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# AI in Public Transport Optimization for Emerging Egyptian Cities

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**Abstract** **Purpose:** This paper investigates how Artificial Intelligence (AI) can optimize public transport in the New Administrative Capital (NAC) in Egypt to improve sustainable urban mobility, with reflections on applicability in new cities across the MENA region. The study emphasizes the AI applications in the optimization of public transportation, including dynamic bus scheduling, route optimization, demand-responsive transit (DRT), and multimodal integration with the Light Rail Transit (LRT) and monorail. **Methodology:** This paper employs a quantitative, scenario-based methodology using microsimulation to utilize anticipated NAC transport information, simulation models, and benchmarks from international cases. Three scenarios were examined: (1) baseline fixed routes, (2) AI-enhanced dynamic scheduling and routing, and (3) AI-integrated DRT coupled with LRT and monorail. The evaluation criteria encompassed efficiency metrics (waiting time), accessibility indicators, and sustainability measures ($CO_2$ reduction). **Results:** This paper illustrates that AI-driven optimization can decrease waiting times by 50%, increase accessibility by 27%, and lower emissions by 23% relative to the baseline. These results are similar to what has been implemented in Singapore, Shenzhen, and Helsinki. The results also fit with the concepts about mobility in emerging smart cities in MENA region, such as NEOM and Masdar City, where AI is a key part of sustainable urban planning. **Originality:** This paper systematically evaluates AI-driven public transport optimization in Egypt and offers insights that are applicable to other emerging cities in the MENA region. It shows how NAC can be a model for the area in helping to create sustainable urban mobility plans that fit with the SDGs.

**Keywords** Artificial Intelligence, Public Transport, Sustainable Mobility, Demand-Responsive Transit, New Administrative Capital, MENA, Smart Cities

## 1. Introduction

Urban mobility has become a major issue in the sustainable development of modern cities. As cities grow and more people want to commute, conventional methods of planning transportation continue to fail in making it more efficient, accessible, and environmentally friendly. The United Nations' Sustainable Development Goals (SDGs), especially SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), seek urban mobility systems that are safer, more inclusive, and better for the environment [1]. In this perspective, the incorporation of Artificial Intelligence (AI) into public transportation systems is increasingly regarded as a revolutionary approach to attaining sustainable and resilient mobility [2], [3].

Egypt is a great place to investigate AI-driven solutions for mobility around cities. Egypt Vision 2030 focuses on building infrastructure that sustains smart city growth and better connections between newly built cities. The New Administrative Capital (NAC) is the most important project among these. It is meant to ease traffic in Greater Cairo and highlight Egypt's ability to develop a technologically proficient smart metropolis [4], [5], [6].

The NAC has significant plans for its infrastructure, including a new light rail transit (LRT) and monorail system, but it will be challenging to build a public transportation system that works well and makes sense from its inception. Without strategic planning, the city could end up with the same challenges with traffic and car dependence that existing Egyptian cities have [7], [8].

AI applications in optimization of public transportation, such as dynamic bus scheduling, demand-responsive transit, and multimodal integration, have shown a lot of potential around the world. For instance, predictive models in Singapore and Shenzhen have made bus systems more energy-efficient and reduced wait times [9], [10]. In Europe, AI-driven demand-responsive transport (DRT) pilot projects in Helsinki and London showed better coverage and more satisfied passengers than fixed-route systems [11], [12]. These international experiences demonstrate the capacity of AI in providing adaptable, data-informed mobility systems. However, data from the MENA region is still insufficient, with just preliminary applications emerging in cities such as Dubai and Nairobi [13], [14].

The NAC is a one-of-a-kind opportunity for the Egyptian context. It is a planned greenfield city with built-in smart infrastructure, so that it can use AI-based mobility solutions from the beginning. This avoids the path-dependency and legacy difficulties and challenges that existing older cities face now. But this means that there is a need to think carefully about the problems in the local areas, such as how easy it is to get data, how much it costs, and how well it is accepted by the community [15].

The paper examines the role of AI in enhancing public transport optimization in the NAC, concentrating on dynamic scheduling, route optimization, demand-responsive buses, and integration with LRT/monorail systems. The study aims to address the following research questions:

- How can AI make public transportation in the NAC more efficient and accessible?
- What are the possible environmental sustainability benefits of AI-driven optimization, such as lower emissions and better energy efficiency?
- What are the institutional and social challenges that need to be overcome for effective implementation in the Egyptian context?

