developed contexts explores advanced technological solutions, including dynamic routing algorithms, drone deliveries, and autonomous vehicles [11–15].

However, a significant and critical gap remains in the application of scalable, practical, and automated analytics specifically tailored for the West African context. The high cost and scarcity of expert data science talent often prevent local small and medium-sized logistics enterprises (SMEs) from adopting and maintaining advanced optimization techniques [13,14]. This is where Automatic Machine Learning (AutoML) presents a transformative potential. AutoML platforms automate the complex, iterative processes of model selection, feature engineering, and hyperparameter tuning, thereby democratizing access to advanced predictive analytics for organizations lacking deep technical expertise [15].

This study aims to address a notable gap in the literature. While existing last-mile optimization and machine learning research is abundant in developed, data-rich contexts, there is limited work on applying accessible, automated solutions like AutoML to the unique and constrained environments of West African urban logistics. This research contributes by: (1) empirically identifying the dominant, context-specific barriers to LMD efficiency in Accra and Ouagadougou; (2) developing and validating a practical AutoML framework tailored for data-scarce, high-variability settings; and (3) quantifying the operational and environmental benefits of this approach through an integrated simulation, providing evidence-based policy and managerial recommendations.

2. Literature Review

2.1. The Last-Mile Challenge in Developing Economies

The last-mile logistics problem is a well-established domain within transportation and supply chain research. In developing economies, its significance is even more pronounced. Studies consistently show that the last mile can account for up to 50% of total logistics costs, a proportion drastically higher than in developed nations [10]. This cost inflation is driven by a multifaceted set of factors. Chronic and unmanaged traffic congestion, a direct consequence of rapid motorization outpacing road infrastructure development, leads to significant and unpredictable delays [16]. Poor road conditions, including unpaved surfaces and lack of maintenance, not only slow vehicles but also accelerate wear-and-tear, increasing fleet maintenance costs [17,18]. Furthermore, inefficient routing practices, often reliant on driver experience rather than systematic optimization, compound these issues [19,20].

The urban form in many African cities, marked by high-density informal settlements and a lack of coherent spatial planning, introduces unique hurdles. The absence of formal street names and property numbering systems makes location finding a time-consuming and error-prone process, heavily reliant on landmarks and verbal descriptions [21,22]. This challenge is intimately tied to the pervasive informal economy, where many small businesses and end-consumers operate in spaces not captured by formal addressing databases, creating "logistical blind spots" [23].

2.2. Technological Interventions and the Data Scarcity Problem

A growing body of work emphasizes the role of information and communication technology (ICT) as a potential mitigator for these challenges. Mobile technology has been pivotal in enhancing communication between dispatchers and drivers [24]. Geographic Information Systems (GIS) have been employed for basic spatial analysis and depot location planning [25]. More recently, machine learning (ML) has emerged as a key enabler for predictive analytics in logistics, with applications in demand forecasting, delivery time prediction, and dynamic routing [26,27].

However, the implementation of traditional ML in regions like West Africa faces significant barriers. The primary hurdle is the scarcity of local data science expertise required to build, tune, and maintain complex models [13,28].

Secondly, there is a pronounced issue of data scarcity and poor quality. Logistics data is often fragmented, manually recorded, unstructured, and trapped in organizational silos, failing to meet the big data requirements of many advanced ML paradigms [29].

This creates a vicious cycle where the lack of data inhibits analytics, and the lack of analytics prevents the systematic data collection that could fuel improvements.

2.3. AutoML as a Pragmatic Solution

Automatic Machine Learning (AutoML) represents a paradigm shift designed to overcome these very barriers. By automating the end-to-end process of applying machine learning from data preprocessing and feature selection to algorithm choice and hyperparameter optimization, AutoML reduces the need for deep human expertise [15,30]. It allows domain experts (e.g., logistics managers) to leverage state-of-the-art ML techniques by focusing on problem framing and data preparation. Recent reviews on the convergence of optimization and ML in last-mile logistics note its significant potential but also highlight a predominant focus on developed, data-rich markets [31,32]. Our study builds directly on this identified gap by applying an AutoML framework explicitly to the West African context, where data is messy and unstructured, and operational constraints are deeply influenced by local socio-technical realities.

2.4. The Sustainability Imperative

The environmental dimension of last-mile logistics is gaining urgent attention globally. The sector's reliance on fossil-fuel-powered vehicles, often older and less efficient models in developing regions, contributes substantially to urban air pollution (e.g., particulate matter) and greenhouse gas (GHG) emissions, notably CO_2 [33–36]. Any proposed logistical optimization, therefore, must be evaluated not only on economic and operational metrics but also on its environmental footprint. Reducing travel distance and idle time directly correlates with lower fuel consumption and emissions, making route optimization a key strategy for sustainable urban transport [34–38]. This study explicitly incorporates fuel consumption and emission estimates as core evaluation metrics, aligning technological optimization with the broader goal of sustainable urban development.

