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Establishment and Application of Passenger Flow Safety Management Evaluation Model with Entropy Weight and TOPSIS for Metro Stations

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ABSTRACT
As a critical component of urban transportation, metro systems demand rigorous passenger flow safety management. This study proposes a comprehensive decision-making analysis method for metro station passenger flow safety management by integrating the entropy weight and TOPSIS methods. It aims to develop an evaluation model that accurately assesses and ranks the safety management practices of metro stations. To achieve this, 17 indicators related to station scale, safety management equipment, safety or security measures, investment in safety management and the effects of passenger flow management are selected to form an evaluation indicator system. The entropy weight method is employed to allocate weights to these indicators, reflecting their interrelatedness and importance. Subsequently, the TOPSIS method is used to establish a decision model that calculates the closeness of each station's management practice to an optimal plan, allowing for the ranking of different stations' safety management practices. The algorithms are developed and optimised using MATLAB, enabling efficient calculation and analysis. A case study involving real metro stations is conducted to validate the feasibility and effectiveness of the proposed evaluation method. The results demonstrate that this model provides an accurate assessment of metro station passenger safety management and offers decision-makers clear directions for improvement.

KEYWORDS
metro station; passenger flow; safety; entropy weight; TOPSIS; evaluation model.

1. INTRODUCTION

1.1 Background

With the continuous acceleration of urbanisation in China and other developing countries, the amount of travel by urban residents has also increased year by year [1]. As an efficient means of public transportation, metro systems carry a large number of passengers every day and occupy an important position in the urban transportation system [2]. However, with the rapid growth of the urban population, the passenger flow density of metro stations continues to rise, resulting in increasing metro station safety hazards and bigger passenger flow management challenges. In history, safety accidents such as stampedes [3], crowding or congestion [4, 5], fire [6, 7] and other accidents or emergencies have occurred frequently in metro stations, some of which have even caused serious casualties and property losses. Therefore, how to effectively deal with the safety management of metro passenger flow has become one of the important problems to be solved. Different cities and metro station authorities often adopt different passenger flow safety management policies or measures, including prediction, early warning and dispatch [8–10], passenger guidance [11], metro line design optimisation [12], adding temporary ticketing channels [13], implementing inbound flow restriction measures [14, 15], calculation or simulation modelling [16, 17] and optimising train scheduling [18–20] et al. However, how to reasonably choose or evaluate the effectiveness of these policies or measures is often difficult. Against this background, it is particularly critical to evaluate the effectiveness of the metro passenger flow safety management model accurately. Only relying on experience and subjective judgment cannot fully grasp the advantages and disadvantages of safety management modes, and it is easy to be affected by personal preferences and limitations. Therefore, it is necessary to use scientific methods and tools to accurately evaluate the metro passenger flow safety management mode. This can not only provide a more scientific and effective safety management mode for metro stations but also reduce the probability of safety accidents and ensure the safety of passengers and staff.

To sum up, it is of great significance to accurately evaluate the effectiveness of the metro passenger flow safety management mode adopted by metro stations to improve the safety level and the overall operation level of the metro system. Therefore, it is necessary to establish a scientific and rigorous evaluation system to comprehensively evaluate the performances of different safety management modes, and provide more reliable support and guidance for the safety management of metro stations.

1.2 Literature review

Currently, a variety of evaluation methods have been adopted to evaluate the safety management mode of passenger flow in metro stations. The evaluation methods commonly used by researchers include the analytic hierarchy process (AHP) or improved AHP, grey system theory, data envelopment analysis (DEA), simulation method, etc.

By constructing a hierarchical structure, the analytic hierarchy process (AHP) decomposes complex problems into multiple levels, then makes pair comparisons to determine the weight of each indicator, obtains the score value of the indicator through expert scoring or data collection, and finally calculates and obtains the evaluation result [21]. This method is easy to operate and can indicate the importance of each indicator, but it has some disadvantages such as strong subjectivity, relying on expert experience and possibly introducing bias. Therefore, when using the analytic hierarchy process, researchers usually optimise and improve it. In 2013, Kepaptsoglou et al. presented a model for rating the service condition of metro stations, the model is derived based on the opinion of a group of experts and explicitly considers uncertainty. Also, they tested the accuracy of this mode by using the data of a real metro system [22]. Based on the combination of subjective and objective AHP with the available particle swarm optimisation (PSO) algorithm and the perfect CRITIC (criteria importance through intercriteria correlation) empowered fuzzy evaluation method on the metro station fire hazard toughness indicator system and its weights were determined, and a fuzzy comprehensive evaluation model of metro station safety toughness under the influence of baggage was constructed by Zhang et al [23]. Baradaran et al identified and prioritised thirteen risks in the Tehran metro using a grey analytic hierarchy process (GAHP) based on expert opinions, focusing on reducing the probability and severity of these risks [24]. The author developed a risk index for elevated corridor metro rail construction in Western India using a fuzzy analytical hierarchy process to evaluate various quality parameters, aiding in identifying and mitigating the most risky activities for timely and cost-effective project completion [25].

