JOURNAL OF INNOVATION AND TECHNOLOGY
eISSN:2805-5179 Vol. 2025, Issue 1, No.07

Comparative Review of AI Applications in Urban Transport: Insights from China's City Brain and Singapore's LTA Smart Mobility

Guo Hanxiang[1*], Leong Wai Yie[1]

[1]Faculty of Business, INTI International University, Nilai, Negeri Sembilan, Malaysia

Email: i25034188@student.newinti.edu.my*, waiyie.leong@newinti.edu.my

Abstract

In recent years, cities around the world have increasingly turned to artificial intelligence (AI) as a means to address pressing challenges in urban mobility, traffic congestion, and emergency response management. Recent literature shows that AI-driven transportation systems have yielded notable improvements in traffic efficiency, commuter satisfaction, and the pursuit of sustainable mobility in both developed and developing contexts. Among the most prominent examples are China's City Brain, developed by Alibaba Cloud, and Singapore's Smart Mobility 2030 strategy, led by the Land Transport Authority (LTA). This review fills a gap in cross-national comparative studies by examining the technical architectures and operational outcomes of these systems and analyzing how governance structures, policy frameworks, and socio-cultural contexts shape their deployment. Drawing on peer-reviewed literature, policy documents, and official reports, the study proposes a multi-dimensional analytical framework for evaluating AI applications in urban transport, offering practical insights and policy implications.

Keywords

AI in transportation, City Brain, Smart Mobility, urban governance, Southeast Asia

Introduction

Cities worldwide are adopting artificial intelligence (AI) to address challenges in urban mobility, congestion, and emergency response. Two of the most notable initiatives include City Brain in China, developed by Alibaba Cloud, and Singapore's Smart Mobility 2030 strategy, implemented by the Land Transport Authority (LTA). Both platforms leverage big data, sensor networks, and algorithmic models to manage complex transportation systems. This review aims to compare these two initiatives in terms of technical design, urban outcomes, and strategic direction. By synthesizing academic and official sources, it highlights practical implications and emerging gaps in AI-based transport policy.

Submission: 26 June 2025; **Acceptance:** 15 August 2025; **Available online:** August 2025

Methodology

The review is grounded in five principal sources, each selected for its relevance, methodological rigor, and depth of analysis:

- Zhang et al. (2019) — comprehensive technical documentation and empirical evaluation of City Brain's performance.
- LTA (2022) Smart Mobility 2030 — detailed policy roadmap and integration of AI into Singapore's public transport strategy.
- Sun et al. (2021) — categorization framework for AI applications in urban mobility.
- UN-Habitat & ITU (2020) — guidance on AI governance, emphasizing transparency, interoperability, and citizen participation.
- Leong et al. (2023) — regional perspective on governance practices in Southeast Asia.

Each source was assessed for analytical scope, evidence base, and contribution to understanding AI deployment in transport. Together, these materials form a balanced foundation for analyzing both the technical and governance dimensions of the two case studies.

Results and Discussion

City Brain Overview

City Brain functions as a centralized AI platform that integrates urban video feeds, GPS tracking, and IoT sensor data to optimize traffic signal control, emergency vehicle routing, and congestion management. Since its deployment in Hangzhou, the system has reported a significant reduction in average travel time—around 15%—and an improvement in emergency vehicle response times by up to 50% (Zhang et al., 2019). The system achieves this through multi-layered modules of cognition, prediction, optimization, and intervention, which operate in near real time with decision loops as short as 30 milliseconds.

Beyond traffic optimization, City Brain has expanded to domains such as illegal parking detection, environmental monitoring, and event-based crowd management. For example, AI-driven traffic heatmaps in Hangzhou's Xiaoshan District have informed urban zoning plans, enabling better synchronization between infrastructure upgrades and traffic demand (Li et al., 2023). In Malaysia's Kuala Lumpur, pilot deployments have demonstrated interoperability between City Brain and existing traffic management centers, though challenges remain in aligning data governance standards and ensuring reliability across heterogeneous sensor networks (Leong, 2024a; 2024b). These expansions suggest that City Brain is evolving into a broader "AI-powered city operating system," with potential for scalability but also raising concerns about algorithmic transparency and data privacy (Leong, 2025).