3. Study Area Context: Accra and Ouagadougou

3.1. Accra, Ghana

As the capital and largest city of Ghana, Accra is the nation's primary economic and administrative hub. Its population has grown exponentially, leading to extensive urban sprawl beyond its original core. The city's road network, a mix of modern highways and a dense web of older, narrower streets, is perennially congested. Key bottlenecks occur at intersections like the Tema Motorway Roundabout and the Kwame Nkrumah Circle. Furthermore, rapid development has led to the proliferation of informal settlements (e.g., Old Fadama, Agbogbloshie) and peri-urban communities with poor road infrastructure and no formal addressing. The logistics sector is vibrant but fragmented, with a mix of international couriers, local haulage companies, and a vast informal network of motorcycle and tricycle delivery operators. The "trotro" (minibus) system, while crucial for passenger movement, adds to traffic complexity.

3.2. Ouagadougou, Burkina Faso

Ouagadougou, the capital of Burkina Faso, presents a different but equally challenging profile. As a landlocked city, its supply chains are longer and more vulnerable to regional disruptions. The urban fabric is less dense than Accra but is characterized by a vast geographical expanse with low-density development [39]. Road infrastructure is a major constraint; while primary arteries are paved, many secondary and tertiary roads are unpaved, turning to dust in the dry season and mud in the rainy season, severely hampering vehicle movement [40–44]. The informal economy dominates, and the lack of a standardized addressing system is acute. Unique local practices, such as the weekly closure of major roads for large open-air markets (e.g., the Tuesday market), introduce predictable but significant disruptions that must be factored into any logistical plan [45–47].

4. Materials and Methods

4.1. Research Design and Data Collection

A sequential explanatory mixed-methods design was employed to ensure a holistic and grounded understanding. This approach involved first collecting and analysing quantitative operational data, followed by qualitative data collection to explain, contextualize, and enrich the quantitative findings. Data was collected from March to August 2023 in both Accra and Ouagadougou.

4.1.1. Quantitative Data

A historical dataset of 4580 anonymized delivery records was obtained through a partnership with a mid-sized logistics company operating in both cities. The dataset spanned a period of six months and included the following key variables per record:

- Timestamp: Date and time of delivery attempt.
- Geospatial Data: GPS coordinates of the distribution depot (origin) and the delivery point (destination).
- Parcel Characteristics: Weight (kg), dimensions (approximated), and type (document, package).
- Vehicle Information: Type (motorcycle, van, pickup truck).
- Operational Metrics: Actual travel time (minutes), delivery status (successful/failed), and reason for failure if applicable.
- Contextual Indicator: A derived historical traffic index (Low/Medium/High) based on the time of day and delivery zone, created from driver logs.

4.1.2. Qualitative Data

To ground the quantitative analysis in local reality, 22 semi-structured interviews were conducted with key stakeholders:

- Logistics Managers (8): To understand strategic challenges, cost structures, technology adoption barriers, and decision-making processes.
- Delivery Drivers (10): To gain insights into daily op-

erational hurdles, navigation strategies, interactions with customers, and perceptions of technology.

- Local Shop Owners (4): To understand the recipient experience, reliability of services, and impact of delivery failures on business.
- Interview transcripts were analyzed using thematic analysis to identify recurring patterns and critical insights

4.2. AutoML Framework for Last-Mile Optimization

We selected the H_2O.ai AutoML platform due to its proven scalability, robust handling of structured data, and ability to produce interpretable model ensembles. The platform automates the training and tuning of a wide range of algorithms (including Generalized Linear Models, Random Forests, Gradient Boosting Machines, and neural networks) and creates a Stacked Ensemble model that combines the best-performing ones to maximize predictive accuracy. The historical dataset was cleaned and preprocessed. Categorical variables were encoded, and a distance km feature was engineered using the Haversine formula based on GPS coordinates.

The data was then split into a 70/30 train-test set, preserving the temporal order to prevent look-ahead bias. The AutoML process was configured to use 5-fold cross-validation for model selection, optimizing for RMSE (Root Mean Squared Error) for regression tasks and log-loss for classification. The 70/30 train-test split preserved temporal order, with the first 70% of the chronological records used for training and the latter 30% for testing, preventing data leakage. For the time-series demand forecasting (Task 3), the model was configured for one-day-ahead forecasting using daily aggregated data. The AutoML process was configured to run for a maximum of 50 base models per task. We framed three core predictive tasks:

1. **Task 1: Delivery Time Estimation (Regression)**
   - Target Variable: total_delivery_time_minutes.
   - Feature Set: distance_km, time_of_day (categorical: morning, midday, afternoon, evening), vehicle_type, parcel_weight_kg, historical_traffic_index, and day_of_week.
2. **Task 2: Next-Stop Sequencing (Multi-class Classification)**
   - To optimize routes in near-real-time, we framed the problem as predicting the optimal_ next_stop from a list of pending deliveries for a given vehicle.
   - Target Variable: The ID of the next delivery location (from a list of 5–10 pending stops).
   - Feature Set: Current vehicle GPS location, geospatial centroid and spread (cluster) of all pending stops, parcel attributes for the pending stops, and aggregate time constraints.
3. **Task 3: Demand Forecasting (Time-Series)**
   - Target Variable: Daily parcel volume per city district.
   - Feature Set: Historical volume, day-of-week, month, and a binary indicator for public holidays.

Model performance was evaluated using Root Mean Squared Error (RMSE) for the regression task and log-loss (cross-entropy) for the classification task. The final stacked ensemble models were selected for deployment in the simulation.

