Sentiment Analysis-Based Subway Passenger Flow Prediction and Decision Support

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Abstract: With the acceleration of urbanization, subways have become vital to public transportation. Accurate passenger flow prediction is key to optimizing operations and improving service. Traditional methods of prediction mainly use historical data, often ignoring emotional factors. Using machine learning algorithms and social media sentiment analysis, this study investigates how public emotion affects subway passenger flow. First, web scraping techniques are used to collect data from Weibo, and the large language model is used for sentiment analysis. Then, a random forest model is constructed using both sentiment data and historical subway passenger flow data for prediction. Experimental results indicate that model incorporating sentiment data is more accurate in predictions than traditional methods, particularly during emergencies or special time periods. This study provides a new perspective for subway management, which can be applied to optimize scheduling strategies.

1 INTRODUCTION

With the acceleration of urbanization, the subway has become a crucial vehicle of urban public transportation. Traffic planning, operational scheduling, and passenger flow management all depend on the ability to estimate passenger flow of subway.

Through a literature review conducted in recent years, there are 46 articles from Peking University Core Journals in CNKI. This indicates that subway passenger flow prediction is a relatively popular research direction. Additionally, an article on predicting passenger flow of subway using social media data was published in IEEE journal as early as 2016. This shows that passenger flow forecasts paired with information from social media has already established a certain research foundation.

However, while these models provide a certain level of prediction accuracy, they overlook the potential influence of public emotion on the flow of subway passengers. Social media is a significant information source in modern society. It reflects a amount of real-time public sentiment and behavioral patterns. Therefore, social media data, particularly sentiment analysis, can offer richer contextual information for subway passenger flow prediction. This can help to understand the causes of emotional fluctuations and enabling decision-makers to implement more human-centered and targeted strategies.

This study integrates sentiment analysis of social media with subway passenger flow prediction models to achieve more comprehensive and precise management. Sentiment-driven passenger flow prediction and management can help identify sections with significant emotional fluctuations in advance. This allows managers to prioritize crowd dispersion or implement other emergency measures. It can also improve responsiveness and effectiveness during unexpected events.

2 LITERATURE REVIEW

2.1 Current Studies on Subway Passenger Flow Prediction

As an essential part of urban public transportation, predicting the flow of subway passengers is crucial for traffic planning, operational management, and emergency response. Accurate passenger flow forecasting enables optimal resource allocation, enhances passenger travel experiences, and strengthens the resilience of transportation systems. Traditional forecasting methods primarily rely on

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historical passenger flow data, using statistical approaches such as time series analysis and regression models. For example, previous studies have proposed a deep learning model based on Long Short-Term Memory (LSTM) networks (Xiong et al., 2019). It effectively captures the nonlinear characteristics of passenger flow and has been validated in multiple subway systems across different cities.

In recent years, there is a rapid development of big data, artificial intelligence, and social media. Subway passenger flow prediction methods have continued to evolve. Research has increasingly focused on multi-source data and deep learning approaches.

2.2 Main Factors Influencing Subway Passenger Flow

Various factors influence subway passenger flow, including macroeconomic conditions, weather, holiday effects, social events, and unexpected incidents. A number of studies have looked at how various factors affect passenger flow. For example, researches have analyzed the effect of weather conditions on short-term passenger flow fluctuations and the influence of socio-economic activities on long-term trends (Wang et al., 2020; Lin et al., 2020). Additionally, other studies have discussed the effects of population density, subway network layout, and competition from other public transportation (Volovski et al., 2021).

Beyond macroeconomic factors, passenger flow in subways is also significantly influenced by individual behavioral patterns. Travel habits are significantly affected by workdays and holidays, peak and off-peak hours, and special events (sports competitions and large-scale concerts). Therefore, incorporating these factors into prediction models and constructing flexible passenger flow forecasting systems has become an important research direction. For example, some studies have developed prediction models based on multi-variable disturbances to forecast passenger flow fluctuations brought on by major events (Xue et al., 2022).