Grey system theory utilises a minimal amount of data for systematic analysis and is particularly suited for evaluating scenarios with incomplete information or high uncertainty. By employing grey correlation analysis and other methodologies, it effectively conducts systematic evaluation and prediction [26]. For instance, Wang et al. applied grey correlation analysis to assess the resilience of urban rail transit systems, analysing factors like potential risks, operational conditions and triggering elements. This method facilitates dynamic hazard evaluation and quantitative risk analysis during system operations [27]. Matara et al. employed the grey system theory alongside the likelihood exposure consequences (LEC) method to evaluate passenger risks in Kenya's railway system. They developed a risk index for 80 identified hazards, which supports enhanced risk management strategies and future research endeavours [28]. Moreover, the grey system theory can predict metro passenger flows. Wang et al. integrated this theory into a time series model to forecast total passenger flows at metro stations, validating their approach through calculation and analysis [29].

Data envelopment analysis (DEA) is a method that employs linear programming to assess the efficiency of multiple units by establishing efficiency frontiers and identifying top and bottom performers [30, 31]. Khadem Sameni et al. applied DEA originally used in studies on port and airport efficiency to rank train stations across Great Britain based on efficiency metrics and facilitate informed decision-making. Their study of 96 high-traffic stations evaluated both technical efficiency and service effectiveness, employing tobit regressions to analyse the impact of traffic types and locations [32]. In another application, Swami et al. utilised DEA to evaluate the efficiency of Delhi Metro's Red and Yellow lines, incorporating commuter feedback from 1,328 responses to assess station performance and suggest improvement strategies [33]. Similarly, Azadeh et al.

employed DEA alongside a comprehensive framework integrating health, safety, ergonomics and resilience engineering to assess the performance of the Tehran-Karaj railway system. Their approach included questionnaire analysis to complement the DEA evaluation [34].

With advancements in computer technology, researchers increasingly utilise simulation methods to assess passenger flow safety management in metro stations. This approach involves developing dynamic passenger flow simulation models to evaluate safety management effectiveness under various conditions. Recent studies have focused on evaluating response measures during fire incidents [35, 36], terrorist attacks [37, 38], congestion issues [39, 40] and other emergencies by establishing numerical calculation models. Some researchers have also explored optimising passenger flow management through simulation techniques [41–43]. However, the simulation method demands meticulous model construction and accurate data for authenticity, making the process complex and time-consuming.

In general, although the existing research has achieved some results, there are still some shortcomings. For example, part of the evaluation system only aims at a single safety problem. The evaluation indicator system established by some researchers is a non-quantitative indicator, which adopts expert evaluation based on experience. Some evaluation models have limitations in weight allocation and decision analysis and fail to fully consider the complexity of passenger flow safety management. In the process of passenger flow safety management of metro stations, the accurate selection of reference or reference objects, that is, by adopting or learning from the management measures of stations with good passenger flow safety management effect, the level of passenger flow safety management of similar stations can be effectively improved. Therefore, how to accurately evaluate the effect of metro passenger flow safety management and determine the reference object becomes very important. This article intends to use the combination of the entropy weight method and technique for order preference by similarity to an ideal solution (TOPSIS) method to propose a comprehensive decision-making analysis method for passenger flow safety management in metro stations, to provide a new perspective and solution for passenger flow safety management.

1.3 Research questions

To cope with the increasingly complex problems and more difficult challenges faced by passenger flow safety management of metro stations, this article mainly focuses on the following issues, namely, proposing a scientific and reasonable decision-making analysis method for passenger flow safety management of metro stations, to select a better scheme more accurately from different passenger flow safety management modes adopted by similar stations. To provide references or a decision-making basis for station management. Specifically, by establishing an evaluation indicator system that considers various factors, and using reasonable mathematical methods to accurately calculate the safety management schemes adopted by metro stations with similar scales and similar passenger flows, a reliable reference object is provided for the optimisation of station management mode and the improvement of measures.

