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A Pilot Study for the Service Level of the Metro Station Renovation Project Based on Passenger Detection and Simulation Techniques

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ABSTRACT

With the rapid expansion of urban rail transit networks, the existing metro stations on older lines require renovation and upgrades when integrated with new line stations to accommodate additional transfer functionalities. This poses new challenges for the station's spatial layout and passenger flow management. This study proposed a comprehensive technical system that leverages YOLO (you only look once) object detection technology in the operation of existing stations, coupled with AnyLogic simulation, to assess the impact of new line stations on passenger flow within old-line stations. The system was designed to predict congestion levels at old-line stations after they were upgraded to transfer stations. Passenger flow dynamics can be accurately monitored by collecting and analysing real-time data using YOLOv8 at the key nodes of existing stations. This approach can help us analyse the effective reference indicators to choose the best congestion mitigation plan. The simulation results provide a scientific basis for predicting and alleviating congestion at key nodes during the station renovation process, offering valuable references for ensuring passenger safety and enhancing the station throughput capacity.

KEYWORDS

metro; renovation; passenger detection; simulation; service level.

1. INTRODUCTION

Many countries in the world are vigorously developing urban rail transit networks. With the prosperous development of the urban metro network, new lines appear constantly, and the spatiotemporal characteristics of the network and the redistribution of the passenger flow constantly change [1]. For the elastic and sustainable development of urban rail transit, it is not only necessary to carry out scientific design and planning of the subway network, but there is also a need for scientific suggestions and decision support for station operation and management [2]. Especially the pressure assessment of key stations and large passenger flow control.

The service level of metro stations is a key indicator of both operational efficiency and passenger satisfaction, which is of great significance to sustainable transportation [3]. Service levels can be measured in multiple dimensions [4], such as passenger behaviour, train design, passenger characteristics, train operation and platform-built environment, which will ultimately be reflected in the spatial distribution, movement trajectory and speed of pedestrians. With the advancement of intelligent technologies and big data in recent years, there has been a growing focus on improving service levels by using data analysis and simulation technology [5, 6]. The design of infrastructure and operational capacity in transportation hubs directly impacts the level of service (LOS) [7]. Velocity, density and flow rate are the key variables for LOS simulation evaluation [8].

The basis of passenger identification is to analyse the spatial distribution of passenger traffic [9]. Against this backdrop, the application of computer vision and artificial intelligence technologies has rapidly advanced, particularly in the monitoring of passenger flow in metro stations. For instance, Garcia et al. applied YOLO to extract the kinematic and posture information of passengers during boarding, alighting and movement, thereby enhancing robustness [10]. Lv et al. improved the YOLO deep learning framework to improve the pedestrian detection accuracy within rail stations, thereby significantly reducing missed detections [11]. Gai et al. developed a high-performance pedestrian tracking algorithm based on YOLOv5. It detected and tracked pedestrians in video footage, matched the targets using the Hungarian algorithm, and predicted the positions using Kalman filtering, thereby enabling effective pedestrian detection and tracking [12]. Additionally, Xiao et al. utilised YOLOv8 technology and custom-built datasets for training, thereby enhancing the recognition of behaviours prone to occlusion and improving the detection efficiency of occluded targets through the use of optimised functions [13]. To address duplicate counting caused by overlapping multi-view perspectives, Lin et al. proposed a region-based prediction algorithm for matching validation [14]. In analysing passenger flow congestion, Zheng et al. utilised real-time surveillance videos near platform screen doors to acquire and analyse instantaneous passenger flow, enabling potential congestion prediction [15].

Concurrently, simulation technologies have become pivotal for the design and renovation of metro stations. Multi-functional simulation tools, such as AnyLogic, have been extensively adopted for traffic flow modelling and predicting passenger behaviour. For instance, Zhang et al. (2022) developed a complex metro station simulation model using AnyLogic to assess the impact of various design schemes on passenger flow distribution and congestion, leading to optimised transfer entrance configurations within the station [16]. Similarly, Li et al. (2020) employed AnyLogic's pedestrian library function to simulate the effects of increased passenger flow on metro station operations, thereby optimising the overall station system [17]. Following modelling and analysis of subway stations using AnyLogic, Wang et al. effectively enhanced the operational efficiency of escalators, entrances and automated fare gates, mitigating congestion phenomena in passenger flow [18]. These studies not only enhance station efficiency but also provide theoretical support for improving passenger experience.

Moreover, some authors [19] point out that pedestrians are not like fluids and each person may react very differently in the same situation. Therefore, the simulation should be based on the behaviour pattern of the pedestrian, taking into account the characteristics and preferences of the pedestrian. However, there is a lack of research addressing the potential instability of passenger flow and sporadic congestion issues that may arise when existing metro stations are converted into new transfer hubs. In particular, the ability to effectively forecast sudden surges in passenger volume and develop corresponding evacuation plans during the operational phase post-construction remains underexplored. Therefore, conducting predictive simulations and data analyses during the design phase is essential for the successful implementation of metro renovation projects.

This study addresses the limitations in predicting potential passenger flow congestion and dynamic evacuation strategies for existing metro station renovations by proposing three innovations. First, a collaborative passenger flow dynamics analysis framework integrating YOLOv8 object detection and AnyLogic simulation is established, enabling multi-dimensional perception of crowd density, movement speed and behavioural preferences. Second, a closed-loop "detection-simulation-optimisation" evaluation methodology is developed to couple microscopic pedestrian behaviours (e.g. path selection, facility interactions) with macroscopic crowd dynamics modelling, offering targeted solutions for early warning of sporadic congestion in station renovation scenarios. Finally, empirical validation through an L-shaped transfer station case study (Huashi Station, Guangzhou Metro) provides a technical paradigm for service-level optimisation in renovated stations. The proposed framework enhances the scientific rigour of renovation plans in facility layout, pedestrian flow design and emergency management through data-driven dynamic assessments, thereby supporting intelligent upgrades of high-density transit nodes both pre- and mid-renovation.

Although this study provides a scientific foundation for subway station renovation through the integration of YOLOv8 detection technology and AnyLogic simulation models, certain limitations persist. First, the acquisition of subway operational data is constrained by practical conditions. Sensitive data, such as real-time passenger flow surveillance footage and facility design parameters, cannot be fully disclosed due to security and confidentiality regulations, potentially leading to oversimplification of simulation input parameters. Second, the limited sharing scope of design blueprints for station renovations necessitates reliance on publicly available documents or partial field measurements for spatial layout details, which may compromise model accuracy. Additionally, the selection of research scenarios is restricted by data declassification levels, failing to encompass all potential complex operational scenarios (e.g. extreme weather or sudden large-scale passenger flow incidents). Subsequent studies should extend boundary conditions to enhance universality. These limitations may partially affect the comprehensiveness of conclusions. Future improvements could involve deepening collaboration with subway operators and establishing dynamic data-sharing mechanisms.