4.3. Discrete Event Simulation Setup

1. **Model Embedding in Simulator:**
   - **Delivery Time Estimation***:* The predicted travel time from the AutoML regression model was used as the dynamic service time for each leg between stops in the simulation.
   - **Next-Stop Sequencing***:* At each decision point (after a stop is completed), the classifier selects the next stop from the set of pending deliveries for that vehicle, based on the current contextual features.
   - **Demand Forecasting***:* The district-level demand forecasts were used to generate the daily delivery list (50 stops) for the simulation scenario, ensuring a realistic spatial distribution of stops reflective of actual demand patterns.
2. **Baseline Routing Logic Justification:**

The traditional method was chosen as the baseline because it directly reflects the current, widespread practice among local SMEs in our study areas, which relies on driver experience and simple FIFO rules due to a lack of formal optimization tools. This provides a realistic benchmark for improvement achievable by introducing accessible AutoML technology.

3. **Operational Constraints:**

The simulation was run for a single vehicle. The vehicle capacity was modeled based on standard van sizes. A route duration limit of an 8-hour shift was enforced. Time windows for deliveries were not explicitly modeled, as they are not strictly enforced in the observed operations. The 50-stop scenario was constructed as a representative, stylized day based on the average daily load for a mid-sized vehicle from our partner company's data. **Figure 1** shows the conceptual diagram of the AutoML-driven last-mile optimisation framework, from data collection and preprocessing to predictive models and route optimisation.

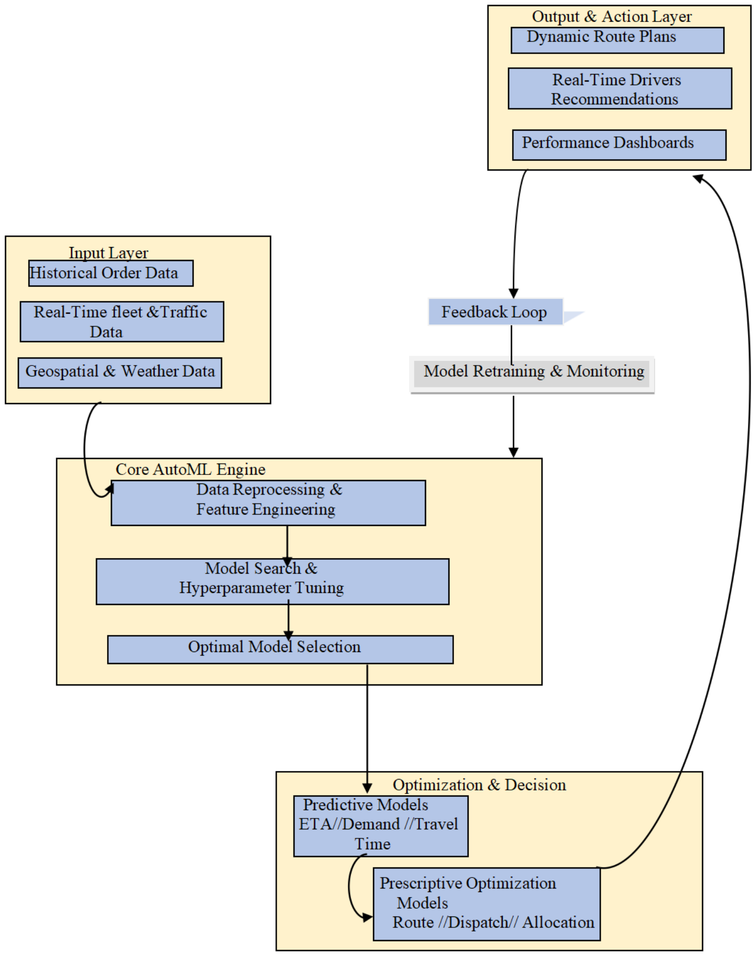

Figure 1. A conceptual diagram of the proposed AutoML-driven last-mile optimization framework.

5. Results and Discussion

5.1. Model Performance and Quantitative Impact

The AutoML process successfully identified high-performing models. For Delivery Time Estimation, a Stacked Ensemble model outperformed all base models, achieving a test set RMSE of 11.2 min. This represented a 39.5% improvement over a baseline multiple linear regression model (RMSE: 18.5 min), underscoring AutoML's ability to capture complex, non-linear relationships. For Next-Stop Sequencing, a Gradient Boosting Machine (GBM) model was the top performer, achieving a prediction accuracy of 87% on the test set, effectively learning efficient sequencing logic that minimizes backtracking. To quantify the operational impact, a discrete-event simulation was conducted on a representative delivery day with 50 stops spread across a dense urban sector in Accra and a more dispersed sector in Ouagadougou. We compared the performance of a traditional routing method (based on driver experience and first-in-first-out order) against routes generated by the AutoML-optimized scheduler. The results, summarized in **Table 1**, are striking.

As shown in **Figure 2**, the 28% reduction in total delivery time is the most significant outcome, directly translating to increased daily delivery capacity.

Table 1. Comparative Performance: Traditional vs. AutoML-Optimized Routes.