The significance of this study is to provide a comprehensive and scientific passenger flow safety management method for metro station authorities. By establishing an effective evaluation and decision analysis model, a reliable passenger flow safety management mode can be found, and more scientific and effective preventive and emergency measures can be formulated.

2. METRO STATION PASSENGER FLOW SAFETY MANAGEMENT EVALUATION MODEL

2.1 Evaluation indicator system

When establishing the decision model indicator system of metro passenger flow safety management, various factors should be considered to establish the indicator system that can comprehensively evaluate the passenger flow safety management of metro stations. Factors related to the passenger flow safety management of metro stations mainly include the building scale of the station, the configuration and operation status of the equipment related to passenger flow management and the investment of security funds, etc. Therefore, the above factors should be considered when establishing the indicator system, and the quantification and availability of each indicator should also be considered. Based on the above principles, an evaluation indicator system was established, as shown in *Table 1*. Among them, there are 3 indicators related to station scale, 5 indicators related to passenger flow safety management equipment, 3 indicators related to safety or security, 3 indicators related to capital investment in passenger flow safety management and 3 indicators related to the passenger flow safety management effects.

Table 1 – Evaluation indicator system for evaluation model for the evaluation of metro station safety management mode

Variables	Meanings	Level-3 Indicators
Effectiveness of metro station safety management mode (A)	Basic station information (A_1)	*Daily ridership* (A_{11})
		Station construction area (A_{12})
		Pass rate of entrances and exits (A_{13})
	Equipment (A_2)	*Number of equipment related to passenger flow safety* (A_{21})
		Application rate of intelligent security equipment (A_{22})
		Uptime proportion of passenger flow safety-related equipment (A_{23})
		Average repair time of equipment failure (A_{24})
		Equipment inspection frequency (A_{25})
	Safety and security (A_3)	*Number of security staff* (A_{31})
		Quality of security personnel training (A_{32})
		Number of emergency drills (A_{33})
	Passenger flow safety management investment (A_4)	*Annual passenger flow safety management budget* (A_{41})
		The proportion of the annual passenger flow safety budget in the total budget (A_{42})
		The proportion of safety training expenses in the total training expenses (A_{43})
	Management effect (A_5)	*Number of accidents* (A_{51})
		Average emergency response time (A_{52})
		Passenger satisfaction (A_{53})

2.2 Indicator values determination

Before the subsequent evaluation calculation, it is necessary to collect values of various indicators related to passenger flow safety in different management modes of each station to be evaluated, including passenger flow, station construction area, entrance and exit passage pass rate, etc. In the process of data collection, attention should be paid to ensuring the timeliness and comprehensiveness of data, to establish a data set that truly reflects the safety situation of metro stations. The indicators are determined or calculated as follows.

1) *Daily ridership* (A_{11}). Calculated as the average of the total number of daily passengers disembarking and transferring at the station in the most recent year.
2) *Station construction area* (A_{12}). The building scale of the station is directly related to the difficulty of its safety management. Larger sites may require more monitoring equipment, security personnel and emergency exits, so the construction area is an important indicator of the building scale of a metro station. The unit of station construction area is m^2.
3) *Pass rate of entrances and exits* (A_{13}). Evaluate whether they are qualified by investigating the width of each entrance and exit channel, the clarity of the channel identification, and whether the channel meets the relevant safety standards, and finally calculate the pass rate of the entrance and exit channels of the station.
4) *Number of equipment related to passenger flow safety* (A_{21}). It refers to the total number of monitoring cameras, security inspection equipment, entrance and exit gates, intelligent broadcasting systems, escalators and lifts, platform security doors and other passenger flow safety management-related equipment.
5) *Application rate of intelligent security equipment* (A_{22}). The proportion of intelligent security equipment adopted by stations, such as intelligent surveillance cameras, intelligent access control systems, etc., reflects the level of technological innovation in the security management of stations.
6) *Uptime proportion of passenger flow safety-related equipment* (A_{23}). It refers to the percentage of uptime of the equipment in the most recent year.
7) *Average repair time of equipment failure* (A_{24}). It refers to the average time between the time when the fault is detected and the time when the fault is successfully repaired. The equation is as follows: average value of time to repair faults = Σ (time taken to repair each fault)/total number of faults.
8) *Equipment inspection frequency* (A_{25}). It refers to the number of routine inspections or inspections of specific equipment, including escalators, elevators, and entrance and exit gates. The inspection aims to ensure the normal running of devices, detect potential problems and maintain devices on time to improve device reliability, stability and service life. The unit of measurement is time/month.