2.3 Application of Social Media Data in Passenger Flow Prediction

2.3.1 Characteristics of Social Media Data and Its Application in Transportation Research

Social media data is real-time, user-generated, and widely covered. It makes highly valuable for urban transportation research. Compared to traditional passenger flow data, social media data provides richer background information, such as users' subjective evaluations of traffic conditions and their future travel plans. Additionally, during emergencies or special events, social media data can offer more timely insights into passenger flow changes than conventional transportation data.

The use of social media data in transportation forecasting has been the subject of an increasing number of studies in recent years. For example, research has found a strong correlation between trending topics on social media and changes in passenger flow. By analyzing text content, real time traffic conditions can be identified, thereby enhancing the precision of short-term forecasts of passenger flow (Essien et al., 2021).

2.3.2 Correlation Between Social Media Data and Subway Passenger Flow

Studies have shown that the volume of discussions related to travel on social media, exhibit a strong correlation with subway passenger flow (Tu et al., 2022). Moreover, sentiment analysis of social media data has demonstrated a certain predictive capability. Research indicates that an increase in negative emotion related to transportation on social media may correspond to a decrease in subway ridership. However, positive sentiment may be associated with an increase in passenger flow (Chen et al., 2023).

2.3.3 Current Methods of Utilizing Social Media Data in Passenger Flow Prediction

At present, social media data is primarily used in passenger flow forecasting through the following approaches:

Keyword Statistical Analysis: Some studies assess changes in passenger flow by counting related phrases on social media(Tu et al., 2022). For instance, passenger flow trends can be indirectly predicted by analyzing fluctuations in the frequency of keywords (e.g.,"subway congestion" and "queueing at subway stations").

Sentiment Analysis: Travel decisions can be predicted by analyzing user sentiments on social media. Studies have found that passenger satisfaction with subway services is closely related to future travel choices (Chen et al., 2023). Therefore, sentiment analysis is a useful tool for predicting commuter behavior patterns.

Spatiotemporal Data Fusion: Combining social media check-in data with traditional transportation data can improve forecasting accuracy (Fu et al., 2022). Check-in data provides users' geographic location information. Prediction models' capacity to generalize can be improved by combining historical passenger flow data.

2.4 Integration of Sentiment Analysis and Subway Passenger Flow Prediction

2.4.1 Existing Research on the Integration of Sentiment Analysis and Passenger Flow Prediction

In recent years, sentiment analysis has been introduced into subway passenger flow prediction. It primarily uses to detect public reactions to traffic conditions and improve prediction model. Additionally, sentiment analysis can be combined with time series models to explore the long-term impact of sentiment fluctuations on passenger flow trends.

2.4.2 Common Methods and Challenges in Research

Traditional sentiment analysis methods include lexicon-based approaches (e.g., sentiment lexicon matching) and machine learning-based approaches (e.g., support vector machines and deep learning). However, the application of emotion analysis in prediction of subway passenger flow still faces several challenges. Firstly, social media data often contains a large amount of irrelevant information. What's more, the sentiment expressed by users may vary depending on the scenario. To enhance sentiment analysis accuracy, high-quality data is required and the process comes with significant computational costs. It is a issue to balance computational efficiency with prediction accuracy.

In the future, studies could integrate multi-source data(e.g., combining images, text, and location information)to further enhance prediction accuracy.

2.5 Summaries

In summary, particularly in the application of machine learning and social media data, significant progress has been made in subway passenger flow prediction research. However, existing studies still face challenges related to data quality, model generalization, and complex factor modeling. Future research could further explore deep learning and multi-source data fusion methods to improve the precision and applicability of passenger flow forecasting. Additionally, with the integration of sentiment analysis technology, the study of passenger behavior patterns is being enhanced . This could further optimize subway passenger flow prediction models, providing theoretical support for the development of intelligent transportation systems.