2. BACKGROUNDS

As a highly efficient and convenient mode of public transportation in modern cities, metro systems have become the primary means of daily commuting for many urban residents. With the rapid pace of urbanisation and growing city populations, the demand for expanding metro networks has become increasingly urgent. Consequently, many existing metro stations, particularly single-line stations, are being upgraded to transfer hubs with the integration of new lines. This transformation has led to a substantial increase in passenger flow and more complex movement patterns within stations, thereby elevating the risk of congestion at various internal nodes, especially during peak hours.

Using the newly constructed Line 11 (*Figure 1*) of Guangzhou Metro as an example, this planned circular line spans a total length of 44.2 km and includes 31 stations, 26 of which serve as transfer stations. Such large-scale network expansion necessitates the upgrading of many existing stations to facilitate multi-line transfers, introducing a series of challenges in passenger flow management and facility layout. Although these upgrades enhance transit efficiency, they also intensify congestion risks at key nodes within stations, particularly during peak hours.

This study focused on the Huashi Station of the Guangzhou Metro as a case study. Situated in Tianhe District, Huashi Station serves as a major transportation hub and exemplifies stations undergoing transformation. Originally, a single-line station on Line 3 is currently being upgraded to a transfer station with the addition of Line 11, which is expected to result in a significant increase in passenger volume. This upgrade not only places higher demands on passenger flow management and facility capacity but also introduces new challenges for operational efficiency and safety management. Therefore, the key issue in metro station upgrades is how to scientifically predict and mitigate congestion after transformation.

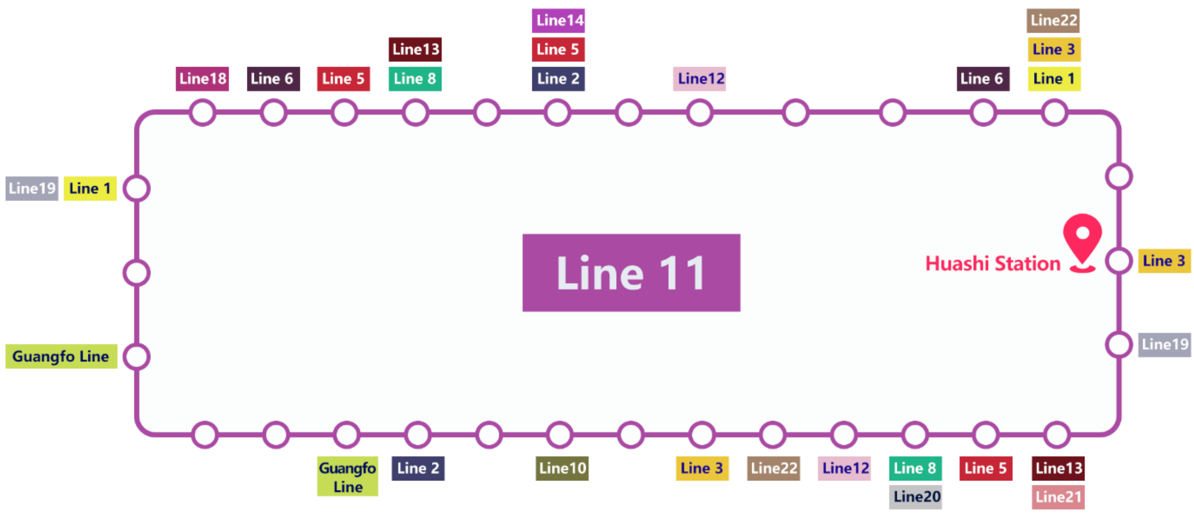

Figure 1 – Stations of Line 11

3. MATERIALS AND METHODS

3.1 Data collection based on object detection and tracking

In the existing stations, we utilised a combination of pre-installed fixed cameras, newly added specialised flow-monitoring cameras and highly adaptable mobile recording devices to collect data, including metrics such as crowd density, pedestrian speed and dwell time within the monitored areas.

YOLO is a widely used object detection and image segmentation model. YOLOv8 [20] supports a broad range of visual AI tasks, including detection, segmentation, pose estimation, tracking and classification.

YOLOv8 is open-sourced. Its tracking algorithms are embedded within BoT-SORT and ByteTrack. Specific code is available in the ./ultralytics/trackers directory of the Ultralytics/ultralytics project on GitHub: https://github.com/ultralytics/ultralytics. YOLOv8 uses Kalman filters to predict the positions of the detection boxes, construct a cost matrix and apply an optimised Hungarian algorithm to match the trajectories with the detection box IDs in the current frame. It also integrates additional logic to enhance the tracking effectiveness.

Given that our detection targets involved crowds and required the tracking of multiple objects with inevitable occlusions, this study used densely packed scene datasets, specifically MOT20 [21] and CrowdHuman [22], for training.

Object tracking relies on object detection. For each detected object, we obtained a detection box ID, along with its size and position information in the current frame of the image (*Figure 2*). Based on the camera's angle and spatial position, the pixel coordinates of the object in the image frame were then converted into the corresponding unified coordinates in a real-world station.

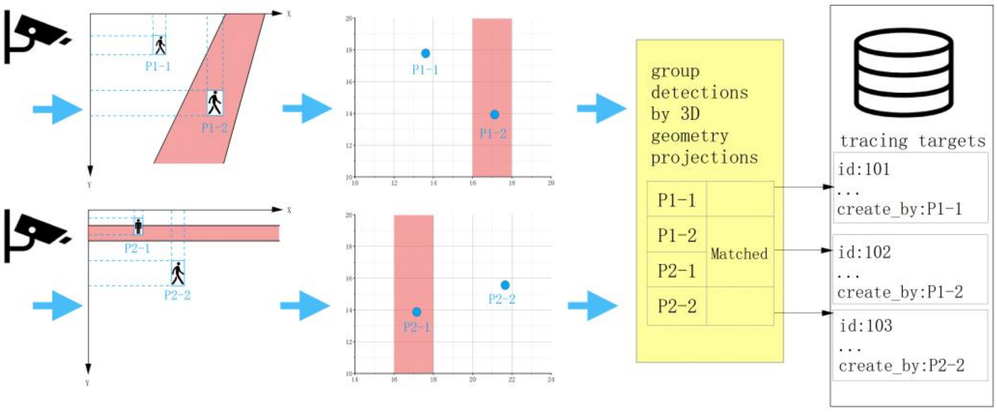

Figure 2 – Pedestrians identified and tagged by YOLO

Using YOLOv8, we recorded all coordinate data of a target from the moment it was identified until it was completely lost, storing this information in a coordinate stack. Each frame of the footage was mapped to the corresponding coordinates, and predictive coordinates were utilised if any frame was lost.