9) *Number of security staff* (A_{31}). It refers to the number of security personnel engaged in passenger flow guidance, emergency management, passenger flow evacuation and other duties related to the station's safety management of the passenger flow.
10) *Quality of security personnel training* (A_{32}). The quality of security personnel training can be assessed by the passing rate of security personnel participating in security training within a year, if there are multiple assessments in a year, the average value can be taken.
11) *Number of emergency drills* (A_{33}). The drill frequency can be quantified as the number of emergency evacuations, passenger flow management and other simulations or drills carried out by the station every year.
12) *Annual passenger flow safety management budget* (A_{41}). It refers to the budget for passenger flow safety management of the station, the unit is 10,000 yuan/year.
13) *The proportion of the annual passenger flow safety budget in the total budget* (A_{42}). The proportion of the annual investment in safety management costs to the total operating budget of the station.
14) *The proportion of safety training expenses in the total training expenses* (A_{43}). The proportion of the annual investment in safety training costs to the total cost of training station staff.
15) *Number of accidents* (A_{51}). It refers to the number of fires, stampedes, terrorist attacks, malicious injury incidents and more than 500 people stranded or congested events in the most recent year.
16) *Average emergency response time* (A_{52}). Response time can be quantified as the average time for security personnel to arrive at the scene after a security incident during the most recent year. The unit is minute.
17) *Passenger satisfaction* (A_{53}). Passenger satisfaction can be obtained through regular satisfaction surveys, which are measured in percentage (%). The average satisfaction obtained from multiple passenger satisfaction surveys conducted in the most recent year is set as the value of this indicator.

2.3 Calculation process

Combining the entropy weight method and the TOPSIS method, an evaluation model for passenger flow safety management is established (*Figure 1*). Initially, the entropy weight method is employed to determine the weight of each indicator, considering its relative importance. Subsequently, the weights and standardised indicator data are input into the TOPSIS model to calculate the comprehensive safety scores of each metro station, ultimately yielding the ranking results. By adopting this model, decision-makers can comprehensively compare the effectiveness of different metro station passenger flow management modes, gain insights into the passenger flow management status of each metro station, and obtain scientific support for the reasonable formulation or selection of appropriate metro station safety management strategies.

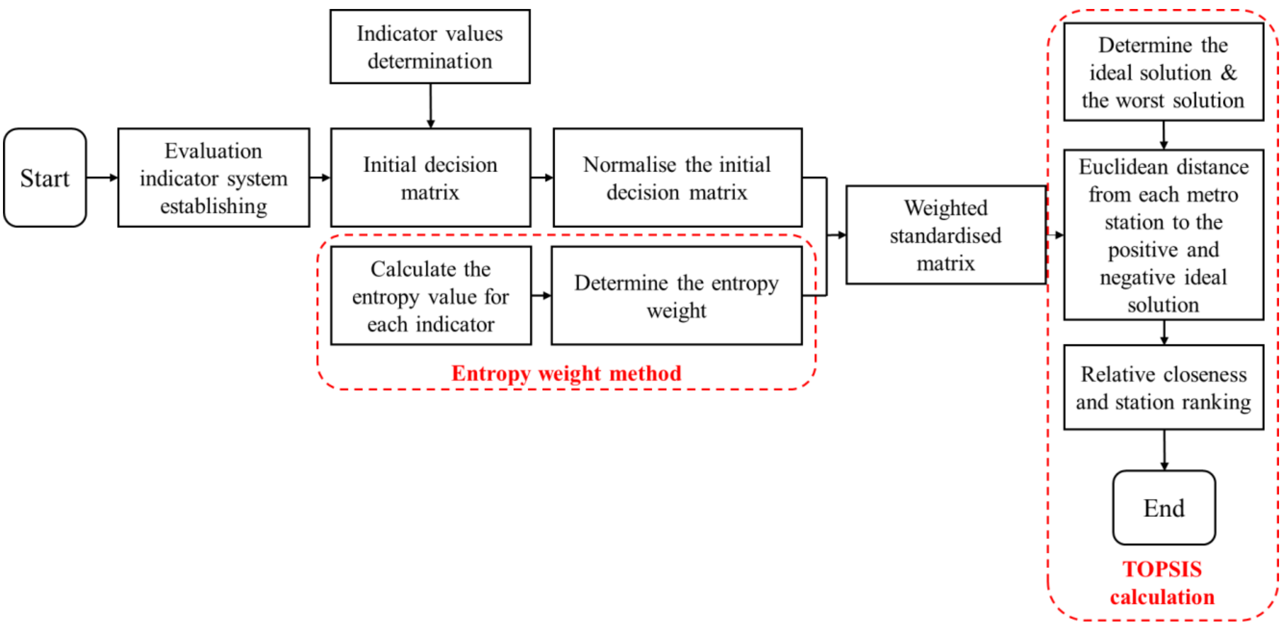

Figure 1 – The modelling procedure for the safety management mode of passenger flow in metro stations of entropy – TOPSIS method

The detailed calculation process using the entropy weight method and TOPSIS model for passenger flow safety evaluation of metro stations is as follows.