3 RESEARCH QUESTIONS

This study explores the following research questions: What is the relationship between social media sentiment fluctuations and changes in subway passenger flow? Can the accuracy of passenger flow forecast be increased by combining sentiment analysis from social media with data on passenger flow? And how can sentiment analysis results be used to optimize subway management decisions?

4 RESEARCH METHOD

4.1 Data Collection

A web scraping technique was used to collect posts related to the Beijing Subway from Weibo, including text data, geotagging data, and timestamps. Web scraping allows for efficient and automated data collection on a large scale, significantly reducing time costs compared to manual data collection.

Additionally, passenger flow data for the Beijing Subway was obtained from the Beijing Rail Transit Command Center to serve as an auxiliary input for passenger volume prediction.

4.2 Sentiment Analysis

A sentiment analysis was conducted on the collected text data using large language models. It will generate sentiment scores and polarity for each post.

Research compares GPT Omni models with BERT (Bidirectional Encoder Representations from Transformers) in sentiment analysis tasks. It found that large language models exhibit strong performance in sentiment analysis (Roumeliotis et al., 2024). This study further validates the effectiveness of large language models in natural language processing tasks. Thus, utilizing large language models for emotion analysis increases productivity and enables the quantification of data, facilitating further analysis.

By analyzing sentiment fluctuations across specific time periods or subway lines, it can provide additional insights into the emotional factors behind passenger flow variations.

4.3 Subway Passenger Flow Prediction Model

Machine learning algorithms, such as Random Forest and LSTM, will be used to build the subway passenger flow prediction model(Ma et al., 2021).Data from passenger flow tracking and sentiment analysis on social media will be combined to train these algorithms. By training the model, it will be possible to predict passenger flow trends for the next few hours or days. It can also provide decision support for subway management authorities.

4.4 Sentiment-Driven Decision Support for Management

Based on sentiment analysis results and passenger flow predictions, the following decision support strategies can be developed:

Congestion Warning: When negative sentiment significantly increases in a particular time period or subway line, potential overcrowding or disruptions can be anticipated in combination with passenger flow predictions. Subway operators can preemptively deploy additional staff for crowd control or schedule more train services.

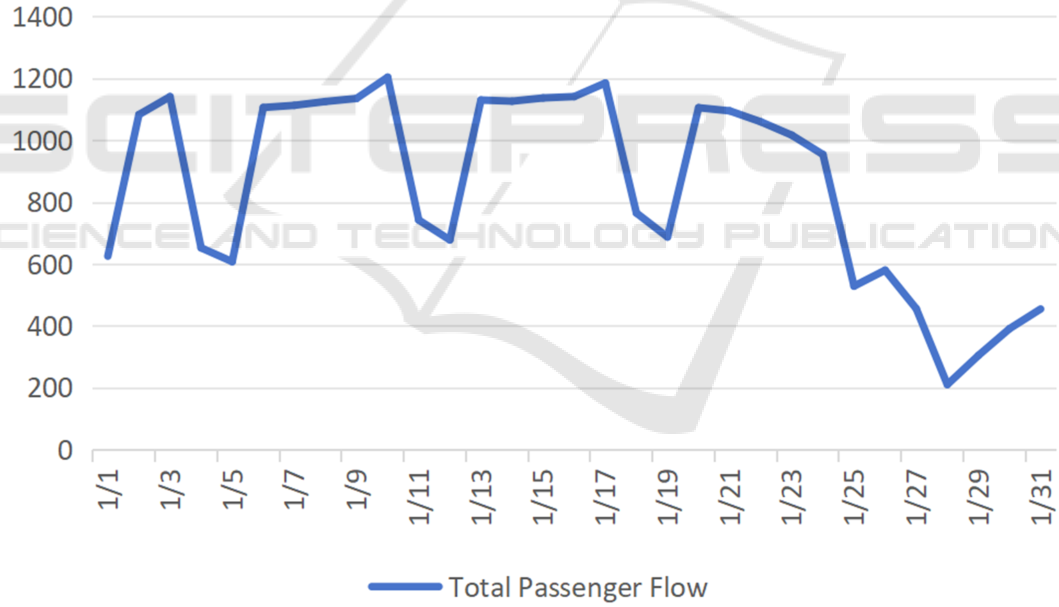
Priority Crowd Management Measures: Lines with significant sentiment fluctuations or pronounced negative sentiment may require priority crowd management measures to prevent disorder.

