Impact Evaluation of Transit Improvement Program: A Social Media Data Mining and Causal Inference Framework

ARTICLE INFO

Keywords:
social media data
transit improvement program
impact evaluation
transit service quality

ABSTRACT

Assessing the effectiveness of transit improvement programs is crucial to improving urban mobility, but traditional methods often lack timeliness and cannot capture passenger travel experiences. Although social media data can provide a wealth of real-time public opinions, there is a major research gap: Few studies have used these data to evaluate the impact of specific transit improvement programs by comparing passenger attitudes before and after implementation. To fill this gap, this paper proposes a new framework that combines advanced text mining with causal inference methods. Our approach uses semantic matching to associate unstructured social media posts with specific transit improvement programs and uses interruption time series analysis (ITSA) to quantify changes in passenger sentiment while controlling for potential time-trend effects. We apply the framework to a case study from Shenzhen Metro and analyze 88253 Weibo posts to evaluate six different transit improvement programs. The results showed that the framework is effective in measuring the impact of the transit improvement programs, showing that technology-oriented upgrades significantly improved public emotional attitudes over time, while other interventions had negligible effects. The study provides transit agencies with a reliable, data-based method to conduct evidence-based project assessments and better understand passenger travel experiences.

1. Introduction

Public transportation plays a vital role in urban mobility systems, providing essential services that can help to achieve the goals of sustainable development by reducing congestion, air pollution, and greenhouse gas emissions (Stjernborg and Mattisson, 2016; Mead, 2021). Despite these benefits, transit operators around the world continue to face continuing challenges to attract and retain passengers, especially when competing with private cars and emerging mobility services (Beirão and Cabral, 2007). To solve this problem, transit agencies continue to implement various transit improvement programs, covering aspects ranging from technology upgrades and infrastructure renovations to policy adjustments and customer service improvements (Luong and Houston, 2015; Fraser et al., 2024).

Assessing the effectiveness of these transit improvement programs is crucial to the strategic planning and operational management of the public transportation system. Traditional evaluation

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methods are heavily based on performance indicators such as passenger count, punctuality performance, and traveler satisfaction surveys (Nathanail, 2008; Eboli and Mazzulla, 2011). Although these indicators can provide valuable information, they often fail to capture the nuanced views and real-time feedback of transit users (Collins et al., 2013a). This limitation is prominent given that passenger perceptions and experiences directly influence their decisions to choose public transportation over other travel modes (Friman et al., 2001; Morton et al., 2016).

With the proliferation of social media and the growing willingness of the public to share their experiences online, a large amount of user-generated content related to public transportation is available (Golder and Macy, 2011; Kaplan and Haenlein, 2010). These data are an important resource for transit agencies trying to understand passenger sentiment and assess the impact of their transit improvement programs (El-Diraby et al., 2019; Zhang et al., 2023). Social media data has many advantages over traditional data sources. It provides real-time feedback, captures spontaneous and unfiltered opinions from users, and has the potential to reach a wider and more diverse audience than traditional surveys (Tasse and Hong, 2014; Haghighi et al., 2018).

Recent research has explored the potential of social media data in transportation planning and analysis. Studies have shown that Twitter data can be used to detect traffic incidents (Fu et al., 2015), analyze public perceptions of transit services (Luong and Houston, 2015; Collins et al., 2013a), and evaluate the public response to transportation policies (Chakraborty et al., 2019). However, these studies typically focus on general sentiment analysis and do not link social media content to specific transit improvement programs or interventions (Ali et al., 2017; Ingvardson and Nielsen, 2019). Crucially, there is a lack of studies using social media data to evaluate specific transit improvement programs before and after their implementation, especially studies using causal inference methods to quantify the impacts (Mathur et al., 2021; Liu and Ban, 2017). This gap significantly limits the practical usefulness of social media analytics for evidence-based decision-making in transit agencies. Moreover, approaches to processing and analyzing social media data in transit evaluation remain underdeveloped, often relying on simplistic techniques that fail to capture contextual intricacies (Houston and Luong, 2015; Kamga et al., 2023). Therefore, there is an urgent need for advanced frameworks to extract meaningful insights from unstructured social media posts and link them to specific transit improvement programs through causal analysis (Haghighi et al., 2018).