In the processing of actual sample data, our sampling interval was 0.1 seconds, and bad data were cleared if the number of valid frames was fewer than five. By combining the coordinate changes with the number of frames, we calculated the target's movement distance and speed. Dividing the number of detected targets by the area of the region provides crowd density in that area.

For multitarget cross-camera tracking, we utilised the overlapping camera regions and applied the LMGP [23] method to eliminate potential ID-switching errors, facilitating the cross-camera tracking of targets (*Figure 3*). When an object was identified as the same across cameras, its data and label information were shared.

Figure 3 – Pedestrian tracking based on overlapping areas

3.2 Passenger flow analysis of existing stations based on YOLOv8

Dimension one: Analysis of passenger flow density across different time periods

The pedestrian walking speed is influenced by various factors, including individual characteristics, environmental conditions, facility performance and capacity [24]. By analysing the number of pedestrians and their speeds in different areas of the station, we partially validated this conclusion.

The data collection areas included entry and exit passageways, exterior concourse corridors and station hall interiors. The passageways consisted of four lanes, each approximately 5 m wide, similar to the width of the exterior concourse corridors. The station hall interior spanned approximately 10 m in width but was cluttered with pillars and facilities.

As shown in *Figure 4*, during the morning peak hours from 8:10 to 8:20, the pedestrian numbers and speeds were high. From 8:50 to 9:00, the peak subsided. At midday, the pedestrian speed was the slowest. In the evening peak hours, compared to the morning, pedestrians walked at a more comfortable pace, and more pedestrians could be seen using their mobile phones.

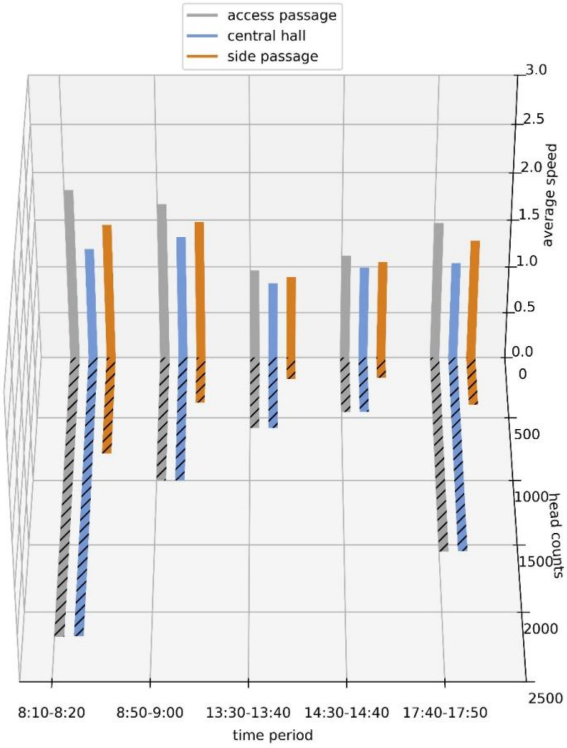

Figure 4 – Comparison of the average speed and number of pedestrians in different areas at different time periods

Although speed is influenced by social activities and time variations, within the same period, the speed in entry and exit passageways can be used as a reference for calculating the rate of speed reduction. This reduction rate can help measure the impact of pedestrian flow in different areas (*Figure 5*). A general reduction in the speed indicates the onset of crowd congestion. This metric is useful for monitoring real-time changes in pedestrian flow and predicting sudden congestion events.

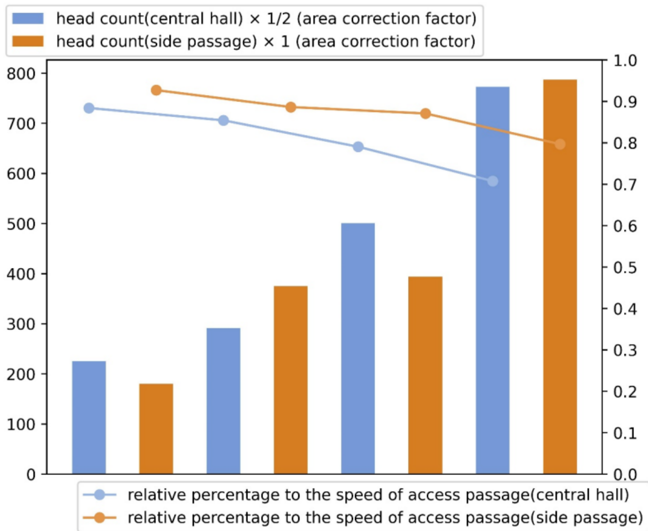

Figure 5 – Density and corresponding speed variation rate in the central hall and side passage

Figure 5 illustrates the adjusted density variations in the central hall and side passages under comparable pedestrian volumes. To account for the spatial discrepancy (the central hall area being approximately twice the width of the side passages), a correction factor of 1/2 was applied to the pedestrian count in the central hall. Although this adjustment does not represent an exact density calculation, it effectively highlights the relative trends in congestion dynamics. The results demonstrate that side passages maintained a more stable traffic capacity, with consistently lower speed reduction ratios (indicative of free-flow conditions), compared to the central hall. This disparity underscores the central hall's role as a high-density buffer zone where pedestrians adapt to spatial constraints (e.g. navigating pillars or distributed facilities), while side passages prioritise unidirectional movement efficiency.

Dimension two: Analysis of regional speed distribution

As shown in *Figure 4*, the traffic performance was the highest in the entry and exit passageways, followed by the exterior concourse corridors, and the lowest in the central area of the station hall. The observed hierarchy of traffic performance across functional areas (entrance corridors > side corridors > central hall) was further quantified by the distinct speed distribution patterns captured in *Figure 6*. Specifically, entrance corridors exhibited a higher prevalence of pedestrians in the 1.6–2.0 m/s range (free-flow state), while the central hall showed a concentration of speeds below 1.2 m/s (constrained flow), aligning with its role as a buffer zone for crowd dispersion.