Metric	Traditional Method	AutoML-Optimized	Improvement (%)
Total Distance (km)	148.5	115.8	22.0%
Total Delivery Time (min)	482	347	28.0%
Estimated Fuel Consumption (L)	41.6	32.4	22.1%
Average Stops per Hour	6.2	8.7	40.3%

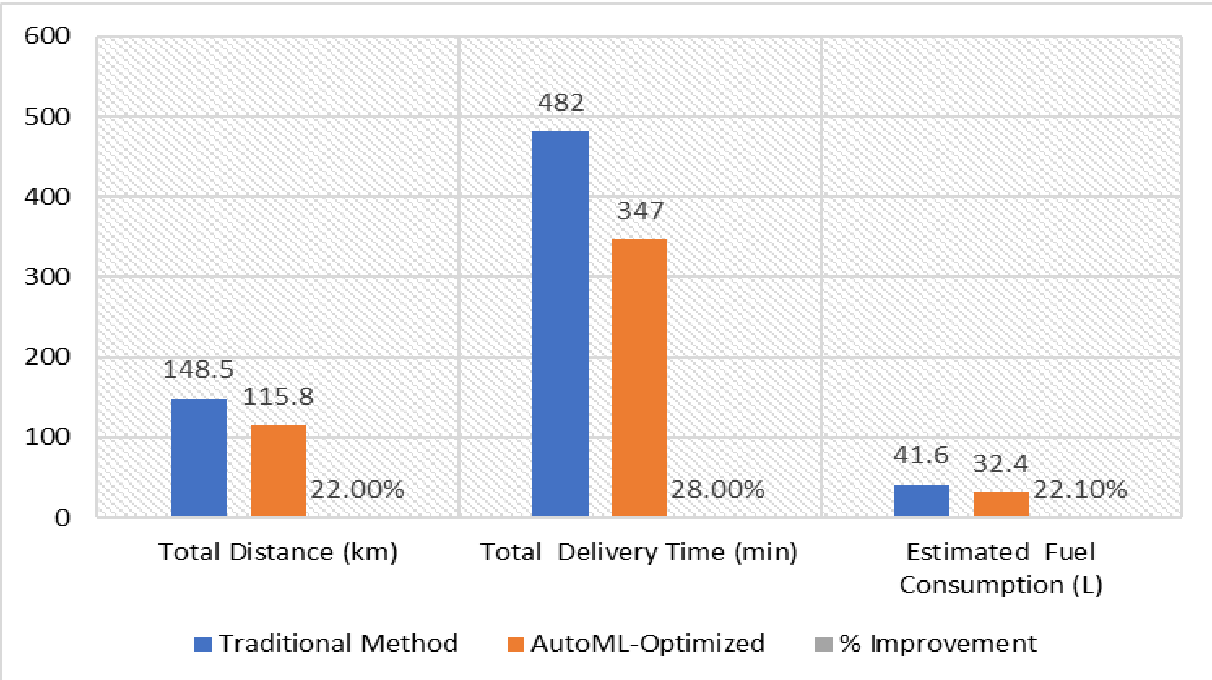

Figure 2. A bar chart visualizing the improvements from **Table 1**.

5.2. Discussion of Findings

5.2.1. Operational Efficiency and Cost Reduction

The quantitative improvements demonstrated in **Table 1** provide a direct answer to the high operational costs plaguing last-mile logistics in the region, as noted in the literature [10,19]. A 22% reduction in distance directly lowers variable costs like fuel and vehicle maintenance. The 28% time saving allows a vehicle to complete more deliveries per shift or reduces overtime wages, improving labor productivity. For a logistics firm, these savings can be the difference between marginal profitability and sustainable growth, or can be reinvested into service quality and competitive pricing. The success of the AutoML model stems from its data-driven adaptability. Unlike rigid rule-based systems, it learned subtle patterns from the historical data. For instance, it internalized the severe slowdown during Accra's midday congestion (12:00–15:00) and learned to avoid certain unpaved road segments in Ouagadougou suburbs during the simulation period, which coincided with the rainy season. This capability to learn from local, messy data is a major advantage over importing optimization models calibrated for Western cities [12,41].

5.2.2. The Critical Role of Socio-Technical Context

The qualitative interviews provided indispensable depth, revealing why pure algorithmic solutions are insufficient. A logistics manager in Ouagadougou emphasized: *"Your model is good, but it must know that the main road to Gounghin is closed every Tuesday for the market. The algorithm must be as adaptable as our best drivers."* This comment highlights that effective optimization requires the integration of tacit, localized knowledge: knowledge that is often excluded from formal datasets. Our approach addressed this by allowing such recurrent events (market days) to be encoded as features in the training data, making the model context-aware. Furthermore, drivers universally cited finding the address as a major stressor and time sink. The classification model's logic of grouping deliveries into tight geospatial clusters effectively creates walking delivery zones. Once the driver reaches the cluster centroid (a major landmark or accessible point), subsequent deliveries within that cluster can be completed on foot or with minimal vehicle movement. This reduces the cognitive load on drivers and indirectly mitigates the addressing problem, a benefit that aligns with human-centered design principles in logistics [42,43]. **Figure 3.** shows the map visualization comparing a traditional delivery route (zigzag, scattered) with an AutoML-optimized route (clustered, linear path) in a dense urban area of Accra.