To address these limitations, this study proposes a novel framework, which combines advanced text mining techniques with causal inference methods, to evaluate the impact of transit improvement programs using social media data. The framework consists of three main components: (1) a text matching process aligns passenger feedback from social networks with specific transit improvement programs; (2) an Interrupted Time Series Analysis (ITSA) that quantifies changes in passenger sentiments before and after transit improvement program implementation; and (3) a set of statistical tests to assess the significance of transit improvement program impacts. The text matching process employs Latent Dirichlet Allocation (LDA) for topic modeling and Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction, followed by neural embeddings for semantic matching. This combination of techniques allows for the identification of relevant social media posts that reflect passenger experiences related to specific transit improvement programs, even when the posts do not explicitly mention program names or use standard terminology (Blei et al., 2003; Lopez Bernal et al., 2016). The ITSA method is suitable for evaluating the impact of interventions that have been implemented at clearly defined times (Wagner et al., 2002; Lopez Bernal et al., 2016). By modeling passenger sentiment trends before and after transit improvement program implementation, ITSA can distinguish between short-term fluctuations and sustained sentiment trends, while controlling for confounding factors such as seasonal patterns and temporal autocorrelation (Schaffer et al., 2021; Koppel et al., 2023).

To validate our framework, we apply it to a case study of the Shenzhen Metro in China, using 88,253 Weibo posts collected from January 2019 to July 2023. The case study focuses on several transit improvement programs implemented by Shenzhen Metro during this period, covering different dimensions of the quality of transit service, such as comfort, reliability, safety, and information provision. The results demonstrate the effectiveness of our approach in capturing significant changes in passenger sentiments following the implementation of these transit improvement programs and provide information on different dimensions of service quality. The contributions of this study are threefold. First, we develop a novel framework to bridge the gap between unstructured social media data and structured transit improvement program evaluation, enabling transit agencies to leverage the wealth of information available on social media platforms. Second, we demonstrate the application of ITSA in the context of transit improvement program evaluation, providing a statistical approach to quantify transit improvement program impacts while accounting for various confounding factors. Third, we offer empirical evidence on the effectiveness of several transit improvement programs in Shenzhen Metro, contributing to the growing body of knowledge on best practices in public transportation management.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on the quality assessment of transit service, social media analytics in transportation, and causal inference methods for transit improvement program impact evaluation. Section 3 describes the methodology in detail, including the text matching process, ITSA model specification, and statistical testing procedures. Section 4 presents the case study of Shenzhen Metro, detailing the data collection, transit improvement program descriptions, and analysis results. Finally, Section 5 concludes with a discussion of the implications, limitations, and future directions of this research.

2. Literature Review

2.1. Transit Service Quality Assessment Frameworks

The evaluation of the quality of public transportation services has been the subject of extensive research in recent decades. Traditional assessment frameworks have focused on objective performance indicators and subjective user perceptions, often captured through structured surveys and predefined metrics (De Oña et al., 2016; Eboli and Mazzulla, 2011). For example, Nathanail (2008) proposed a survey incorporating safety, reliability, cleanliness, comfort, servicing, passenger information, and accessibility as key dimensions of service quality. Similarly, Dell'Olio et al. (2011) developed a multi-criteria approach that balances technical efficiency with service effectiveness and social impact.

The European Committee for Standardization established a widely adopted framework that defines eight quality categories: availability, accessibility, information, time, customer care, comfort, security, and environmental impact (for Standardization, 2002), providing a standardized approach to transit service evaluation. Building on this foundation, Eboli and Mazzulla (2011) introduced an improved method that incorporates objective measures and subjective evaluations to create a more balanced evaluation framework. In the North American context, the Transit Capacity and Quality of Service Manual (Associates et al., 2003) offers a structured approach focusing on availability (frequency, service span, and coverage) and comfort/convenience (passenger load, reliability, and transit-auto travel time). This framework has been widely adopted by transit agencies in the United States and Canada, although Högström et al. (2016) argue that it may not fully capture the intricate aspects of the user experience.

Recent research has emphasized the importance of context-specific evaluation, recognizing that perceptions of service quality vary between different urban environments, demographic groups, and cultural contexts (Dell'Olio et al., 2018; Diab and El-Geneidy, 2017). Zhao et al. (2013) highlighted how different passenger groups value different service attributes, suggesting that evaluation frameworks should be adaptable to local conditions and passenger expectations. Similarly, Wang et al. (2020a) demonstrated that perceptions of service quality are influenced by both objective service attributes and subjective user characteristics, emphasizing the need for advanced assessment approaches.