Emergency Response: If a surge in negative sentiment regarding an emergency event is detected on social media, the model can automatically alert subway operators. This would prompt immediate intervention, such as dispatching more personnel to maintain order and prevent chaos.

5 RESULTS

5.1 Descriptive Statistics

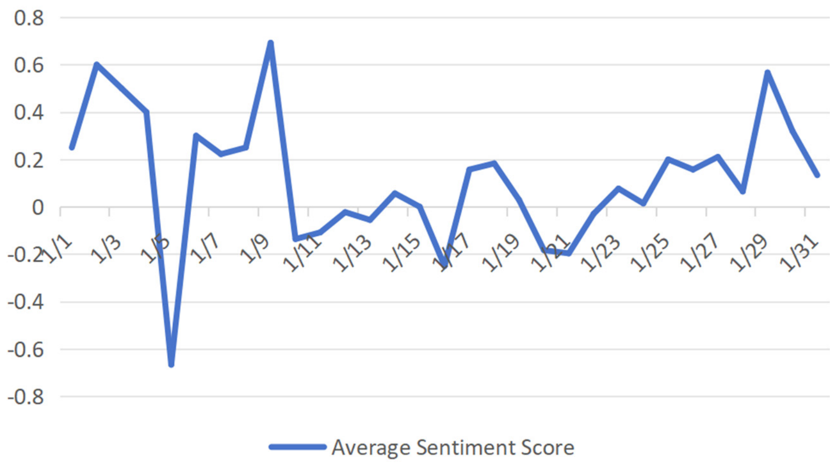
Large datasets were visualized to better capture data characteristics and patterns intuitively.



Alt Text for Graphical Figure: A line chart shows that as the date on the x-axis changes, the subway passenger flow on the y-axis exhibits cyclical variations. Starting from January 25th, the passenger flow significantly decreases.

Figure 1. Total daily passenger traffic of Beijing subway in January 2025 (Picture credit: Original).

Figure 1 presents a line chart of the total daily passenger volume of the Beijing Subway in January 2025.It shows periodic fluctuations, which may be influenced by holidays.