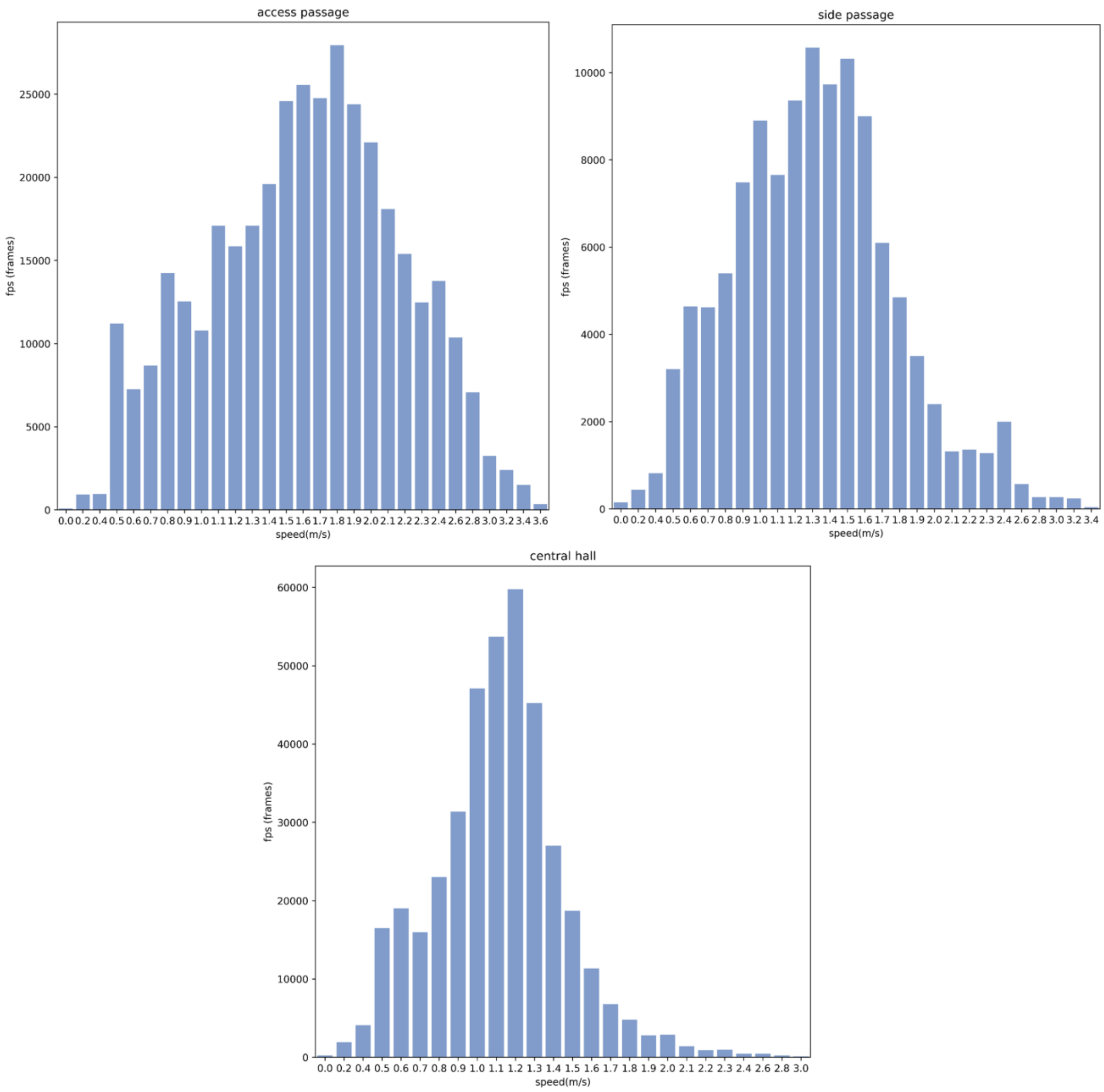

Figure 6 – Frame count statistics for each speed range of pedestrians during the peak period from 8:10 to 8:20

The calculation results are presented in *Table 1*. Regions with superior traffic performance (e.g. entrance corridors) exhibited significantly higher variability in pedestrian speed (standard deviation: 0.603 m/s) compared to low-performance areas (e.g. central hall, standard deviation: 0.386 m/s). This phenomenon can be explained by the speed attenuation mechanism: in high-efficiency zones like entrance corridors, pedestrian speed distribution demonstrates a characteristic alternation between free-flow and constrained-flow states due to unidirectional path selection and facility capacity limitations (e.g. narrow passages). Specifically, when instantaneous density exceeds 1.5 persons/m² (based on *Figure 4* data), pedestrian speed decreases by approximately 25% due to avoidance behaviours, amplifying speed standard deviation. In contrast, the central hall, despite its higher corrected average density (2.8 persons/m²), maintains more uniform speed distribution (36% reduction in standard deviation) through multi-path dispersion and facility redundancy (e.g. distributed ticket machines and columns), which mitigate localised congestion.

Speed metrics further validate the spatial differentiation of traffic performance:

1) Entrance corridor: Peak-hour average speed reached 1.82 m/s (*Table 1*), approaching free-walking speeds (1.5–2.0 m/s), yet exhibited the highest speed variability (standard deviation: 0.603 m/s), indicating frequent transient stagnation (e.g. avoidance or directional changes). This aligns with the observation in Section 3.2.4 of "disordered states triggering premature deceleration" (*Figure 8*).
2) Side corridor: Average speed of 1.45 m/s and standard deviation of 0.524 m/s, with fluctuations primarily arising from interactive effects with the central hall (e.g. lateral pedestrian crossings).
3) Central hall: Lowest average speed (1.19 m/s) and minimal standard deviation (0.386 m/s), reflecting its role as a "buffer pool" for crowd distribution. Even under elevated density, pedestrians maintain relatively stable movement rhythms by adjusting paths (e.g. circumventing columns or selecting alternative facilities), complementing the behavioural pattern described in Section 3.2.3 of "passengers preferring concentrated escalator usage" (*Table 2*).

These findings suggest that speed variability serves as a critical parameter for congestion early warning. A sudden increase in speed standard deviation (e.g. >0.7 m/s in entrance corridors) signals localised bottleneck formation, necessitating diversion measures. Consistently low variability (e.g. <0.4 m/s in central halls) may indicate systemic capacity inadequacy, requiring spatial layout optimisation through facility redesign.

Table 1 – Standard deviation of pedestrian speed in different areas

Area	Access passage	Side passage	Central hall
Average speed (m/s)	1.82	1.45	1.19
Standard deviation of speed	0.603	0.524	0.386

Note: The peak-hour average speed of 1.82 m/s in the access passage lies between leisurely walking speeds (1.1-1.4 m/s) and brisk walking speeds (1.67-2.2 m/s) (ref: https://tinyurl.com/2uzvb4ej), and is consistent with empirical observations of accelerated walking during rush periods.

Dimension three: Analysis of passenger choice behaviour data

In the existing metro station studied, there were two escalators, one staircase, and one elevator between the station hall and platform levels. The tracking of pedestrians on each floor revealed distinct differences in the tendencies of the upward and downward passenger flows (*Table 2*).

Table 2 – Passenger flow ratio of different facilities

	Escalator	Lift	Stairs
Downward passenger selection ratio (peak period) (%)	95.27	4.47	0.26
Upward passenger selection ratio (peak period) (%)	75.59	14.96	9.45
Downward passenger selection ratio (mid-peak period) (%)	97.56	2.29	0.15
Upward passenger selection ratio (mid-peak period) (%)	78.03	20.84	1.13

Escalators are consistently the preferred option for passengers. Compared with those travelling downward, upward passengers are more likely to wait for the elevator. Stairs are generally considered only when there is a high volume of passengers moving upward during the peak periods.