LTA Smart Mobility Overview

Singapore's Land Transport Authority (LTA) employs predictive analytics, real-time sensor networks, and the Fusion Analytics Engine to improve public bus scheduling, monitor passenger demand, and dynamically optimize signal control. Since the implementation of Smart Mobility

2030, bus wait times on selected routes have been reduced by 8–10%, with notable improvements in service reliability during peak hours (LTA, 2022). The iTransport framework enables integration across different Intelligent Transport Systems (ITS), allowing traffic operators to make coordinated adjustments to signals, public transit schedules, and even incident responses.

A distinguishing feature of Singapore's approach is its strong emphasis on inclusive and citizen-focused design. Initiatives such as cooled bus shelters, accessible transport infrastructure for elderly and disabled passengers, and open-data portals like OneMap have enhanced public trust and engagement. Furthermore, the LTA has encouraged private sector participation by providing APIs for developers to create mobility apps, which has expanded the ecosystem of transport-related services available to the public. However, official reports note that predictive accuracy can plateau in high-density urban areas, requiring continuous model retraining to adapt to evolving commuter behaviors.

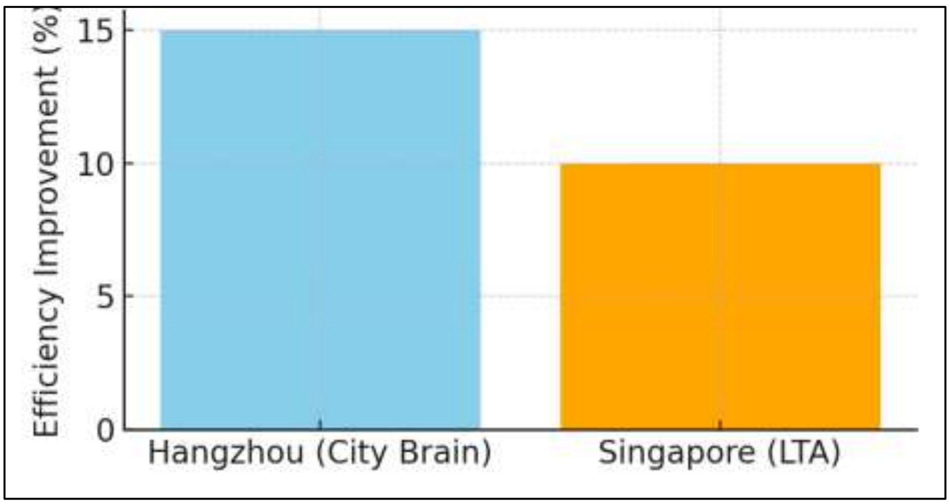

Figure 1. Traffic Efficiency Gains: City Brain vs. LTA

A visual summary of smart city governance priorities in Southeast Asia, based on Leong et al. (2023), is presented in Figure 3 below.

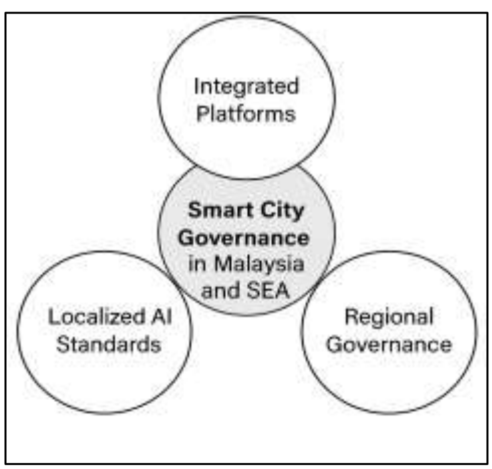

Figure 2. Smart City Governance Framework in Southeast Asia

Comparative Insights

While both City Brain and LTA Smart Mobility aim to enhance urban mobility through AI, their design philosophies and governance contexts differ significantly. City Brain's centralized model excels in rapidly processing vast, citywide datasets, enabling top-down, real-time orchestration of traffic systems. This is facilitated by China's governance structure, which allows large-scale integration of data sources across different city departments. However, this approach is heavily reliant on robust cloud infrastructure and can face challenges related to system resilience, especially during data surges or sensor outages.