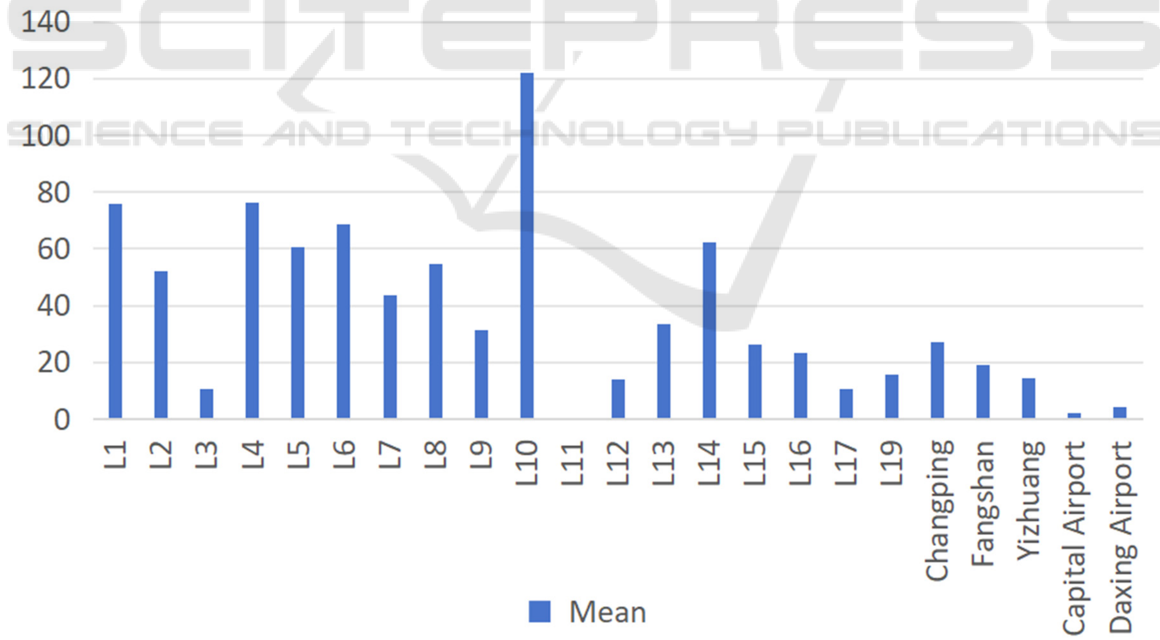


Alt Text for Graphical Figure: A line chart shows irregular fluctuations in the sentiment score (y-axis) over time (x-axis date), with the largest fluctuations occurring between January 3rd and January 11th.

Figure 2. Average sentiment score of Beijing subway in January 2025 (Picture credit: Original).

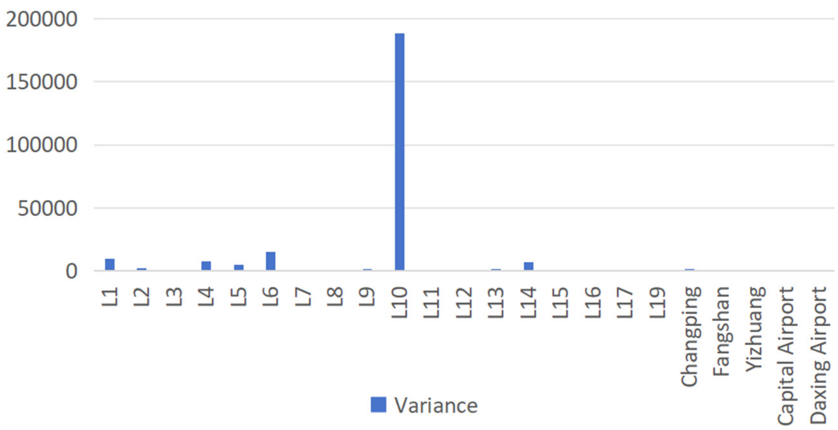
Figure 2 displays the average sentiment scores of collected social media posts related to the Beijing Subway for January 2025. These scores indicate public sentiment fluctuations over the month.

Comparing Figures 1 and 2, the sentiment scores from January 25 to January 31 were more stable and positive compared to January 1 to January 11, which could be associated with lower passenger volumes. The sentiment score on January 6 was notably negative, possibly due to an unexpected incident.



Alt Text for Graphical Figure: A bar chart displays the average daily subway passenger flow corresponding to different subway lines on the x-axis. Line 10 shows the highest average flow, while Line 11 shows the lowest.

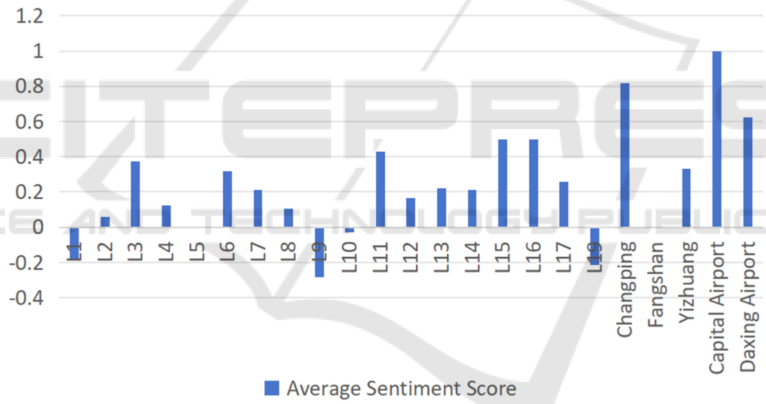
Figure 3.Average total passenger flow of each line in January 2025 (Picture credit: Original).