This paper provides not only a theoretical approach, but also a practical contribution by responding to these questions. It contributes to the worldwide research community on AI and public transportation by focusing on the MENA region, which hasn't been studied much in previous research. It additionally provides policymakers and urban planners in Egypt with an approach that is effective for the Egyptian local context. Finally, this study is aligned with Egypt's Vision 2030 and the SDGs by recommending AI-enabled approaches to make the NAC's urban mobility system more sustainable.

## 2. Literature Review

### 2.1. AI in Public Transport: Broad Trends

AI has become a crucial instrument to assist with public transportation in operating more effectively in both planning and real-time management in recent years. Jevinger carried out a mapping review of 87 studies and determined that the applications of AI in public transportation are mainly classified into three categories: prediction (of demand, passenger flows, traffic), state estimation, and resource allocation (routing, scheduling) [2]. The analysis indicates that completely autonomous public transit is still rare, and that most AI systems are more like decision support tools than full automation.

Other recent works reinforce this pattern. Gheorghe and Soica highlight the importance of combining AI with IoT and real-time analytics to adapt transport operations dynamically and reduce delays, especially in congested corridors [16]. In the same vein, Choudhary proposes an integrated AI–IoT framework for transit optimization that achieves notable reductions in waiting time, idle time, and operational cost, using deep learning for demand forecasting and reinforcement learning for scheduling decisions [17].

This previous research collectively demonstrates the maturation level of AI integration in public transportation, showing the transition from just theoretical models to systems that are capable of dynamically adapting to evolving conditions; however, it is limited by data accessibility and institutional capability.

### 2.2. Key AI Methods for Transit Optimization

Several methodological strands support AI-driven public transport interventions:

- **Routing & Scheduling with heuristic / metaheuristic methods**

Guo surveys “AI approaches on urban public transport routing” and shows how metaheuristic techniques (genetic algorithms, simulated annealing, ant colony optimization) are commonly used to search for near-optimal route and schedule configurations under varying demand and traffic constraints [18].

- **Reinforcement Learning & Adaptive Control**

To deal with headway variations (i.e. irregular gaps between vehicles), new research uses reinforcement learning to change dispatching or dwell times on as needed. For instance, a recent study employed reinforcement learning to mimic various disruptions and enhance line regularity in Serbian cities, hence increasing system resilience [19].

- **Deep Learning for Demand & Flow Prediction**

LSTM, CNN, and hybrid architectures are applied to predict the passenger demand or station flows, which feed into the routing/scheduling decisions. In rail systems, for instance, a deep learning + ant colony optimization hybrid was used to choose stop-skipping strategies adaptively based on predicted station demand [20].

- **Simulation and Scenario Testing**

Transit-Gym and other simulation tools let transit operators evaluate alternate route plans, vehicle assignments, and demand profiles, including trade-offs in energy use [21].

These methods are often used in combination: a demand prediction model feeds into an optimization module (e.g. RL or metaheuristic), whose output is validated via simulation.

## 2.3. International Applications: Dynamic Scheduling & Demand-Responsive Transport

### 2.3.1. Dynamic Scheduling & Route Optimization

In contexts such as Belgrade and Novi Sad, AI has been used to mitigate headway irregularities by ranking influencing factors and optimizing static line parameters, especially under multiple disturbance conditions [19]. Researchers have also utilized AI to change routes and headways in European cities based on changes in traffic and demand in real time [22].

Guo highlights that dynamic routing is more complex than static routing because of spatiotemporal variability and computational complexity. However, in many modern systems, this flexibility leads to significant improvements in waiting times and resource efficiency [18].

### 2.3.2. Demand-Responsive Transit (DRT) / On-Demand Services

With improvements in AI and networking, DRT models have become more popular. Hybrids that combine fixed-route lines with on-demand feeders (DRT) enable low-density or off-peak locations while keeping backbone service [23]. Some pilot projects in Europe and Asia have indicated cheaper costs, less "deadheading" (empty runs), and higher coverage [24].

Wang et al. suggest that the integration of DRT with conventional transit systems, alongside the assessment of accessibility improvements through isochrone-based metrics, can illustrate the increase in reachable opportunities (such as jobs and services) facilitated by DRT, resulting in a more equitable spatial distribution in terms of accessibility [25].