This phenomenon is influenced by passenger flow characteristics. Upward passengers originate from two train lines on a platform on which trains operate in cycles. Consequently, unlike the continuous changes observed in downward passenger flows, upward passenger flows can experience more concentrated pressure.

Figure 7 illustrates the cyclical variation in the number of people on the platform.

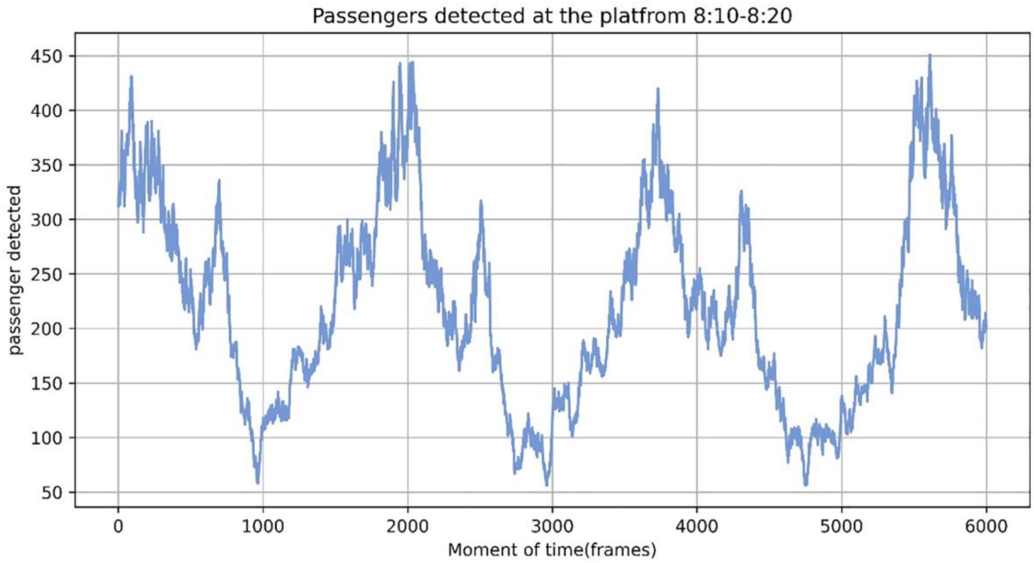

Figure 7 – Passengers detected on the platform at peak time

Dimension four: Data analysis of passenger security check waiting time

These data study focused on security check areas. Typically, there were at least two cameras for security checks: one positioned at the top of the station hall level to monitor the entire security area and the transition zone leading to it, and the other positioned above the security gate for the close-up identification of pedestrians.

The transition area leading to a security check is essentially unidirectional. Based on this setup, we observed speed changes in the transition area as it approached the security check when the number of people present exceeded 10.

By sampling crowd trajectories during the same morning peak period, we discovered that under identical high-density conditions, orderly and disorderly states had a distinctly different impact on subsequent pedestrians.

Figure 8 shows that when a disordered situation occurred, the crowd could begin to decelerate earlier.

Conversely, when a queue is formed during the security check, the crowd approaching it may even experience slight acceleration (*Figure 9*).

This indicated that organised services created positive expectations among pedestrians, which was ultimately reflected in their speed.

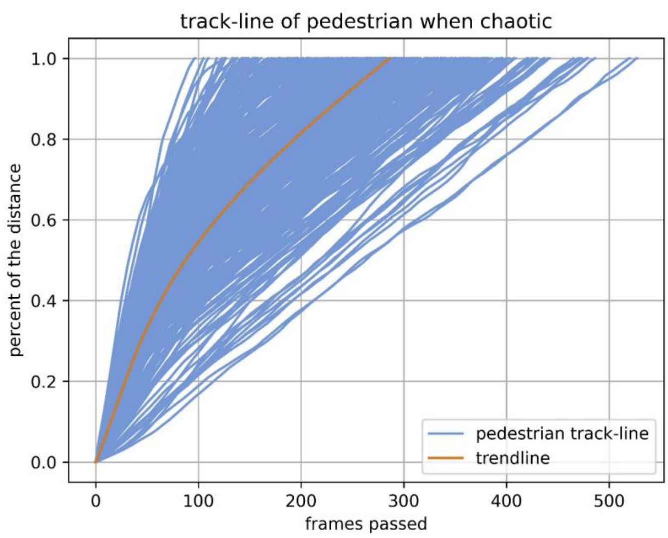

Figure 8 – Pedestrian track-lines on a distance-time graph when a disordered situation occurred

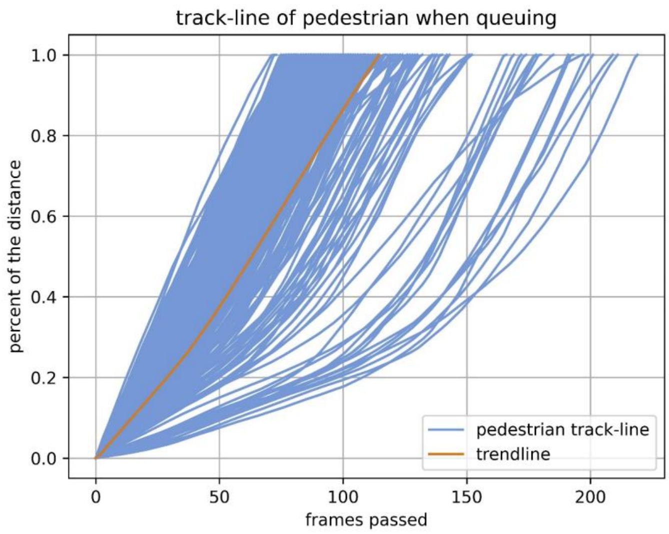

Figure 9 – Pedestrian track-lines on a distance-time graph when a queue forms

Dimension five: Pedestrian characteristics analysis based on route selection

The pedestrians followed specific routes, which allowed us to assign the particular labels to them. For instance, passengers entering certain entrances can be associated with designated blocks. Similarly, those using a no-bag corridor or a bag corridor can be labelled as "no-bag" or "bag", respectively. At the transfer stations, passengers coming from a specific corridor could be identified as originating from a particular line, which was crucial for optimising the transfer operations.

With the introduction of various ticket codes, passengers can be categorised as either physical ticket holders or non-physical ticket holders.

Early ticket machines frequently caused queuing and were typically positioned against walls to accommodate the required space. Consequently, ticket machines were generally not situated on a pedestrian's primary route. Passengers were identified as physical ticket holders if their route included a stop at the ticket machine with a delay of more than 10 s. This method facilitated statistical analysis (*Table 3*).