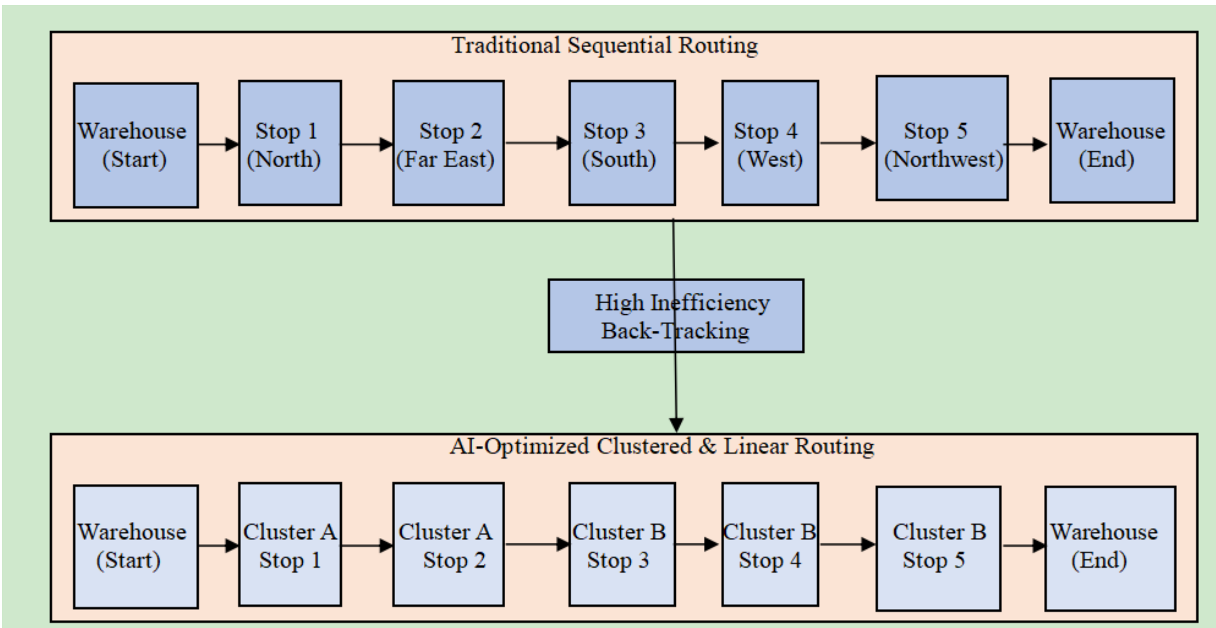

Figure 3. A map comparing a traditional vs. optimized route.

5.2.3. Environmental and Strategic Sustainability

The estimated 22.1% reduction in fuel consumption has clear environmental benefits, directly reducing tailpipe emissions of CO_2 and local pollutants. In an era where environmental, social, and governance (ESG) criteria are gaining importance, this offers logistics companies a tangible way to reduce their carbon footprint. Moreover, as regional bodies like the ECOWAS consider stricter emissions standards, such efficiency gains become a strategic compliance measure, future-proofing operations against tighter regulations. The savings also buffer against volatile global fuel prices, enhancing economic resilience [33,34].

5.2.4. Policy Implications

The findings suggest several policy directions for urban planners and national governments:

1. **Invest in Open Urban Data Infrastructure:** Governments should prioritize the development of standardized digital addressing systems and open Application Programming Interfaces (APIs) for (ano-

nymized) traffic data. This public good would lower the barrier for all logistics firms to deploy advanced analytics [44].

2. **Promote Digitalization in the Logistics Sector:** Support programs, such as tax incentives or grants for SMEs to adopt logistics management software and IoT sensors (for vehicle tracking), can catalyze the data collection needed for optimization [45].
3. **Integrate Logistics into Urban Planning:** New urban developments must include provisions for logistics spaces, micro-distribution hubs, designated loading bays, and secure parking to prevent last-mile vehicles from clogging primary streets [46].
4. **Incentivize Green Fleet Transition:** Policies promoting the adoption of electric motorcycles and vans for last-mile delivery, coupled with investments in renewable energy for charging, can amplify the environmental benefits of route optimization [35,47].

5.3. Limitations and Future Research

This study has limitations that outline paths for future work. First, the data came from a single partner, which may affect the generalizability of the exact magnitude of improvements across all operators. Second, the current framework uses historical and near-real-time data but does not perform second-by-second dynamic re-routing in response to accidents or sudden roadblocks.

Future research should explore:

1. The integration of real-time IoT data streams (GPS pings, traffic sensors) with Reinforcement Learning (RL) algorithms to create truly adaptive, self-correcting routing systems [48–50].
2. The development of business models for shared, urban consolidation centers that leverage the demand forecasts from our AutoML model to enable cargo bundling and the use of smaller, cleaner vehicles for the final delivery leg [51,52].
3. A deeper investigation into the social equity dimensions of last-mile optimization, ensuring that efficiency gains do not come at the cost of excluding deliveries to poorer, harder-to-reach neighborhoods [50,53].

6. Conclusions

This study demonstrates the tangible viability and significant impact of applying an AutoML framework to optimize last-mile logistics in the complex West African urban context of Accra and Ouagadougou. By bridging advanced, yet accessible, machine learning methodologies with on-the-ground operational realities, we have shown that substantial efficiency gains are achievable even in data-scarce environments. The AutoML-driven optimization yielded a 28% reduction in delivery time, a 22% decrease in distance traveled, and a proportional 22.1% saving in fuel consumption. Theoretically, this research contributes by validating a pragmatic framework for context-aware digitalization in developing economies, moving beyond mere technological transfer to grounded integration. Practically, it provides a blueprint for logistics managers and policymakers. For firms, it demonstrates that strategic investment in systematic data collection and off-the-shelf AutoML tools can yield a compelling return on investment. For policymakers, it underscores the urgency of fostering enabling digital and physical infrastructures from open data platforms to resilient road networks and EV charging stations.