### 2.3.3. Intermodal Integration: Bus + Rail / Metro

Successful public transportation systems are becoming more reliant on seamless integration between modes. AI is used to coordinate multimodal transfers by changing the times that buses leave so that they arrive at the same time as trains or to make up for delays [16]. In dense transit systems like the metros of Paris and Hong Kong, AI-based flow forecasting helps keep stations from getting too crowded and changes frequency ahead of time.

In order to make this kind of integration, data systems need to be able to function together, agencies need to be able to communicate with each other in real time, and institutions need to be aligned with each other [26]. Table 1 summarizes the different AI applications used in different cities from international Experiences. In each city, the AI application has resulted in enhancing one of the efficient factors related to public transportation.

## 2.4. Evidence from MENA / Egypt & Relevance to NAC

While literature is sparser in MENA regarding AI-driven public transport, several pieces hint at the domain’s untapped potential:

- In Egypt, the new Cairo monorail system is being developed to link the New Administrative Capital with Greater Cairo, positioning it as a backbone for future multimodal integration (Cairo Monorail project). This infrastructure can serve as a foundation for AI-coordinated bus–rail systems [15].
- Studies of Egypt's current public transportation generally highlight structural shortcomings, such as planning that favors car use, insufficient infrastructure for people who don't own cars, and maintenance systems that have fallen apart (for example, Kalila's study of Cairo's accessibility). These gaps indicate how important it is to use information to transform mobility policies [28].
- Further AI transit work is still in its early stages in North Africa or the Middle East, but research like "AI-Driven Approach for Enhancing Sustainability in Urban Public Transportation" indicates that the methodologies may be used in different places and can be adapted [19].

**Table 1.** AI Applications in Public Transport Optimization: International Experiences

| City / Country | AI Application | Description | Outcomes | Reference |
|---|---|---|---|---|
| Singapore | Dynamic bus scheduling | AI models adapt headways to demand | 15% lower waiting times | [9] |
| Shenzhen, China | Electric bus fleet optimization | AI + big data for 16,000 buses | Lower energy use, higher reliability | [27] |
| Helsinki, Finland | Demand-Responsive Transport (DRT) | AI ride-pooling for minibuses | 30% fewer empty runs | [11] |
| London, UK | Go Sutton DRT pilot | AI-matched ride requests | Increased accessibility, user satisfaction | [12] |
| Dubai, UAE | Metro–bus AI integration | Predictive analytics synchronize modes | Reduced wait times, better reliability | [13] |

These findings indicate that although Egypt does not possess advanced AI-transit implementations, the infrastructural initiatives in NAC and urban growth present an opportunity to surpass outdated limitations.

### 2.5. Synthesis, Gaps, and Directions for NAC

From the literature examined, numerous significant findings and deficiencies are relevant to this paper's focus on NAC:

1. Data is a gating constraint: Many AI systems rely on high-resolution GPS, passenger counts, traffic data, and ridership logs, which are frequently absent or incomplete in cities lacking advanced digital transit infrastructure [2].
2. Institutional preparation is essential: AI models cannot function on their own; they need coordination amongst transportation agencies, technologies that can work jointly, legal rules for sharing data, and enough staff [16].
3. Scaling up from a pilot project to a city-wide project is not simple: Some interventions work effectively on a small scale or in a few corridors, but they don't perform equally when demand is more varied or the network is more complicated.
4. Fairness and social acceptance: AI systems need to be created in a way that everyone can use them, and they need to be affordable, easy to get to, and trusted by the public.
5. Integration from the start: Adding AI to old systems is tougher; planned cities like NAC may build AI-friendly infrastructure (IoT sensors, data platforms, multimodal corridors) from the beginning.

Therefore, NAC is an excellent opportunity to use AI to improve public transportation without having to deal with all of the problems that come with retrofitting older cities. The challenge will be to adapt international methodologies to fit the local context (such data, institutional capability, and cost) and come up with a robust yet adaptable model.

## 3. Methods

### 3.1. Research Design and Framework

This study utilizes a quantitative, simulation-based approach to assess the impact of AI applications on sustainable urban mobility in Egypt's New Administrative Capital (NAC). The methodological framework integrated PTV VISSIM microsimulation for quantitative performance modeling with a comparative scenario analysis to evaluate accessibility, passenger average waiting time, and emissions.