Step 1: Assuming the evaluation of m metro stations with n evaluation indicators respectively, the initial decision matrix $A=(a_{ij})_{m\times n}$ can be established. In the matrix, a_{ij} represents the value of the j-th indicator for the i-th metro station (where i = 1, 2, ..., m; j = 1, 2, ..., n).

Step 2: Normalise the initial decision matrix to obtain a standardised matrix $R=(r_{ij})_{m\times n}$. For indicators where higher values are preferable, *Equation 1* can be used for the normalisation.

$$r_{ij}=\frac{a_{ij}-\min_j a_{ij}}{\max_j a_{ij}-\min_j a_{ij}} \tag{1}$$

For indicators where lower values are preferable, *Equation 2* can be used for the normalisation.

$$r_{ij}=\frac{\max_j a_{ij}-a_{ij}}{\max_j a_{ij}-\min_j a_{ij}} \tag{2}$$

For indicators where moderate values a_{best} are preferable, *Equation 3* and *Equation 4* can be used for the normalisation.

$$M=\max\left(|a_{ij}-a_{best}|\right) \tag{3}$$

$$r_{ij}=1-\frac{|a_{ij}-a_{best}|}{M} \tag{4}$$

Step 3: Use *Equation 5* to calculate the entropy value for each indicator;

$$H_j=-\frac{1}{\ln m}\sum_{i=1}^{m} f_{ij}\ln f_{ij} \tag{5}$$

where, $f_{ij}=\frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$. If $f_{ij}=0$, then $f_{ij}\ln f_{ij}=0$.

Step 4: Determine the entropy weight for each indicator according to *Equation 6*.

$$\omega_i=\frac{1-H_j}{n-\sum_{j=1}^{n} H_j},\ 0\leqslant\omega_j\ll 1,\ \sum_{j=1}^{n}\omega_j=1 \tag{6}$$

Step 5: The weighted standardised matrix $Y=(y_{ij})_{m\times n}$ is obtained by multiplying the standardised matrix $R=(r_{ij})_{m\times n}$ by the weights calculated using the entropy weighting method. Where:

$$y_{ij}=r_{ij}\times\omega_j \tag{7}$$

Step 6: Determine the ideal solution and the worst solution. In the weighted standardised matrix: the maximum value of the positive indicator and the minimum value of the negative indicator are selected to form an ideal solution (*Equation 8*). Conversely, the minimum value of the positive indicator and the maximum value of the negative indicator are selected to form a negative ideal solution (*Equation 9*).

$$Z^+=\left(\max_{1\leqslant i\leqslant m} y_{ij}|\ j\in j^+,\ \min_{1\leqslant i\leqslant m} y_{ij}|j\in j^-\right)=(Z_1^+,\ Z_2^+,\ ...,\ Z_n^+) \tag{8}$$

$$Z^-=\left(\min_{1\leqslant i\leqslant m} y_{ij}|\ j\in j^+,\ \max_{1\leqslant i\leqslant m} y_{ij}|j\in j^-\right)=(Z_1^-,\ Z_2^-,\ ...,\ Z_n^-) \tag{9}$$

Step 7: The Euclidean distance from each metro station to the positive and negative ideal solution is calculated separately by *Equation 10* and *Equation 11*.

$$D_i^+=\sqrt{\sum_{j=1}^{n}(y_{ij}-z_j^+)^2}\qquad (i=1,2,....,\ m) \tag{10}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(y_{ij} - z_j^-)^2} \qquad (i = 1, 2, ..., m) \tag{11}$$

Step 8: Calculate the relative closeness to the positive ideal solution of each metro station by *Equation 12*.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

The value of C_i ranges from 0 to 1. The closer the value of C_i is to 1, the closer the solution is to the positive ideal solution.

2.4 Programming of the model in MATLAB

To reduce the workload of manual calculation and speed up the calculation, fast calculation can be realised by writing MATLAB code. The interface for calculating using MATLAB code is shown in *Figure 2*.