Table 3 – Time spent in different areas by passengers with physical tickets and non-physical tickets

Time period	8:50-9:00	13.30-13.40	14.30-14-40	17.40-17.50
Number of ticket buyers	2	7	4	1
Proportion	<0.2%	<2.5%	<0.9%	<0.1%
Average entry time (with ticket)	144s	312s	191s	77s
Average entry time (without physical ticket)	38s	89s	63s	49s
Average dwell time in hall (with ticket)	24s	66s	48s	33s
Average dwell time in hall (without physical ticket)	13s	22s	20s	17s

The statistics indicate that app-based QR codes for station entry could become the predominant method, resulting in the enhancement of metro service levels.

Residents could not use physical metro tickets, and most ticket buyers were visitors or occasional travellers. Consequently, the responses and behaviours of these newcomers are valuable for optimising complex metro stations. This distinction between physical and non-physical ticket holders could be particularly relevant for metro stations connected to airports, docks and long-distance train stations.

3.3 Selection of data collection areas based on AnyLogic

Application of the AnyLogic simulation tool

To quantify the impact of newly opened subway lines on passenger flow in existing stations, an analysis of pedestrian capacity and traffic efficiency was conducted based on passenger flow simulation. Currently, two widely recognised and cited models dominate pedestrian traffic simulation: microscopic and macroscopic models. Microscopic models represent pedestrians as discrete particles and focus on their interactions, including the social force model, cellular automaton model, multi-grid model, agent-based model and others [25]. Considering the microscopic-level requirements for subway station passenger flow simulation, pedestrian interaction dynamics and prior research experience [26], this study employs the social force model implemented in the AnyLogic simulation software for analysis [27]. The software utilises an enhanced social force model to account for psychological and physical forces governing pedestrian behaviour, avoidance manoeuvres and vector-based continuous motion calculations.

The social force model captures pedestrians' spatial demands, simulates acceleration/deceleration patterns, and provides data-driven insights for facility performance evaluation. Additionally, it resolves path conflicts among pedestrians and models avoidance behaviours. Pedestrian traffic modelling can be categorised into three levels: macroscopic, mesoscopic and microscopic. Evaluation frameworks exemplified by Fruin's level of service (LOS) assessment effectively quantify pedestrian service quality at the microscopic level [28]. Consequently, this study adopts Fruin's LOS criteria to evaluate platform-level pedestrian service performance, with detailed hierarchical metrics outlined in *Table 4*.

Table 4 – Fruin evaluation system

Level of service	Space per capita (m2/ped)	Density (ped/m2)
LoS A	≥3.24	≤0.27
LoS B	2.32~3.24	0.43~0.31
LoS C	1.39~2.32	0.72~0.43
LoS D	0.93~1.39	1.08~0.72
LoS E	0.46~0.93	2.17~1.08
LoS F	≤0.46	>2.17

During evacuation processes in public spaces, large crowds often aggregate and move at high densities within limited timeframes. When passing through bottleneck areas, they frequently experience mutual pushing and stagnation, which may escalate into public safety incidents. Due to their narrow layouts and the requirement for instantaneous evacuation of massive passenger flows, subway platforms are particularly prone to high-density crowd stagnation at critical evacuation facilities, posing significant safety risks. In studies on bottleneck-area evacuations, scholars have quantitatively investigated crowd psychological responses and movement speeds under varying density conditions [29]. Additionally, to address safety challenges in urban rail transit systems, a congestion risk assessment and mitigation methodology has been proposed to enhance passenger safety and operational efficiency [30]. Existing research reveals an inverse proportionality between pedestrian walking speed and crowd density. At 2–4 persons/m^2, frequent bodily contact occurs without collisions, but movement speed becomes markedly constrained. At 4–6 persons/m^2, unavoidable physical contact leads to delayed crowd movement. When density exceeds 6 persons/m^2, bodily compression occurs, and crowd movement approaches stagnation [31]. Building upon these findings and relevant standards, this study implements a Java-based module within the AnyLogic platform to simulate autonomous pedestrian deceleration mechanisms triggered by excessive density in forward areas. The design and validation process of this module are detailed in Section 3.3.2.

AnyLogic is a versatile simulation modelling tool that has been widely utilised in transportation, logistics and manufacturing. Its robust modelling and simulation capabilities enable precise simulation of complex systems' operational states and dynamic changes, supporting optimised decision-making. When studying metro station service levels, AnyLogic can model passenger flow within stations, allowing for the evaluation of service levels and congestion under various conditions.

Construction of the AnyLogic simulation model

The simulation models for both pre- and post-renovation conditions were developed based on the actual layout of the metro station, with the parameters set for the capacity, flow and service facilities in various areas. By simulating the passenger flow under different scenarios, the congestion and service levels were analysed, with the identification of the optimal positions for YOLOv8 cameras to ensure the effective coverage of key areas within the station.

This study employed image capture equipment to conduct on-site photography, informed by the investigation of the existing components at Huashi Station. At Huashi Station, the measured peak passenger flow before renovation was approximately 9,650 people per hour, and the predicted flow after renovation was 32,864 people per hour, with a super-peak coefficient of 1.3. The distribution ratio was established based on the flow distribution at the entrances and exits, and the parameters for the internal facilities and equipment were obtained from "Guangzhou Metro New Line Construction Standards" (*Table 5*).

Table 5 – Passenger flow simulation in existing metro stations

Part description	Category	Capacity (people/hour)
Passage	Single direction	4800
	Mixed direction	3900
Stairs	Upward	258
	Mixed	2580
Escalator	Operating speed	7800
Turnstile	Entry turnstile	1500
	Exit turnstile	1200
Ticketing	Manual ticketing	1200
	Automatic ticketing	240
	Manual inspection	2600

The platform layout plan was imported into AnyLogic software to construct service facilities, architectural structures and spatial configurations within the designated area. Using the pedestrian library modules in AnyLogic, behavioural logic workflows were established for pedestrians, which can be broadly categorised into: Pedestrian generation (Pedsource), Path selection (SelectOutput), Movement (PedGoTo), Facility interaction (PedService), Waiting area arrival (PedWait), Pedestrian termination (PedSink).

Following the model and pedestrian logic workflow construction, device and pedestrian parameters were calibrated. For service facility module parameters, computational values were assigned in accordance with the Guangzhou Metro New Line Construction Standards, supplemented by field survey data to define pedestrian attributes for each module. Integrated with parameters acquired through YOLO detection, a Java-coded YOLO module was implemented to enforce speed reduction for pedestrians when congestion occurs in forward target areas, as illustrated in *Figure 10*.