### 3.2. Data Collection and Model Inputs

The simulation included data sets about land use, transportation, and operations from the NAC master plan, official papers from the Egyptian Ministry of Transport, and design documents for the LRT and monorail networks. Using GIS-based shapefiles, the network geometry, road hierarchy, and public transport routes were turned into digital files and brought into PTV VISSIM. Traffic demand matrices were created using projections of population density and land use, with the assumption that the modeled area will have about 450,000 passenger trips each day. The average operational data for Cairo and New Cairo were used as a local benchmark for the bus frequencies, stop spacing, and dwell periods. Emission factors were taken from VISSIM's Environmental Module using COPERT coefficients to figure out how much $CO_2$ and $NO_x$ each type of vehicle and speed profile would release.

### 3.3. Scenario Development

The research is organized around three main scenarios. Each scenario is designed to test the incremental integration of AI applications into the NAC public transport system:

- Baseline Scenario (current fixed-route bus network without optimization): fixed-route and fixed-frequency bus operations representing conventional planning without any AI intervention. This scenario serves as the reference line for all performance factors.
- Scenario A (AI-enhanced dynamic bus scheduling and route optimization): this scenario incorporates reinforcement learning (RL) logic within the VISSIM environment to simulate dynamic bus headways and adaptive route assignment based on real-time passenger demand.
- Scenario B (integrated AI-based demand-responsive transit (DRT) with Light Rail Transit (LRT) and monorail systems): this scenario extends Scenario A by adding AI-controlled demand-responsive buses that serve low-density residential zones and first/last-mile connections to LRT and monorail stations.

All scenarios are simulated for a two-hour peak period, representing the morning commute between 7:00 and 9:00 a.m., to capture the most critical network conditions. Scenario outputs are subsequently interpreted not only in performance terms but also through an indicative cost–benefit lens to support implementability and prioritization.

### 3.4. Performance Indicators, Rationale, and Limitations

Scenario performance was evaluated using three quantitative indicators selected for their relevance to public transport service quality, spatial equity, and environmental sustainability: accessibility, average passenger waiting time, and $CO_2$ emissions. These measures are widely used in public transport appraisal because they represent complementary dimensions of user experience (waiting and access) and system externalities (emissions). Accessibility was operationalized as the proportion of the urban area (or neighborhoods) reachable within a defined generalized travel-time threshold, reflecting the practical objective of increasing access to key destinations and trunk stations through improved feeder services and transfer quality. Average passenger waiting time was measured as the time between passenger arrival at stops and boarding, capturing the operational effect of headway management, schedule adherence, and transfer synchronization. $CO_2$ emissions were derived from VISSIM environmental outputs and normalized to the scenario context to reflect the combined effect of congestion conditions, vehicle operating regimes, and potential reductions in vehicle-kilometers traveled through optimized service design.

The selection of these indicators is directly aligned with the intervention logic of the scenarios: Scenario A primarily targets waiting-time reduction through dynamic headway control and route adjustments, while Scenario B expands accessibility and reduces emissions by improving first/last-mile coverage via DRT and reducing transfer penalties through multimodal coordination. Together, the indicator set enables a balanced assessment of efficiency (time), equity (spatial coverage), and sustainability (emissions), consistent with the study's framing around SDG 11 and SDG 13.

Limitations derive mainly from the data maturity of the NAC context and the nature of scenario-based microsimulation. First, since full operational datasets are not yet available for the mature functioning of the NAC network, demand matrices and service parameters necessarily rely on forecasted assumptions and planning documentation, which introduces uncertainty in absolute magnitudes (while still supporting robust relative scenario comparison). Second, AI components are represented as scenario logic (dynamic scheduling and DRT operational rules) rather than a live-deployed AI control system integrated with real-time streams (e.g., AVL/APC and smartcard data). Third, the emission estimates reflect modeled operating conditions and embedded factors; while appropriate for comparative analysis, they should be interpreted as indicative without field calibration. These limitations do not negate the comparative value of the scenarios but motivate future work integrating real operational data streams and longitudinal monitoring once services are fully operational.

In addition to the three core quantitative indicators (accessibility, waiting time, and emissions), the study includes an indicative economic appraisal that translates scenario outcomes into decision-relevant benefit categories (time savings, operational efficiency, and emissions externalities). This appraisal is presented as a planning-level screening analysis rather than a full project finance model.

## 4. Case Study: New Administrative Capital (Egypt)

### 4.1. Overview of the NAC

The New Administrative Capital (NAC), which is located approximately 45 km east of Cairo, is Egypt's most ambitious new city development under Egypt Vision 2030. NAC is planned for a population of 6–7 million residents and is envisioned as a "smart capital" with integrated Information and Communication Technology (ICT) systems, digital governance, and sustainable infrastructure [4]. The main goals of the project are to ease traffic in Greater Cairo and to serve as the new seat of government, housing ministries, embassies, and important business centers, see Figure 1 [29].