In contrast, LTA's modular and service-oriented model reflects Singapore's policy environment, which emphasizes public-private collaboration, citizen engagement, and transparency in data usage. By adopting open-data practices, LTA allows third-party innovation while maintaining centralized oversight for core transport functions. This model can be more adaptable to incremental upgrades and policy shifts, but it may not deliver the same speed in system-wide optimization as City Brain.

For cities considering the adoption of similar AI-driven transport systems, the comparison highlights three key lessons:

1. Governance alignment – The technical architecture must be compatible with local data governance policies and institutional capacities.
2. Scalability and resilience – Systems must be designed to handle unexpected surges in data volume without compromising decision speed or accuracy.
3. Citizen centric design – Long-term success requires integrating user experience, accessibility, and trust-building measures alongside technical efficiency.

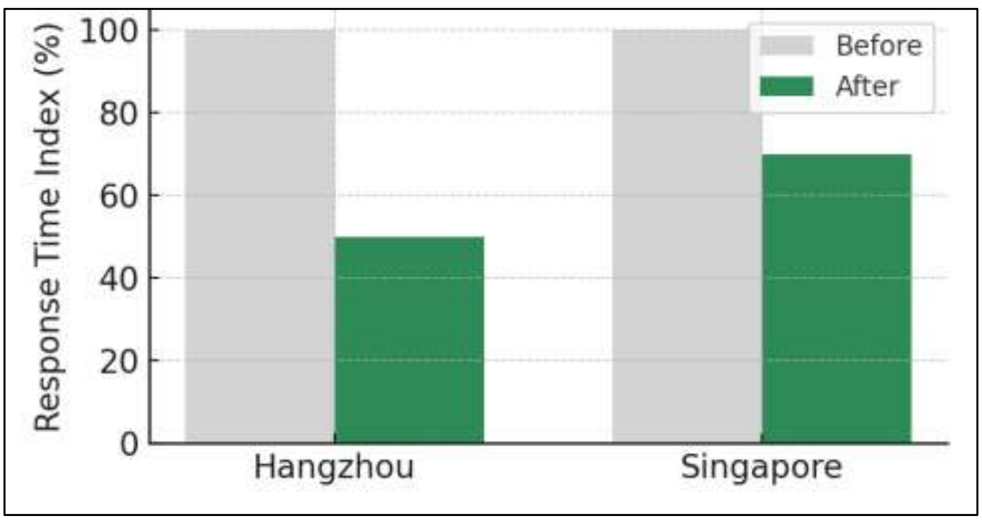

Figure 3. Emergency Response Time Before and After AI

Figure 4 summarizes the core functional modules that constitute AI-based transport platforms, including cognition, prediction, optimization, and intervention.

Figure 4. Core Functional Modules of AI Transport System

To clearly compare these studies, the following table summarizes their main focuses, key technologies, and impacts.

Table 1. Comparison of City Brain and LTA Transport Systems

System or Source	Focus or Contribution	Key Areas Highlighted	Notable Insights or Impacts
City Brain (Zhang et al.,2019)	Citywide traffic optimization and emergency response	Video analytics, predictive control, centralized AI orchestration	↓15% travel time, ↑50% emergency response
LTA (Singapore)	Adaptive public transport, inclusive mobility design	Fusion Analytics Engine, modular deployments, citizen interaction	↓10% bus waiting time; improved commuter experience
Sun et al. (2021)	AI transport applications review	Predictive analytics, adaptive control, real-time dispatching	General categorization of AI transport systems
UN-Habitat & ITU (2020)	AI governance in urban settings	Transparency, interoperability, citizen participation	Policy guidelines emphasizing inclusive governance
Kitchin (2016)	Ethical considerations for smart city technology	Algorithmic transparency, bias risks, data privacy concerns	Highlighted ethical and governance risks
Leong et al. (2023)	Smart city governance in Malaysia and SEA	Integrated platforms, localized AI standards, governance	Regional-specific governance and technical insights

Conclusion

Both City Brain and Singapore's LTA Smart Mobility program illustrate the trans formative potential of AI in reshaping urban transportation. City Brain's centralized architecture offers powerful real-time optimization capabilities, while LTA's modular framework provides adaptability and citizen-centric service delivery. The comparative analysis in this study highlights three critical lessons for policymakers and practitioners. The Governance alignment is ensuring that technical architectures align with local policy, data governance frameworks, and institutional capacity is fundamental to sustainable deployment. The scalability and resilience where AI-driven systems must be capable of handling rapid data growth, system disruptions, and unexpected operational challenges without compromising performance. Finally, the citizen-centric design is building public trust through transparency, inclusivity, and accessibility is essential for long-term adoption and social acceptance. Looking ahead, research should explore integrating AI with autonomous vehicle systems, establishing cross-city data-sharing standards, and developing robust sustainability metrics. Policymakers are encouraged to adopt standardized governance protocols, transparent data practices, and inclusive public engagement strategies to ensure equitable, durable benefits.