Ultimately, building efficient, sustainable, and inclusive last-mile logistics systems is not merely a commercial imperative but a foundational requirement for sustainable urban development in West Africa. As cities continue to grow, leveraging data-driven tools like AutoML will be essential to untangle the knots of congestion, cost, and pollution, paving the way for more resilient and economically vibrant urban futures.

Author Contributions

E.A.O.A.: writing—original draft, visualization, validation, methodology, investigation, formal analysis; I.R.M.: data curation, software; Q.J.: supervision, conceptualization; M.A.O.-A.: review & editing, investigation, project administration. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by the Natural Science

Foundation of Xinjiang Uygur Autonomous Region, grant number 2024D01A19.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data presented in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

APIs	–	Application Programming Interfaces
AutoML	–	Automatic Machine Learning
GBM	–	Gradient Boosting Machine
CO_2	–	Carbon Dioxide
ESG	–	Environmental, Social, and Governance
EV	–	Electric Vehicle
GPS	–	Global Positioning System
GHG	–	Greenhouse Gas
GBM	–	Gradient Boosting Machine
IoT	–	Internet of Things
ICT	–	Information and Communication Technology
RMSE	–	Root Mean Square Error
RL	–	Reinforcement Learning

References

[1] Rodrigue, J.-P., 2020. The Geography of Transport Systems, 5th ed. Routledge: London, UK.

[2] Morganti, E., Seidel, S., Blanquart, C., et al., 2014. The Impact of E-Commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. Transportation Research Procedia. 4, 178–190. DOI: https://doi.org/10.1016/j.trpro.2014.11.014

[3] Li, Z., 2024. The Impact of E-Commerce Last-Mile Delivery on Environmental Sustainability. In Proceedings of the 5th Management Science, Informatization, Economic Innovation and Development Conference, Guangzhou, China, 8–10 December 2023; pp. 1–15. DOI: https://doi.org/10.4108/eai.8-12-2023.2344383

[4] Viu-Roig, M., Alvarez-Palau, E.J., 2020. The Impact of E-Commerce-Related Last-Mile Logistics on Cities: A Systematic Literature Review. Sustainability. 12(16), 6492. DOI: https://doi.org/10.3390/su12166492

[5] Arvis, J.-F., Mustra, M.A., Ojala, L., et al., 2010. Connecting to Compete 2010: Trade Logistics in the Global Economy. World Bank: Washington, DC, USA. Available from: https://lpi.worldbank.org/sites/default/files/2023-02/LPI_2010_Report.pdf

[6] Kuteyi, D., Winkler, H., 2022. Logistics Challenges in Sub-Saharan Africa and Opportunities for Digitalization. Sustainability. 14. DOI: https://doi.org/10.3390/su14042399

[7] Liu, S., Cao, Y., Gao, Q., et al., 2025. Spatial Accessibility in Last-Mile Logistics: A New Dimension of Urban–Rural Integration. Land. 14(8), 1691. DOI: https://doi.org/10.3390/land14081691

[8] Bosona, T., 2020. Urban Freight Last Mile Logistics—Challenges and Opportunities to Improve Sustainability: A Literature Review. Sustainability. 12(21), 8769. DOI: https://doi.org/10.3390/su12218769

[9] Agnusdei, G.P., Gnoni, M.G., Sgarbossa, F., et al., 2022. Challenges and Perspectives of the Industry 4.0 Technologies within the Last-Mile and First-Mile Reverse Logistics: A Systematic Literature Review. Research in Transportation Business & Management. 45, 100896. DOI: https://doi.org/10.1016/j.rtbm.2022.100896

[10] Allen, J., Browne, M., Cherrett, T., 2012. Investigating Relationships between Road Freight Transport, Facility Location, Logistics Management and Urban Form. Journal of Transport Geography. 24, 45–57. DOI: https://doi.org/10.1016/j.jtrangeo.2012.06.010

[11] Reiffer, A.S., Kübler, J., Kagerbauer, M., et al., 2023. Agent-Based Model of Last-Mile Parcel Deliveries and Travel Demand Incorporating Online Shopping Behavior. Research in Transportation Economics. 102, 101368. DOI: https://doi.org/10.1016/j.retrec.2023.101368

[12] Giuffrida, N., Fajardo-Calderin, J., Masegosa, A.D., et al., 2022. Optimization and Machine Learning Applied to Last-Mile Logistics: A Review. Sustainability. 14(9), 5329. DOI: https://doi.org/10.3390/su14095329

[13] Özarık, S.S., da Costa, P., Florio, A.M., et al., 2024. Machine Learning for Data-Driven Last-Mile Delivery Optimization. Transportation Science. 58(1), 27–44. DOI: https://doi.org/10.1287/trsc.2022.0029

[14] Müller, N., Burggräf, P., Steinberg, F., et al., 2025. An Analytical Review of Predictive Methods for Delivery Delays in Supply Chains. Supply Chain Analytics. 11, 100130. DOI: https://doi.org/10.1016/j.sca.2025.100130

[15] Pal, S., 2023. Optimizing the Last Mile: Advanced Predictive Analytics for Delivery Time Estimation in Supply Chain Logistics. International Journal for Innovative Research in Multidisciplinary Field. 9(11), 55–61.