### 4.2. Transport Infrastructure in the NAC

The NAC's transport masterplan emphasizes multimodal integration that involves not only the internal transportation inside NAC, but also the connections to the nearby cities, see Figure 2. All these modes are centered on mass transit:

- **Light Rail Transit (LRT):** This mode connects Adly Mansour station, which is located in east Cairo, to the NAC over 70 km, with multiple interchange stations [30].
- **Cairo Monorail:** There is one main elevated monorail line, which is under construction; the monorail links Nasr City to the NAC [31].
- **Bus and Shuttle Services:** There are planned fleets of electric buses and demand-responsive shuttles to serve as internal circulators and feeders inside NAC and connect the different districts and neighborhoods together.
- **Smart Solutions:** There are planned digital ticketing, smart traffic systems, and IoT-based data monitoring for the public transportation systems.

Table 2 compares the planned public transportation capacities against the current status of execution. Despite this ambitious vision of providing a multimodal system in NAC, the mobility within the NAC currently relies heavily on private vehicles and informal minibuses, replicating the same scheme of car-dependency existing in Cairo [29].

**Table 7.** Emissions reduction Simulation Across the Three Scenarios (Source: The Author)

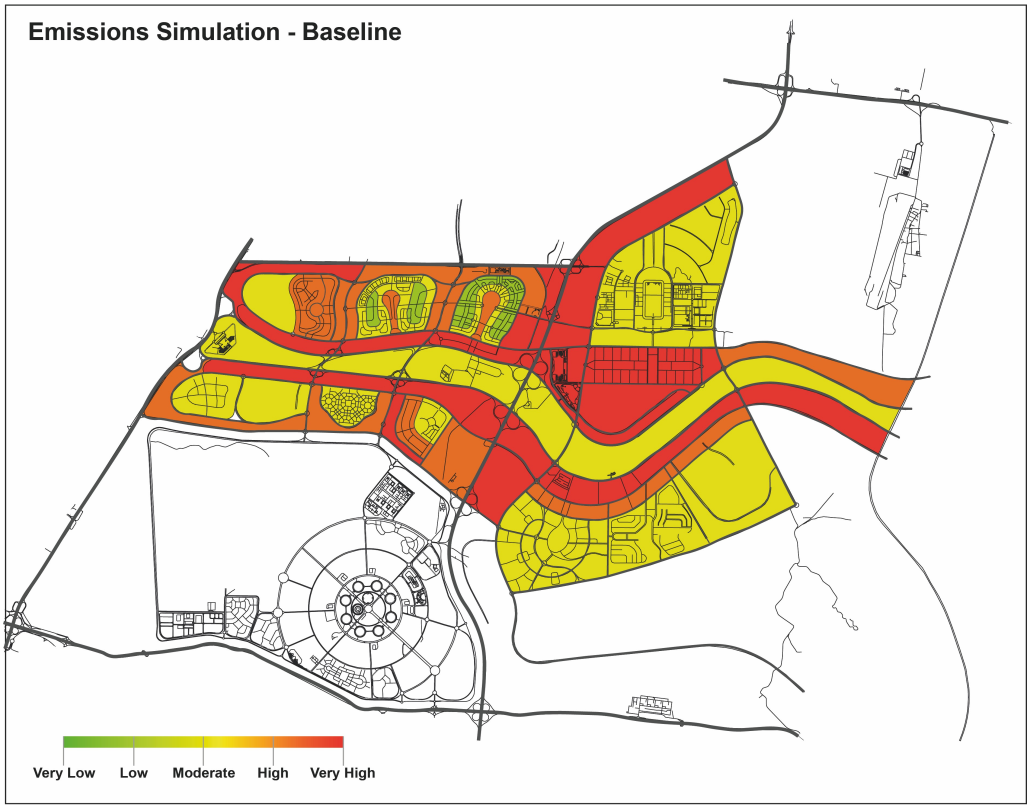
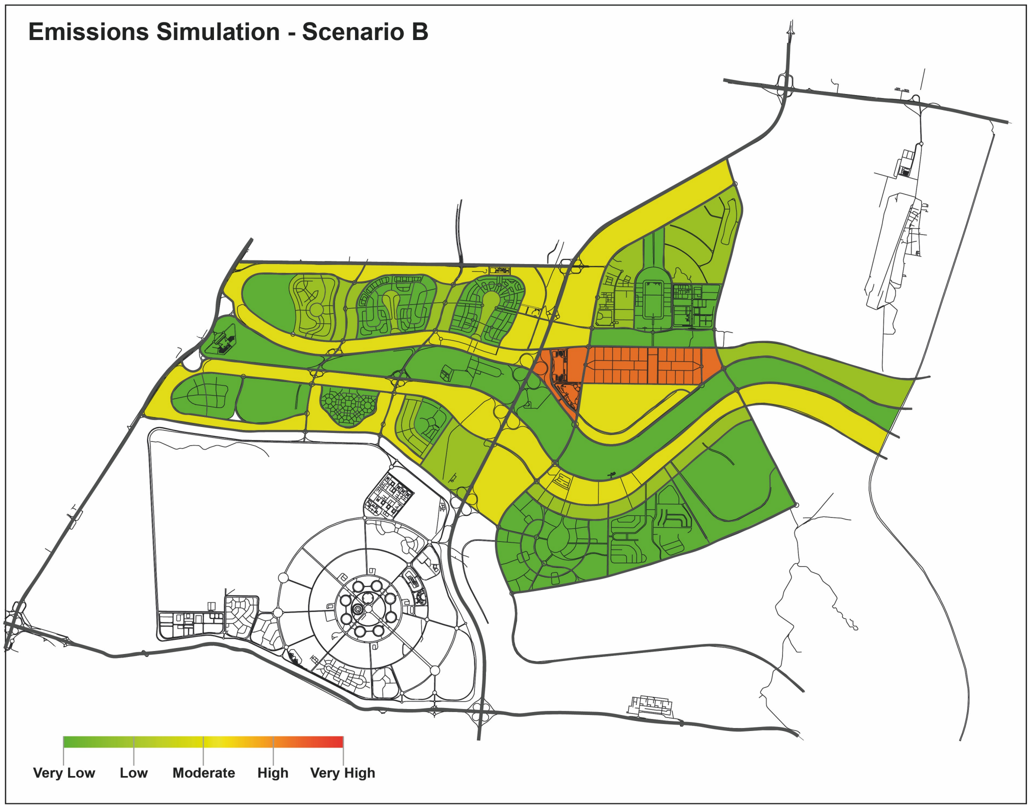
| **Scenario** | **Simulation Analysis** |
|---|---|
| **Baseline** |  |
| **Scenario A**<br>(AI Bus Optimization) | |