Alt Text for Graphical Figure: A bar chart shows the variance of daily subway passenger flow for different subway lines (x-axis), where the variance for Line 10 is significantly greater than that of the other lines.

Figure 4. Variance of total passenger flow of each line in January 2025 (Picture credit: Original).

Figures 3 and 4 illustrate the average passenger volume and variance across different subway lines in January 2025. The results indicate that Beijing Subway Line 10 had the highest passenger volume and the most significant fluctuations. The focus should be on this line in future predictions.



Alt Text for Graphical Figure: A bar chart shows the average sentiment score corresponding to different subway lines on the x-axis. Lines 1,9, 10, and 19 show negative scores, while the remaining lines show positive scores.

Figure 5. Average sentiment score of different lines in January 2025 (Picture credit: Original).

Figure 5 presents the average sentiment scores related to different subway lines in January 2025. Negative sentiment was observed for Lines 1, 9, 10, and 19, which may indicate congestion or past incidents on these routes.

5.2 Correlation Analysis

The association between sentiment scores and variations in passenger flow was investigated using a correlation analysis.

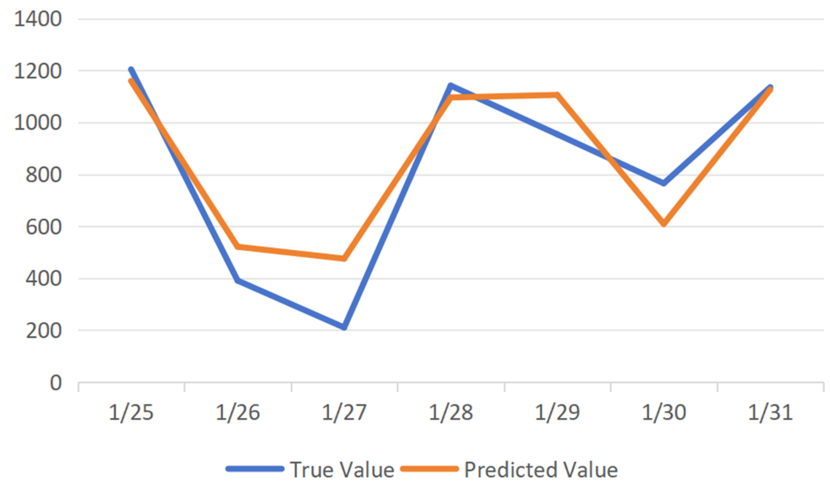
Table 1: Correlation Analysis Between Sentiment Score and Passenger Flow

r	CI95%	p-val
-0.468	[-0.74, -0.07]	0.024

Table 1 shows that the Pearson correlation coefficient is -0.4682, showing that sentiment scores and passenger volume are negatively correlated.the p-value is 0.0242, which is less than 0.05, implying that the association is statistically significant.