Acknowledgement

There is no grant or funding bodies to be acknowledged for preparing this paper

References

Abirami, S., Pethuraj, M., Uthayakumar, M., & Chitra, P. (2024). A systematic survey on big data and artificial intelligence algorithms for intelligent transportation system. Case Studies on Transport Policy, 17, 101247. https://doi.org/10.1016/j.cstp.2024.101247

Gheorghe, C., & Soica, A. (2025). Revolutionizing Urban Mobility: A Systematic Review of AI, IoT, and Predictive Analytics in Adaptive Traffic Control Systems for Road Networks. Electronics, 14(4), 719. https://doi.org/10.3390/electronics14040719

John, J., David Amar Raj, R., Karimi, M., Nazari, R., Yanamala, R. M. R., & Pallakonda, A. (2025). Artificial Intelligence for Smart Cities: A Comprehensive Review Across Six Pillars and Global Case Studies. Urban Science, 9(7), 249. https://doi.org/10.3390/urbansci9070249

Kitchin, R. (2016). The ethics of smart cities and urban science. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2083), 20160115. https://doi.org/10.1098/rsta.2016.0115

Land Transport Authority. (2022). Smart Mobility 2030: Singapore ITS strategic plan. Singapore: Ministry of Transport. https://www.lta.gov.sg/content/dam/ltagov/getting_around/driving_in_singapore/intelligent_transport_systems/pdf/smartmobility2030.pdf

Leong, W. Y., Heng, L. S., & Leong, Y. Z. (2023). Smart city initiatives in Malaysia and Southeast Asia. IET Conference Proceedings, (15), 1143–1149. https://doi.org/10.1049/icp.2023.2440

Leong, W.Y., Leong, Y.Z., & Kumar, R. (2025). Green Mobility Solutions through Intelligent Fleet Management and Smart Logistics. International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics

(IC3ECSBHI2025), India, Jan 16-18, 2025. pp. 897-902, https://doi.org/10.1109/IC3ECSBHI63591.2025.10991052

Leong, W.Y., Leong, Y.Z., & Leong, W.S. (2024a). RFID Highway Sensing in Malaysia. 2024 Asian Conference on Communication and Networks (ASIANComNet), Bangkok, Thailand, 2024, pp. 1-5, https://doi.org/10.1109/ASIANComNet63184.2024.10811063

Leong, W.Y., Leong, Y.Z., & Leong, W.S. (2024b). Business Ethics in Logistics and Supply Chain Management", International Conference on Logistics and Industrial Engineering, ICLIE, Ho Chi Minh City, DEC 2024, pp. 1-6. https://doi.org/10.1109/ICLIE61478.2024.11015398

Saadi, A., Abghour, N., Chiba, Z., Moussaid, K., & Ali, S. (2025). A survey of reinforcement and deep reinforcement learning for coordination in intelligent traffic light control. Journal of Big Data, 12, 84. https://doi.org/10.1186/s40537-025-01104-x

Villarini, B., Radoglou-Grammatikis, P., Lagkas, T., Sarigiannidis, P., & Argyriou, V. (2023). The role of AI in smart mobility: A comprehensive survey. Electronics, 14(9), 1801. https://doi.org/10.3390/electronics14091801

Wolniak, R., & Stecuła, K. (2024). Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. Smart Cities, 7(3), 1346-1389. https://doi.org/10.3390/smartcities7030057

Zhang, J., Hua, X.-S., Huang, J., Shen, X., Chen, J., Zhou, Q., Fu, Z., & Zhao, Y. (2019). City brain: practice of large-scale artificial intelligence in the real world. *IET Smart Cities*, *1*(1), 28–37. https://doi.org/10.1049/iet-smc.2019.0034