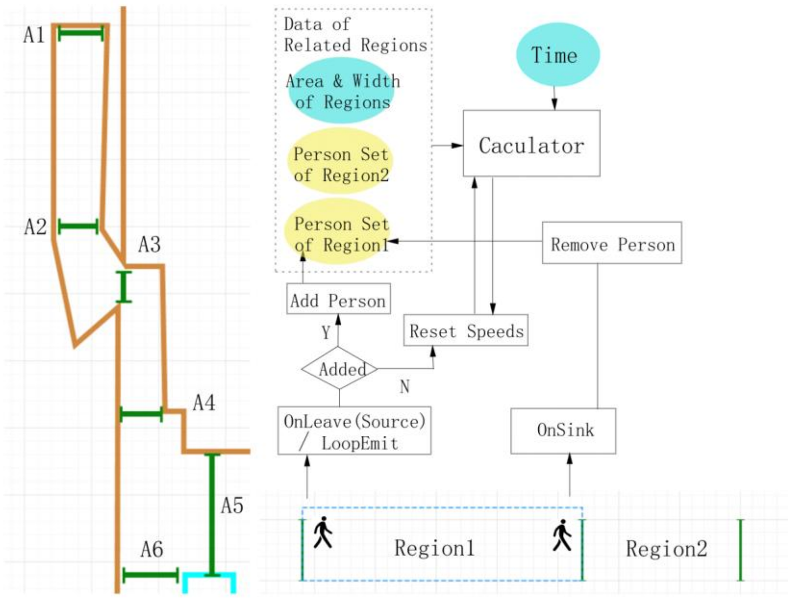

Figure 10 – t2t simulation strategy

During model construction, we divide the model into multiple zones. For convenience, this pattern is termed t2t (targetLine to targetLine) modelling. Unlike traditional origin-destination (O-D) modelling, even a single pedestrian's path is completed by relying on multiple data sources. For example, a pedestrian is generated at A1, flows to the A2 sink, then regenerated at A2 and flows to the A3 sink. The advantage is that there is no need to wait for the pedestrian to complete the entire journey to count as valid data. Only if a t2t movement is completed within the monitoring scope, it becomes data for pedSource. The model exclusively processes t2t data retrieved from services. This allows us to simulate a pedestrian's movement from A1→A2→A3 in advance, without requiring prior knowledge of whether they will ultimately choose A5 or A6.

The data update cycle is set to 10 minutes. In reality, a single t2t movement typically takes no more than 2 minutes under congestion-free conditions. The 10-minute interval is designed to account for extreme scenarios such as queuing. Prolonged dwell times are rare; only staff who are considered noise data are always lingering in one area.

Each time a pedestrian is created, its speed will be set depending on reality average speed, thus the overall pass time is consistent with that in reality. These t2t data rely on YOLO-based extraction and constitute a time-delayed model grounded in historical data.

The predictive model is also grounded in t2t (targetLine-to-targetLine) modelling and dynamically updates pedestrian speeds through a weighted calculation that incorporates: pedestrian count in the relevant area, pedestrian density, time period (peak vs. non-peak hours), throughput capacity of the area (determined by passage width) and pedestrians' intrinsic speed. The correlation coefficients are iteratively calibrated by comparing model outputs with actual t2t data. After training with multi-day t2t data, the coefficients yielding the minimal travel time error are selected as the final parameters for the predictive model. The simulation results of the current Huashi Station layout are presented in *Figure 11*, while the remodelled scenario based on the proposed renovation plan is shown in *Figure 12*. The simulation commenced with pedestrian entrance into the building (initial density set to zero). Data were recorded at one-second intervals over a one-hour period, yielding 3,600 discrete data points for analysis.

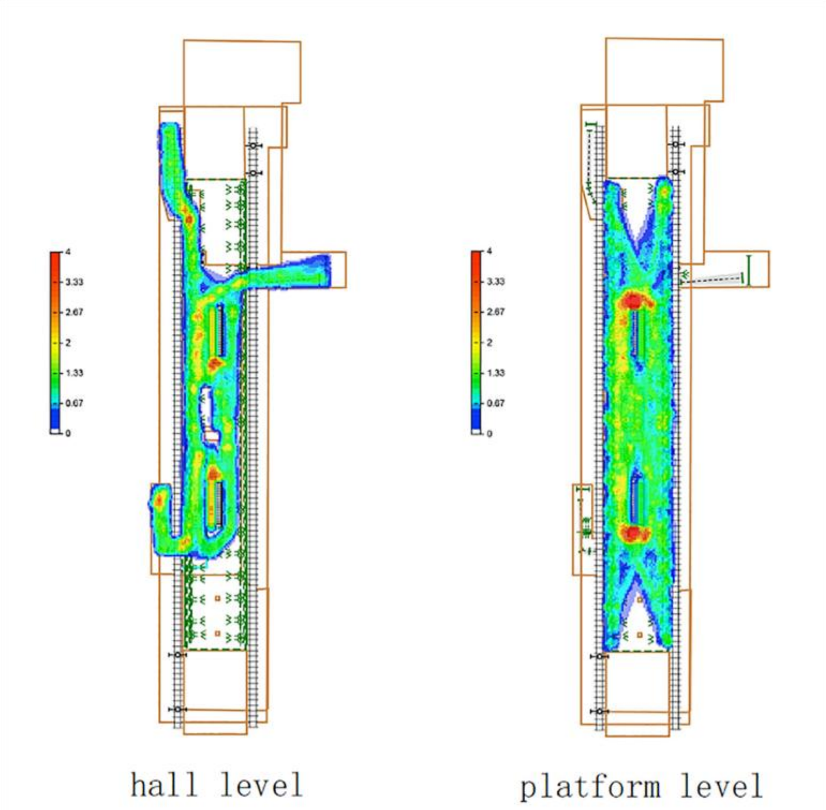

Figure 11 – Passenger flow simulation in existing metro stations

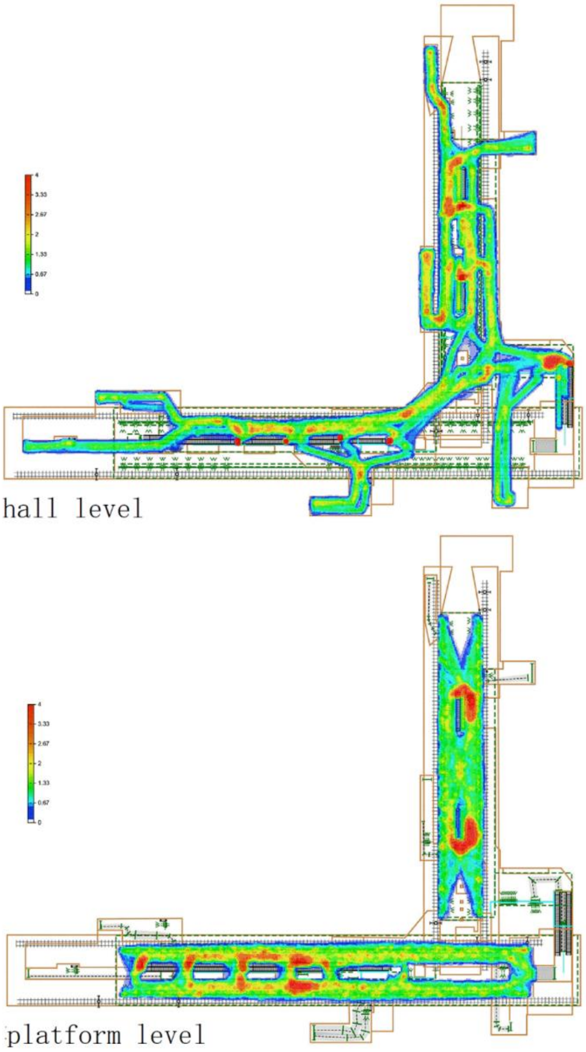

Figure 12 – Passenger flow simulation in metro stations after integration of new lines