5.3 Modeling and Prediction

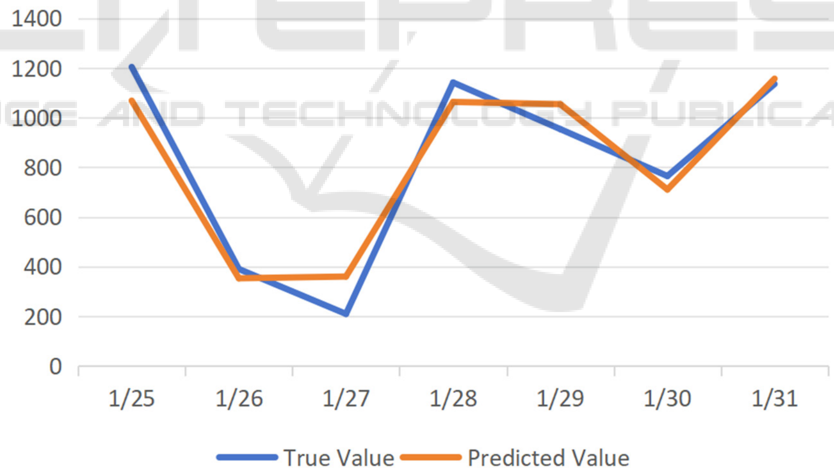
First, a Random Forest model was constructed based on data on past passenger volumes. The actual facts and the anticipated outcomes were contrasted, as shown in Figure 6.



Alt Text for Graphical Figure: A line chart shows both the predicted and actual values of subway passenger flow. On January 26th, January 27th, and January 30th, there are significant differences between the predicted and actual values.

Figure 6. Passenger Flow Forecast Comparison based on historical data (Picture credit: Original).

Next, sentiment data was integrated with historical passenger flow data, and a new Random Forest model was developed. The predicted results were compared with the actual values, as shown in Figure 7.



Alt Text for Graphical Figure: A line chart shows both the predicted and actual values of subway passenger flow. On January 27th, there is a significant difference between the two values.

Figure 7. Passenger Flow Forecast Comparison after incorporating sentiment data (Picture credit: Original).

Table 2. Model Comparison and Evaluation

	MSE	MAE	RMSE	R^2
Model 1	19832.58	114.66	140.83	0.85
Model 2	8861.93	82.53	94.14	0.93

Table 2 compares the performance of the traditional prediction model with the model incorporating sentiment data. The results reveal that adding sentiment data improves model performance. Specifically, after incorporating sentiment data, Mean Squared Error (MSE) decreased from 19,832.58 to 8,861.93. Mean Absolute Error (MAE) dropped from 114.66 to 82.53.Root Mean Squared

Error (RMSE) reduced from 140.83 to 94.14.These improvements indicate that incorporating sentiment data significantly reduces prediction errors and enhances model accuracy. Furthermore, the coefficient of determination (R^2) increased from 0.85 to 0.93. It shows that the model with sentiment data explaining data variability better and significantly improving its goodness-of-fit.

Overall, the inclusion of sentiment data effectively enhances the predictive power and stability of the model. It also validates the critical role of sentiment factors in passenger flow forecasting.

6 DISCUSSION

6.1 Passenger Flow Influencing Factors

6.1.1 Key Aspects of Existing Research on Subway Passenger Flow Prediction

Researchers often predict passenger flow using historical data. However, external environmental factors, such as weather conditions, holidays, and unexpected events like pandemics, also play a significant role. The structure of the transportation network has a major impact as well. Factors like the layout of transfer stations, congestion levels on subway lines, and accessibility to other modes of transport all influence ridership. Additionally, socioeconomic factors cannot be overlooked. Urban population density, economic development levels, and the distribution of employment centers are closely linked to subway passenger flow.

6.1.2 Relationship Between Sentiment Factors and Other Factors

Sentiment factors interact with traditional factors (such as weather and events). For example, adverse weather conditions may trigger negative emotions, which in turn reduce people's willingness to travel. This will further suppress passenger flow. Unexpected events may also induce negative emotions (such as anxiety and panic), leading passengers to opt for alternative transportation methods. Peak hours are typically associated with negative emotions, indicating a high volume of passenger flow during these periods.

Sentiment directly influences passengers' travel choices and also act as a mediating variable. It can amplify or mitigate the effects of traditional factors on passenger flow. For instance, during large-scale performances, passengers generally experience high levels of positive emotions (e.g.,excitement and anticipation). These positive emotions may encourage people to travel even in bad weather, thereby weakening the negative impact of poor weather on passenger flow. Similarly, during the holiday, the increase in positive sentiment significantly boosts subway ridership, especially at stations near tourist attractions and shopping districts.