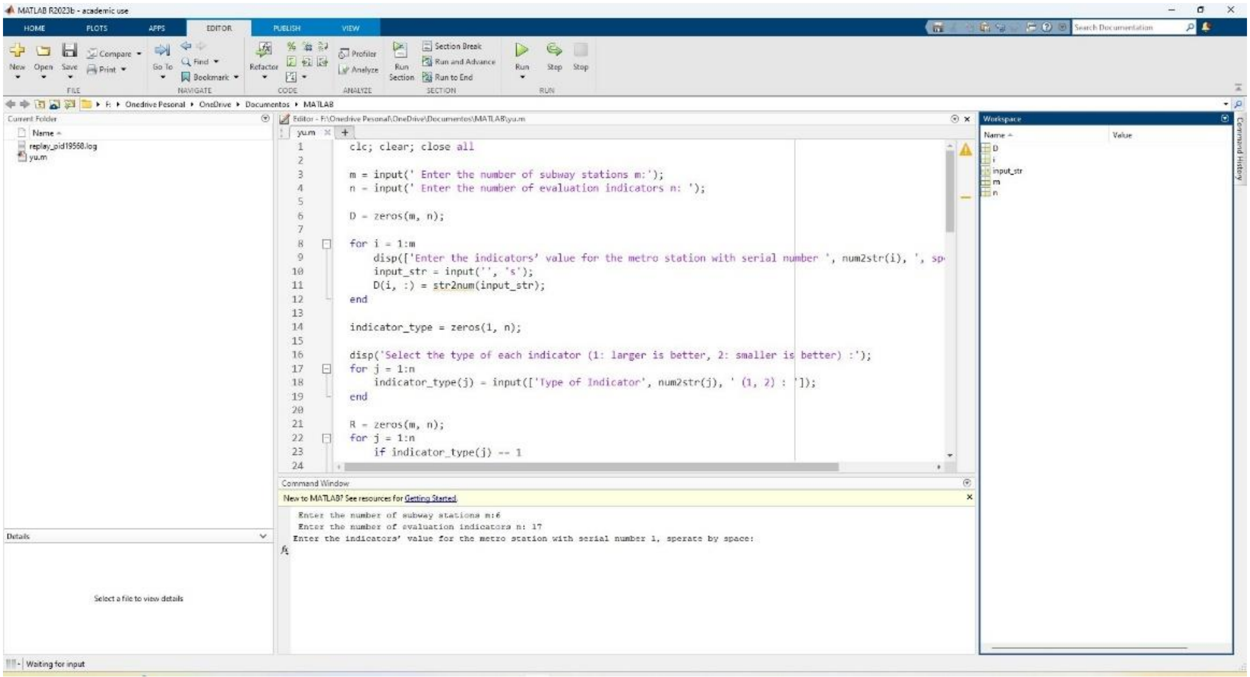

Figure 2 – The programmatic interface of the calculation process using MATLAB

2.5 Application of evaluation results

Based on the comprehensive evaluation results of the entropy weight method and the TOPSIS method, different passenger flow management modes of metro stations can be compared and ranked. According to the ranking results, the management measures of the top-ranking stations can provide a reference for the lower-ranking stations or other similar metro stations to improve the safety level of passenger flow management.

3. CASE STUDY

3.1 Information on metro stations

To verify the effectiveness of the proposed model for the safety management mode of passenger flow in metro stations based on the entropy weight method and TOPSIS method, 6 metro stations (#1, #2, #3, #4, #5 and #6) with relatively similar scale and passenger flow intensity were selected as cases to calculate and evaluate their safety management mode. The values of indicators for these 6 metro stations are listed in *Table 2*. The data for these indicators were obtained from official metro operation reports, on-site inspections and passenger surveys conducted over six months. The reliability of the data was ensured through cross-verification with independent sources, regular updates and validation by metro safety management experts. These measures ensured that the data accurately reflected the current state of safety management practices in the selected metro stations, providing a robust basis for the evaluation.