[16] Birikorang, G., Birikorang, B., 2024. Preparing Ghana for the Artificial Intelligence Ghanaians Want. AI in Education, Culture, Finance, and War. 2(1). DOI: https://doi.org/10.60690/sdwyd559

[17] Ansah, R.K., Obiri-Yeboah, K., Akipelu, G., 2020. Improving the Freight Transport of a Developing Economy: A Case of Boankra Inland Port. Journal of Shipping and Trade. 5, 10. DOI: https://doi.org/10.1186/s41072-020-00065-z

[18] Hutter, F., Kotthoff, L., Vanschoren, J., (Eds.), 2019. Automated Machine Learning: Methods, Systems, Challenges. In Automated Machine Learning. Springer: Cham, Switzerland. DOI: https://doi.org/10.1007/978-3-030-05318-5

[19] Basma, H., Rodríguez, F., Hildermeier, J., et al., 2022. Electrifying Last-Mile Delivery: A Total Cost of Ownership Comparison of Battery-Electric and Diesel Trucks in Europe. International Council on Clean Transportation: Washington, DC, USA. Available from: https://theicct.org/publication/tco-battery-diesel-delivery-trucks-jun2022/

[20] Bull, A.E., Thomson, I., 2006. Urban Traffic Congestion: Its Economic and Social Causes and Consequences. CEPAL Review. 2002, 105–116. Available from: https://api.semanticscholar.org/CorpusID:150619566

[21] Silva, V., Amaral, A., Fontes, T., 2023. Towards Sustainable Last-Mile Logistics: A Decision-Making Model for Complex Urban Contexts. Sustainable Cities and Society. 96, 104665. DOI: https://doi.org/10.1016/j.scs.2023.104665

[22] Tomala, J., Mierzejewski, M., Urbaniec, M., et al., 2021. Towards Sustainable Energy Development in Sub-Saharan Africa: Challenges and Opportunities. Energies. 14(19), 6037. DOI: https://doi.org/10.3390/en14196037

[23] Hernández, F., Sotelo, R., Forets, M., 2024. Optimization Algorithms for Adaptative Route Sequencing on Real-World Last-Mile Deliveries. Ingenius. 31, 64–80. Available from: https://api.semanticscholar.org/CorpusID:266734357

[24] Atiga, O., 2021. A Comparative Analysis of the Public and Private Medical Commodity Supply Chains in Ghana: The Case of the Last Mile Delivery in the Upper East Region [Master's Thesis]. University of Johannesburg: Johannesburg, South Africa.

[25] Olsson, J., Hellström, D., Vakulenko, Y., 2022. Customer Experience Dimensions in Last-Mile Delivery: An Empirical Study on Unattended Home Delivery. International Journal of Physical Distribution & Logistics Management. 53(2), 184–205.

[26] Alcorn, L., Karner, A., 2021. Integrating Formal and Informal Transit into One Hybrid Passenger Transport System in Lagos, Nigeria. Transportation. 48, 1361–1377. DOI: https://doi.org/10.1007/s11116-020-10099-8

[27] Moldabekova, A., Philipp, R., Reimers, H.-E., et al., 2021. Digital Technologies for Improving Logistics Performance of Countries. Transport and Telecommunication Journal. 22(2), 207–216. DOI: https://doi.org/10.2478/ttj-2021-0016

[28] Fiatornu, S.Y., 2006. GIS a Tool for Transportation Infrastructure Planning in Ghana: A Case Study to the Department of Feeder Roads. In Proceedings of the 5th FIG Regional Conference, Accra, Ghana, 8–11 March 2006; pp. 1–14. Available from: https://www.fig.net/resources/proceedings/fig_proceedings/accra/papers/ts06/ts06_04_fiatornu.pdf

[29] Banjanin, M., Stojčić, M., Popović, Đ., et al., 2025. Classification Machine Learning Models for Enhancing the Sustainability of Postal System Modules within the Smart Transportation Concept. Sustainability. 17(19), 1–22. DOI: https://doi.org/10.3390/su17198718

[30] Alalawneh, A.A.F., Alkhatib, S.F., 2021. The Barriers to Big Data Adoption in Developing Economies. Electronic Journal of Information Systems in Developing Countries. 87(1), e12151. DOI: https://doi.org/10.1002/isd2.12151

[31] Butala, L., Mwanza, B.G., 2024. Analyzing the Utilization of Data Analytics in Supply Chain Decision-Making among Small and Medium Enterprises in Lusaka, Zambia. African Journal of Management and Business Research. 17(1), 475–501. DOI: https://

doi.org/10.62154/ajmbr.2024.017.010528

[32] He, X., Zhao, K., Chu, X., 2019. AutoML: A Survey of the State-of-the-Art. Knowledge-Based Systems. 212, 106622. DOI: https://doi.org/10.1016/j.knosys.2020.106622