Sentiment considerations' effects on subway passenger flow exhibits spatiotemporal heterogeneity. For example, negative sentiment on weekdays may have a more pronounced effect on passenger flow than on weekends.

6.2 Recommendations for Optimizing Subway Services and Enhancing Passenger Experience

6.2.1 Sentiment Monitoring and Response

Subway operators can utilize social media sentiment analysis to monitor passengers' opinions on subway services and identify potential factors causing fluctuations in passenger flow (e.g., equipment failures, overcrowding). Timely optimizations and adjustments can help mitigate the spread of negative emotions.

6.2.2 Optimized Passenger Flow Management

Dynamic Scheduling: During periods of high negative sentiment (e.g., holidays, post-incident scenarios), subway operators can dynamically adjust train dispatching and increase service frequency.

Predictive Optimization: By analyzing historical sentiment data, subway operators can predict which routes or time slots are prone to generating negative emotions and take preemptive measures to optimize management strategies.

6.2.3 Enhancing Travel Environment and Passenger Experience

Research suggests that passenger satisfaction with cabin comfort, transfer convenience, and station environments is closely linked to overall positive sentiment. To enhance travel experiences, subway operators can improve station signage and provide more guidance information to reduce passenger anxiety caused by getting lost. They can also enhance travel environments through music, lighting adjustments, and ambient improvements to boost the proportion of positive emotions.

6.3 Future Research Directions

6.3.1 Refinement of Sentiment Analysis

Future studies can explore the impact of different sentiment intensities on passenger flow and the dynamic effects of sentiment transitions (e.g., how shifts from positive to negative sentiment influence ridership trends). The impact of specific emotion categories (such as anger, anxiety, and impatience) in different travel scenarios could also be investigated. For example, impatience may be linked to subway congestion during rush hours, whereas anxiety may correlate with unexpected incidents or service disruptions. A deeper analysis of these emotional factors could enhance predictive accuracy and improve travel behavior modeling.

6.3.2 Integration of Multi-Modal or Multi-Source Data

A single data source may not adequately convey the complexity of passenger flow variations. The integration of multi-modal data (e.g., real-time location tracking, video surveillance, and social media analytics) can help develop more adaptable forecasting models, improving accuracy across diverse travel scenarios.

7 CONCLUSION

This study explores the integration of social media sentiment analysis with subway passenger flow prediction. It investigates the relationship between sentiment fluctuations and passenger volume changes while validating the role of sentiment data in forecasting. A combination of literature review and empirical analysis reveals that social media sentiment data offers valuable insights into behavioral patterns. These enhance accuracy in passenger flow predictions. Additionally, incorporating deep learning and multi-source data fusion further optimizes predictive models. It offers subway operators more precise decision-making support.

This study employs sentiment analysis, descriptive statistics, and correlation analysis on the data. Results indicate a significant correlation between social media sentiment trends and subway passenger flow. An increase in negative sentiment may indicate a short-term decline in passenger volume, while positive sentiment is often associated with increased ridership. Moreover, particularly in scenarios involving unexpected events or special holidays, integrating sentiment analysis with machine learning models significantly improves prediction accuracy . Under such conditions, sentiment-driven forecasting outperforms traditional models in terms of fit. Based on these findings, this study proposes a sentiment-driven management decision framework. It includes crowding warnings, priority-based passenger dispersion strategies, and emergency response plans. These helps subway operators optimizing resource allocation and improve operational management.

The key contribution of this study lies in the introduction of social media sentiment analysis as an additional information source. Combing with data mining and deep learning techniques, it enhances the precision of subway passenger flow forecasting. Compared to traditional models, this approach considers raw passenger data and incorporates passenger emotions, making predictions more interpretable and practical. In the future, this methodology can be extended to other urban public transportation systems and applied to smart city management. It might also offer insightful information for emergency response plans and urban transportation planning.

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