Table 2 – Level-3 indicators for 6 metro stations to be evaluated

No.	Level-3 indicators	Metro stations					
		#1	#2	#3	#4	#5	#6
1	*Daily ridership (A_{11})*	45,833	56,479	54,279	56,601	55,489	55,761
2	*Station construction area (A_{12})*	15,432	15,330	15,678	15,899	15,643	15,723
3	*Pass rate of entrances and exits (A_{13})*	100%	100%	100%	100%	100%	80%
4	*Number of equipment related to passenger flow safety (A_{21})*	40	38	39	43	45	42
5	*Application rate of intelligent security equipment (A_{22})*	80%	75%	85%	77%	82%	79%
6	*Uptime proportion of passenger flow safety-related equipment (A_{23})*	98%	97%	99%	92%	91%	93%
7	*Average repair time of equipment failure (A_{24})*	2	2.5	1.5	2.7	1.8	2.2
8	*Equipment inspection frequency (A_{25})*	10	8	12	9	11	10
9	*Number of security staff (A_{31})*	10	8	7	8	9	11
10	*Quality of security personnel training (A_{32})*	90%	88%	92%	87%	91%	89%
11	*Number of emergency drills (A_{33})*	6	5	7	5	6	5
12	*Annual passenger flow safety management budget (A_{41})*	150	130	170	140	160	145
13	*The proportion of the annual passenger flow safety budget in the total budget (A_{42})*	15%	12%	18%	14%	16%	12.5%
14	*The proportion of safety training expenses in the total training expenses (A_{43})*	20%	18%	22%	17%	21%	19%
15	*Number of accidents (A_{51})*	3	2	4	2	3	2
16	*Average emergency response time (A_{52})*	5	6	4	6	5	6
17	*Passenger satisfaction (A_{53})*	85%	92%	87%	80%	84%	82%

3.2 Calculation results

After inputting the indicators of the 6 stations in MATLAB, the calculation results are obtained as shown in *Figure 3*. According to the calculation results shown in *Figure 3*, Station #3 has the highest relative closeness to the ideal solution, so it is the metro station with the best effectiveness of passenger flow safety management. When metro stations with similar conditions are planned to update their passenger flow safety management mode or measures, authorities can learn from or refer to the treatment measures of Station #3.

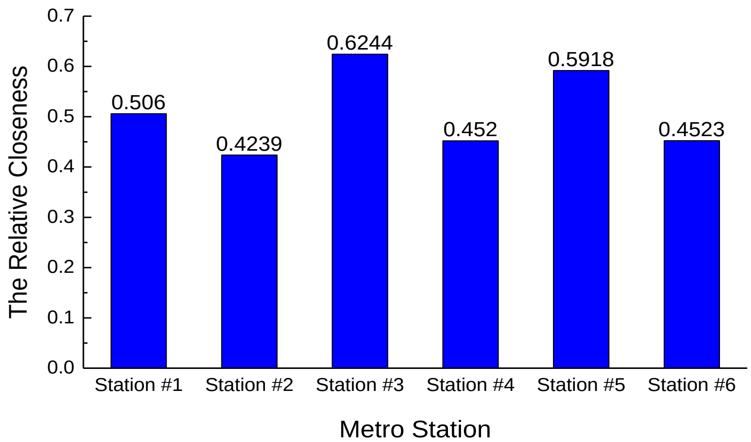

Figure 3 – The relative closeness between the 6 metro stations and the ideal solution

4. DISCUSSIONS

4.1 Implications of the findings

The integration of the entropy weight method and the technique for order preference by similarity to an ideal solution (TOPSIS) method provides a robust framework for evaluating and enhancing passenger flow safety management in metro stations. The developed evaluation indicator system, encompassing 17 critical factors, offers a comprehensive approach to addressing the multifaceted nature of metro safety management. The model effectively balances the relative importance and interrelationships among various safety indicators, allowing for precise determinations of each metro station's safety management performance relative to an optimal standard.

The case study involving six metro stations demonstrates the model's ability to differentiate safety management performance among stations with relatively similar scales and passenger flow intensity. The results indicate that Station #3 has the highest relative closeness to the ideal solution, suggesting it has the most effective passenger flow safety management. This finding implies that metro stations with similar conditions can benefit from adopting or adapting the safety measures implemented at Station #3.