Table 7 continued

| | |
|---|---|
| **Scenario B**<br>(AI + DRT + LRT / Monorail) |  |

5.2.4. Integrated Interpretation

Therefore, the results from the simulation for the three factors confirm that public transportation optimization based on AI applications can simultaneously address both operational efficiency and sustainability goals. Scenario B, which is based on AI integration in demand-responsive transit (DRT) with the existing LRT / monorail network, offers the best overall performance. This performance included higher spatial equity of access to public transportation from all neighborhoods, reduced average waiting times for all users, and lower carbon dioxide emissions. These improvements validated the quantitative assumptions established earlier in the literature review based on applications in other cities and positioned the NAC as a demonstrative case for data-driven mobility optimization in emerging smart cities in the MENA region.

Because NAC-specific unit costs and willingness-to-pay parameters are not publicly available at the required resolution, the appraisal is presented as a benefit-structure and break-even framework using ranges consistent with international practice. To support decision-making, an indicative economic appraisal was developed to translate the scenario outcomes into monetizable benefit categories and to clarify the conditions under which AI-enabled operations are likely to be cost-effective. In public transport optimization, the dominant benefit streams typically include (i) passenger time savings driven by reduced waiting time and improved transfer reliability, (ii) operator efficiency gains (e.g., lower deadheading and better fleet utilization in demand-responsive operations), and (iii) externality benefits from reduced emissions and congestion-related operating regimes. In this study, Scenario A and Scenario B respectively provide significant improvements in waiting time and combined improvements in accessibility and emissions, indicating that benefits accrue both to users (generalized time) and to the system (operational and environmental performance).