[33] Bruni, M.E., Fadda, E., Fedorov, S., et al., 2023. A Machine Learning Optimization Approach for Last-Mile Delivery and Third-Party Logistics. Computers & Operations Research. 157, 106262. DOI: https://doi.org/10.1016/j.cor.2023.106262

[34] Shuaibu, A., Mahmoud, A., Sheltami, T., 2025. A Review of Last-Mile Delivery Optimization: Strategies, Technologies, Drone Integration, and Future Trends. Drones. 9(3), 158. DOI: https://doi.org/10.3390/drones9030158

[35] Comi, A., Savchenko, L., 2021. Last-Mile Delivering: Analysis of Environment-Friendly Transport. Sustainable Cities and Society. 74, 103213. DOI: https://doi.org/10.1016/j.scs.2021.103213

[36] Moufad, I., Jawab, F., 2019. A Study Framework for Assessing the Performance of the Urban Freight Transport Based on PLS Approach. Archives of Transport. 49(1), 69–85. DOI: https://doi.org/10.5604/01.3001.0013.2777

[37] Juang, J., Williams, W.G., Ramshankar, A.T., et al., 2024. A Multi-Scale Lifecycle and Technoeconomic Framework for Higher Education Fleet Electrification. Scientific Reports. 14, 4938. DOI: https://doi.org/10.1038/s41598-024-54752-z

[38] Figliozzi, M., 2010. The Impacts of Congestion on Commercial Vehicle Tour Characteristics and Costs. Transportation Research Part E: Logistics and Transportation Review. 46(4), 496–506. DOI: https://doi.org/10.1016/J.TRE.2009.04.005

[39] Davydov, A., 2022. International Energy Agency and U.S. Economic Policy. Russia and America in the 21st Century. 4. DOI: https://doi.org/10.18254/s207054760021607-4

[40] Florini, A., 2011. The International Energy Agency in Global Energy Governance. Global Policy. 2(S1), 40–50. DOI: https://doi.org/10.1111/J.1758-5899.2011.00120.X

[41] Van de Graaf, T., 2014. The International Energy Agency. In Handbook of Governance and Security. Edward Elgar Publishing: Cheltenham, UK. pp. 489–503. DOI: https://doi.org/10.4337/9781781953174.00038

[42] Graaf, T.D., 2012. Obsolete or Resurgent? The International Energy Agency in a Changing Global Landscape. Energy Policy. 48, 233–241. DOI: https://doi.org/10.1016/J.ENPOL.2012.05.012

[43] Miller, J.F., Muntwyler, U., 2016. International Cooperation on Public Policies and Strategies for Hybrid & Electric Vehicles under the International Energy Agency. World Electric Vehicle Journal. 8(4), 842–845. DOI: https://doi.org/10.3390/wevj8040842

[44] Limão, N., Venables, A.J., 2001. Infrastructure, Geographical Disadvantage, Transport Costs, and Trade. World Bank Economic Review. 15(3). DOI: https://doi.org/10.1596/17438

[45] Janjevic, M., Winkenbach, M., 2020. Characterizing Urban Last-Mile Distribution Strategies in Mature and Emerging E-Commerce Markets. Transportation Research Part A: Policy and Practice. 133, 164–196. DOI: https://doi.org/10.1016/j.tra.2020.01.003

[46] Tefft, J., Jonasova, M., Zhang, F., et al., 2021. Urban Food Systems Governance: Current Context and Future Opportunities. World Bank Group: Washington, DC, USA. Available from: https://hdl.handle.net/10986/35936

[47] Lutz, C., 2000. Food Markets in Burkina Faso. University of Groningen: Groningen, Netherlands. Available from: https://pure.rug.nl/ws/portalfiles/portal/3123231/200010.pdf

[48] Burns, L.D., 2013. Sustainable Mobility: A Vision of Our Transport Future. Nature. 497, 181–182. DOI: https://doi.org/10.1038/497181a

[49] Miskolczi, M., Földes, D., Munkácsy, A., et al., 2021. Urban Mobility Scenarios until the 2030s. Sustainable Cities and Society. 72, 103029. DOI: https://doi.org/10.1016/j.scs.2021.103029

[50] Acheampong, R.A., Lucas, K., Poku-Boansi, M., et al. (Eds.), 2022. Transport and Mobility Futures in Urban Africa. Springer: Cham, Switzerland. DOI: https://doi.org/10.1007/978-3-031-17327-1

[51] Laranjeiro, P.F., Merchán, D., Godoy, L.A., et al., 2019. Using GPS Data to Explore Speed Patterns and Temporal Fluctuations in Urban Logistics: The Case of São Paulo, Brazil. Journal of Transport Geography. 76, 114–129. DOI: https://doi.org/10.1016/j.jtrangeo.2019.03.003

[52] Pieterse, E., Parnell, S., Haysom, G., 2018. African Dreams: Locating Urban Infrastructure in the 2030 Sustainable Development Agenda. Area Development and Policy. 3(2), 149–169. DOI: https://doi.org/10.1080/23792949.2018.1428111

[53] Rześny-Cieplińska, J., 2023. Overview of the Practices in the Integration of Passenger Mobility and Freight Deliveries in Urban Areas. Case Studies on Transport Policy. 14, 101106. DOI: https://doi.org/10.1016/j.cstp.2023.101106