4.2 Comparison with previous studies

The proposed model distinguishes itself from traditional evaluation methods such as the analytic hierarchy process (AHP), grey system theory, data envelopment analysis (DEA) and simulation methods, each of which has its advantages and limitations. The AHP method involves expert opinion and considers uncertainty but is criticised for its subjectivity and potential bias due to reliance on expert experience. Improved versions of AHP attempt to mitigate these limitations by incorporating objective data. Similarly, the entropy weight method in our model aims to provide an objective weight assignment, reducing the subjectivity inherent in traditional AHP approaches. Grey system theory, suitable for situations with incomplete data, has been effectively used for systematic evaluation and prediction in urban rail transit. While grey system theory excels in handling uncertainty, our model leverages the entropy weight method to objectively determine the weight of each indicator and TOPSIS to comprehensively evaluate safety performance, thus providing a more structured and quantifiable assessment. DEA focuses on efficiency frontiers and performance benchmarking. While DEA provides valuable insights into relative efficiency, our model extends beyond efficiency to include a broad spectrum of safety indicators, offering a holistic view of passenger flow safety management. Simulation methods, applied in various studies to evaluate and optimise passenger flow under different scenarios, are known for their detailed and dynamic analysis but are often complex and time-consuming. The proposed model, validated through real-world case studies, offers a practical and scalable alternative that balances complexity with usability.

4.3 Strengths and limitations of the model

The key strengths of the proposed model lie in its comprehensive indicator system and methodological rigour. By incorporating the entropy weight method, the model assigns objective weights to each safety indicator, reflecting their relative importance based on actual data variability. The TOPSIS method further enhances the model by providing a clear, quantifiable measure of each station's safety management performance relative to an ideal solution. Additionally, the use of MATLAB for algorithmic optimisation underscores the model's efficiency and scalability, ensuring it can perform complex calculations quickly, making it a valuable tool to ensure secure and efficient metro station operations. Despite these strengths, the model has certain limitations. The accuracy of the assessment is highly dependent on the quality and comprehensiveness of the selected indicators; any omissions or inaccuracies could affect the overall assessment. Furthermore, the general indicator system may not fully capture specific local conditions and factors, necessitating customisation for different metro systems.

5. CONCLUSIONS

To conclude, the integration of the entropy weight method and the technique for order preference by similarity to an ideal solution (TOPSIS) method presents a robust framework for evaluating and enhancing passenger flow safety management in metro stations. By developing an extensive evaluation indicator system encompassing 17 critical factors, the model comprehensively addresses the multifaceted nature of metro safety management. The model effectively balances the relative importance and interrelationships among various safety indicators, allowing for precise determinations of each metro station's safety management performance relative to an optimal standard. The practical implementation of this model, validated through real-world case studies, demonstrates its feasibility and effectiveness in providing accurate assessments and actionable insights for safety improvements.

However, the model's accuracy is dependent on the quality and comprehensiveness of the selected indicators, highlighting a potential limitation. Any omissions or inaccuracies in these indicators could affect the overall assessment. Additionally, the model may require customisation for different metro systems, as specific local conditions and factors may not be fully captured by the general indicator system. Future research could focus on expanding the indicator system to include additional factors that impact passenger flow safety and conducting further case studies across different metro systems and cities to refine and validate the model's applicability in diverse contexts. Integrating real-time data and advanced analytics, such as machine learning, could also enhance the model's predictive capabilities and responsiveness to dynamic conditions.

In summary, this model not only enhances the understanding of safety dynamics within metro stations but also equips decision-makers with a systematic approach to optimising passenger flow safety. The use of MATLAB for algorithmic optimisation underscores the model's efficiency and scalability, making it a valuable tool for urban rail transportation authorities, aiming to elevate safety standards and ensure secure and efficient metro station operations.

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DECLARATION

In the composition of this paper, AI tools were employed to refine the choice of words and the expression of the English language.

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基于熵权法和 TOPSIS 法的地铁车站客流安全管理评价模型的建立与应用

于恒

摘要

作为城市交通的关键组成部分，地铁系统需要进行严格的客流安全管理。本研究提出了一种结合了熵权法和 TOPSIS 法的综合决策分析方法，用于地铁车站客流安全管理。本研究的主要目的是建立地铁车站客流管理安全评估模型，以准确地地地铁车站的客流安全管理模式作出评价与排名。为此，选取了 17 个与车站规模、安全管理设备、安全或安保措施、安全管理投资和客流管理效果相关的指标，构建评估指标体系。并进一步采用熵权法为这些指标分配权重，反映它们的相互关系和重要性。随后，使用 TOPSIS 方法建立决策模型，计算每个车站安全管理模式与最佳方案的接近程度，从而对不同车站的安全管理模式进行排名。之后在 MATLAB 中实现了模型的程序化，提高

了计算和分析的效率。最后，通过对实际地铁车站开展案例研究，验证了所提出评估模型的可行性和有效性。案例分析结果表明该模型能够准确地对地铁车站客流安全管理模式进行评价，从而为决策者提供了明确的改进参考。

关键词

地铁车站；客流；安全；熵权法；TOPSIS；评价模型