An indicative break-even formulation can be expressed as: Annual Benefits ≈ (Passenger-hours saved × Value of Time) + (Reduced operating km × unit operating cost) + ($CO_2$ reduced × social cost of carbon). Even under conservative valuation, the simulated reduction in waiting times under Scenario A and the combined waiting/accessibility/emissions improvements under Scenario B imply material annual benefit potential, particularly as NAC trip volumes scale with occupancy growth and public-sector relocation. The policy implication is that cost-effectiveness depends less on the existence of benefits (which are structurally implied by the scenario outputs) and more on implementation design: data platform costs, AVL/APC coverage, dispatching software, institutional readiness, and phased deployment aligned with ridership ramp-up. Accordingly, a staged procurement strategy—starting with corridor-level dynamic headway management, followed by demand-responsive feeder services around trunk stations—can reduce investment risk while capturing early benefits, see Table 8.

**Table 8.** Indicative Cost-Benefit Structure for AI-Enabled Public Transport in NAC (Source: the author)

| Category | Examples of cost elements | Examples of benefit elements | Scenario linkage |
|---|---|---|---|
| **Digital/AI platform costs** | AVL/APC integration, scheduling/dispatch platform, data storage, cybersecurity, staff training | Higher reliability, reduced bunching, improved dispatch responsiveness | A and B |
| **Service operations** | Demand-responsive fleet procurement/contracting, driver staffing, maintenance | Reduced empty runs, better fleet utilization, increased ridership capture | B |
| **User impacts** | App development, customer support, digital inclusion measures | Waiting-time savings, improved access to trunk stations, transfer reliability | A and B |
| **Environmental impacts** | Monitoring/reporting tools | $CO_2$ reduction, improved operating regimes, potential electrification synergy | A and B |

### 5.3. Policy and Institutional Implications

While the simulations illustrated a strong quantitative potential in the optimization of public transportation in NAC, the institutional and governance considerations play a vital role in shaping the actual outcomes. The implementation of AI-based public transportation optimization in the NAC needs a coherent multi-level governance framework that integrates data management, regulatory adaptation, capacity building, and citizen engagement. Table 9 summarizes the main barriers to AI adoption in NAC and corresponding policy recommendations. Therefore, in addition to these proposed scenarios, NAC requires:

- **Mobility Data Integration Platforms:** NAC must develop interoperable platforms for traffic, passenger, and vehicle data similar to the data hub created by Singapore's Land Transport Authority [2].
- **Public–Private Partnerships (PPPs):** PPPs are essential to create a viable demand-responsive system, as seen in Go Sutton in London. These PPPs help the government to operate and manage public transportation in a more efficient way [12].
- **Affordability & Equity Measures:** The AI-driven optimization for public transportation must serve all community classes, avoiding exclusion of low-income residents who may rely on informal transport, which would affect the whole system. Additionally, the system must consider gender equity to avoid additional private cars on streets. Subsidy frameworks and inclusive pricing policies are essential [33].
- **Cultural Acceptance:** The government, together with the local community, must consider awareness campaigns and user-friendly digital applications in order to build trust in AI-driven systems, addressing the potential reluctance among NAC residents [34].
- **Capacity Building and Technical Expertise:** The successful use of AI applications in public transportation optimization relies strongly on human capacity as much as algorithmic design. Training programs in AI analytics, mobility modeling, and transport economics should be institutionalized through partnerships between the Ministry of Transport, universities, and international organizations such as the World Bank and ITDP [35].

### 5.4. Lessons for NAC and New Cities in the MENA Region

The simulation results and the institutional analysis of the NAC present broader lessons for other emerging cities in the MENA region, which are facing similar challenges, including rapid urbanization, spatial dispersion, and private cars dependency. Other cities such as NEOM in Saudi Arabia, Masdar City in UAE, and Lusail in Qatar are experimenting with AI-driven mobility frameworks to achieve sustainable and low-carbon cities. The NAC case study illustrates how quantitative modeling and AI integration, together with policy reform, can produce both operational efficiency and socio-environmental benefits, through different aspects:

1. **Integration of AI applications in Urban Planning:** The simulations illustrated that accessibility and environmental performance can be improved more when AI optimization is embedded within the urban planning process, not added afterward. Additionally, integrating dynamic bus scheduling and DRT into early infrastructure planning revenues compounded benefits. It is essential to ensure early synchronization between land-use density, public transport systems, and digital infrastructure.
2. **Regional Data Interoperability:** Most of the cities in the MENA region collect mobility data in fragmented systems. The NAC case study proposes Central Mobility Data Hub that provides a reliable framework for regional interoperability.
3. **Contextual Adaptation and Equity:** While AI applications enhance efficiency, regional variations in income, digital literacy, and service affordability, it requires context-specific adaptation. The NAC results indicate that AI-driven public transportation optimization can improve accessibility, but only if supported by equitable fare structures and multimodal inclusivity.
4. **Capacity Building:** It is essential to increase the local technical skills to ensure smooth running and adaptation of the public transportation systems. Establishing regional centers in partnership with universities and private operators could accelerate the diffusion of AI-driven mobility expertise across the MENA region.