The simulation analysis revealed the following. (1) Renovating the original station into a transfer station increased the passenger flow pressure at the concourse and platform levels, particularly at the transfer corridors and entrances/exits. (2) The influx of transfer passengers resulted in higher average densities at escalator entrances and platforms, causing congestion, with the density fluctuations in escalator areas being significantly greater than those at the overall concourse level. (3) The pressure points were highly correlated, and a larger inbound passenger flow at the concourse level increased the density at security checkpoints, whereas the increased crowd density at the platform level quickly led to congestion in the corridors. Therefore, this study recommends the installation of cameras at key locations such as station hall entrances, security checkpoints, main hall areas, escalator entrances and platforms to capture images. Identifying safety risk points along passenger flow trajectories will help determine the critical nodes for targeted data collection and analysis.

4. DISCUSSION AND CONCLUSIONS

Based on the integrated application of YOLOv8 human detection technology and AnyLogic passenger flow simulation models at Guangzhou Metro's Huashi Station, and by comparing the real passenger flow data with the simulated models, the following conclusions can be drawn:

1) Utilising the YOLOv8 object detection model for data collection, combined with big data analytics tools, enabled the rapid capture and assessment of passenger flow dynamics in metro stations, providing a low-

latency overview of passenger movement.

2) The AnyLogic simulation model generated a passenger flow prediction and simulation model based on the existing metro station spatial model, offering essential parameters and key node information regarding passenger movements.
3) Combining the YOLOv8 object detection model with the AnyLogic simulation model facilitated the development of a low-latency passenger flow model for metro stations. This model can be referenced and validated against actual conditions, providing a foundation for further optimisation of the spatial layout of metro stations.

The integration of the YOLOv8 object detection model with the AnyLogic simulation model not only evaluated the metro station passenger flow organisation but also offered a scientific basis and guidance for expansion or renovation designs. This approach helped identify issues in existing facilities and layouts, optimised passageways and spatial configurations, enhanced emergency evacuation capabilities, improved service facilities, and elevated overall service quality and passenger satisfaction. During the expansion process, leveraging these data enabled a more intelligent and efficient design, ensuring that the station met passenger needs more effectively and enhanced the travel experience in future operations.

As the chief designer of this project, the author further identified that the proposed technical framework demonstrated significant adaptability in the renovation practices of L-shaped transfer stations within the Guangzhou Metro system, such as Shachong Station. These stations, characterised by asymmetric transfer paths and angular spatial bottlenecks, were optimised through the deployment of a YOLOv8 real-time monitoring system and multi-scenario AnyLogic simulations. Specifically targeting peak-hour congestion delays at L-shaped corridor intersections, the framework facilitated: streamline optimisation (e.g. installation of diagonal guidance signage), spatial reconfiguration (e.g. expansion of angular buffer zones) and facility innovation (e.g. dynamic flow-control gates).

Building on these implementations, the framework is currently being extended to the ongoing Shiliugang Station expansion project, a new L-shaped transfer hub interfacing with the existing Longtan Station. Planned approaches include three-dimensional spatial thermal simulations and behavioural trajectory clustering analysis to establish a hierarchical response mechanism spanning station halls, corridors and critical facilities. This initiative aims to provide a replicable technical paradigm for the intelligent retrofitting of similar transfer stations.

In this study, we discovered a strong temporal and spatial correlation in the occurrence of congestion at various nodes. Before platform congestion occurs, there is often a "temporal precedence" of congestion at ticket gates and escalators. After a certain period of congestion at these upstream nodes, the congestion gradually spreads to the platform. By employing object detection techniques combined with data analysis, this "temporal precedence" of congestion can be effectively captured. It is important to note that the current framework prioritises pre- and post-renovation simulations, as its primary goal is to inform infrastructure upgrades. However, the integration of YOLOv8's low-latency detection capability (Section 3.2.1) inherently supports real-time operational monitoring. By more strategically positioning image collection areas at each node and refining the monitoring of various dimensional indicators, future work could extend this framework to real-time applications by implementing edge computing devices for on-site data processing and integrating adaptive control algorithms (e.g. dynamic signage or gate scheduling). This, in turn, provides critical reference for metro station operation management and enables the implementation of appropriate measures, thereby enhancing the station's ability to handle peak traffic. Additionally, the system can issue early warnings when abnormal passenger flow behaviour is detected, significantly reducing response time for management teams and improving overall safety.

Future research will address the limitations of data consistency and availability by developing a comprehensive set of evaluation metrics for passenger flow dynamics. This research should focus on accurately reflecting the spatial and dynamic characteristics of passenger movement and examining the interactions between individual behaviours and overall passenger flow under various abnormal conditions. The objective is to integrate these insights to optimise the metro station passenger flow organisation, offering new perspectives for metro station design and capacity expansion. This area remains a key focus for future research.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors on request.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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APPENDIX

Actions

On exit:

```
String fromT = "A1_1";
String toT = "A1_2";
String areaName = getAreaName(fromT, toT);
// record the info of pedSource on Pedestrian
ped.fromT = fromT;
ped.toT = toT;

speedControl(ped, areaName);

getPedSetByArea(areaName).add(ped);
```

Figure A1 – Additional processing of pedSource based on t2t modelling

```
 public
double
 getSpeed( Pedestrian ped ) {

        Set<PolygonalNode<Agent>> relatedNodes = getRelatedNodes(ped);
        List<String> areaNameList = getRelatedArea(ped, relatedNodes);
        List<Double> densityList = getDensityList(areaNameList);
        Date date = new Date();

        double speed = calSpeed(ped, areaNameList, densityList, date);

        return speed;
 }

 void speedControl( Pedestrian ped, String areaName ) {

        int strategyId = getRefreshStrategyId(areaName);
        if (strategyId > 0) {
            // use Publish-Subscribe Pattern
            PedSubscriber subscriber = new PedSubscriber(this, ped);
            setPublisher(strategyId, subscriber);
        } else {
            // update only once
            double speed = getSpeed(ped);
            ped.setSpeed(speed, MPS);
        }
 }
```

Figure A2 – Code excerpts: Dynamic speed adjustment module