**Table 9.** Barriers to AI adoption in NAC and corresponding policy recommendations (Sources: Mentioned Below)

| Barrier | Description | Recommendation | Sources |
|---|---|---|---|
| Data integration | Fragmented datasets | Establish centralized transport data hub | [2] |
| Institutional coordination | Multi-agency operations | PPPs and unified governance model | [12] |
| Affordability | Risk of exclusion | Subsidy models for AI-based services | [25] |
| Social acceptance | Limited trust in AI | Public awareness + user-friendly apps | [16] |
| Capacity Building | Limited staff technical capabilities | Training programs in AI analytics, mobility modeling, and transport economics | |

Finally, the NAC case study on an AI-driven transport optimization framework can serve as a nucleus for a MENA Mobility Innovation Corridor, linking ongoing experiments in NEOM, Masdar, and Lusail. The dynamic scheduling, autonomous shuttles, and emission monitoring can enhance the sustainable urban transport, which is aligned with both Egypt's Vision 2030 and the UN SDGs. The lessons derived from this case study stress the need for integrated urban planning, regional cooperation, and inclusive governance to ensure that AI-driven mobility becomes not only a technological asset but also a driver of sustainable urban transformation across the region.

# 6. Conclusions

This research illustrated the potential of AI applications to substantially improve the sustainability and efficiency of public transportation systems in Egypt's New Administrative Capital (NAC) by using simulation-based modeling. Three scenarios were examined using PTV VISSIM microsimulation to look at the operational and environmental benefits of AI applications in public transportation optimization. These scenarios included a baseline fixed-route model, an AI-based dynamic scheduling model (Scenario A), and a fully integrated AI + DRT + rail model (Scenario B).

The numbers showed that AI-based optimization leads to many gains in performance. Scenario A can cut average wait times by around 25% and boost accessibility coverage by 15% compared to the baseline. Meanwhile Scenario B, illustrated a 27% jump in accessibility, a 50% drop in passenger wait times, and a 23% reduction in $CO_2$ emissions. These results show that AI-driven multimodal coordination can increase operational dependability, user satisfaction, and environmental performance.

The research underscores that the effective integration of AI applications in public transportation requires institutional, legislative, and data governance frameworks. To achieve the simulated efficiencies in the real world, it is necessary to set up a centralized mobility data hub, get different public and private sectors to work together, and improve the local skills in AI analytics. Furthermore, equal access and societal acceptance must be focused on to guarantee that digital innovation fosters inclusive mobility rather than exacerbating spatial gaps.

This research has an impact that goes beyond Egypt. The NAC offers a scalable framework for emerging cities in the MENA region, such as NEOM, Masdar, and Lusail, where greenfield urbanization presents distinctive potential to integrate AI-driven public transportation from the beginning. These cities can speed up the move toward low-carbon, resilient, and people-centered transportation systems that fit with their national development goals and the UN SDGs 9, 11, and 13.

Meanwhile, this study provides valuable insights into the potential of using AI-applications in public transportation optimization to achieve sustainable urban mobility in NAC, however, there are several limitations that should be acknowledged. The PTV VISSIM simulations were based on modeled traffic demand and assumed service parameters rather than full-scale empirical data from on-ground operations. This is due to the limited available data from the governmental resources and the fragmentation of the data between the different ministries. This may affect the accuracy of the predicted percentages for accessibility and emission outcomes. The absence of official datasets for socioeconomic and behavioral aspects limits the assessment of the social acceptance and equity impacts. Future research should focus on integrating real operational data and machine learning models for dynamic scheduling and DRT, as well as conducting agent-based behavioral studies to capture passenger decision-making and mode shifts. The economic appraisal remains indicative pending local unit-cost and value-of-time calibration.

Finally, this research shows that AI is not just a way to improve technology, but a tool that can enhance commuting in cities in a way that is environmentally friendly. The application on NAC illustrates how data intelligence, when combined with strategic governance and human capability, can change mobility planning in the MENA area. This can help in creating a new generation of smart cities that are ready for the future and respond to climate change.

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