Despite these advancements, traditional evaluation methods continue to face limitations in terms of cost, timeliness, and potential response biases (Hensher et al., 2003). Survey-based approaches often capture only a subset of user perceptions, which could miss temporal variations in service quality and user experiences (Chang et al., 2013). Furthermore, pre-defined evaluation criteria may not always align with the aspects of the service that matter most to travelers in specific contexts (van den Berg et al., 2019; Tyrinopoulos and Antoniou, 2008).

2.2. Social Media Data in Transportation Research

The expansion of social media platforms has created new opportunities to access large volumes of public opinion on various aspects of urban life, including transportation services (Collins et al., 2013b; Schweitzer, 2014). Unlike structured surveys, social media offers spontaneous, real-time expressions of user experiences, potentially capturing dimensions of service quality that may not be included in pre-defined evaluation frameworks (Gal-Tzur et al., 2014; Luong et al., 2015).

The early applications of social media data in transportation research focused primarily on event detection and traffic monitoring (Steiger et al., 2015; Yuan et al., 2016). However, researchers have increasingly recognized the value of these data sources in understanding public perceptions of transportation services. For example, Collins et al. (2013b) analyzed Twitter data to identify patterns in public discourse about public transportation in Chicago, demonstrating the potential of social media to capture temporal and spatial variations in passenger experiences. Similarly, Schweitzer (2014) examined tweets related to public transit agencies in the United States, finding significant associations between sentiment expressed on Twitter and service quality metrics.

More recent studies have employed advanced data mining and natural language processing techniques to extract meaningful insights from social media content. Zhang et al. (2019) developed a framework for analyzing geo-tagged tweets to understand spatial patterns in sentiment toward transit services in New York City. Wang et al. (2020c) employed topic modeling and sentiment analysis to identify key themes in the public discussion about high-speed rail in China, revealing insights that would be difficult to capture through traditional surveys. The integration of geo-location data with social media content has further enhanced the value of these platforms for transportation research. For instance, Rashidi et al. (2017) demonstrated how geo-tagged social media data can be used to analyze travel behavior and mode choice, while Maeda et al. (2019) developed a method to extract transportation-related information from location-based social media to support infrastructure planning.

Despite these advancements, researchers have identified several challenges in using social media data for transportation analysis. Efthymiou and Antoniou (2013) highlighted concerns about sample representativeness, noting that social media users may not reflect the full population of transit riders. Nguyen-Phuoc et al. (2016) discussed issues related to data quality, including the presence of spam, irrelevant content, and varying levels of linguistic complexity. Furthermore, Tse et al. (2018) emphasized the challenges of accurately interpreting sentiment and context in short, informal social media posts.

2.3. Causal Inference in Transit Improvement Program Evaluation

Establishing causal relationships between transportation interventions and observed outcomes represents a significant methodological challenge in transit improvement program evaluation (Karner and Niemeier, 2016; Hong and Shen, 2020). Traditional before-after comparisons often fail to account for secular trends, seasonality, and confounding factors that can influence the observed changes independently of the intervention (Lechner, 2011; Imbens and Rubin, 2015).

Quasi-experimental designs have emerged as valuable approaches for strengthening causal inference in transit improvement program evaluation. Among these, interrupted time series (ITS) analysis has gained prominence as a robust method for assessing the impact of interventions when randomization is not feasible (Bernal et al., 2017; Lopez Bernal et al., 2017). The ITS approach examines the trajectory of an outcome measure before and after an intervention, accounting for pre-existing trends to isolate the effect of the intervention (Wagner et al., 2002; Bernal et al., 2016). Kontopantelis et al. (2015) demonstrated the application of ITS analysis in evaluating policy interventions, highlighting its ability to control for time-varying confounders and detect both immediate and gradual effects. In the transportation context, Morrison and Lin (2018) employed ITS analysis to evaluate the impact of a new light rail line on traffic congestion, distinguishing the intervention effect from seasonal and long-term trends. Similarly, Baek and Sohn (2016) used this approach to assess the effectiveness of improved transit service to increase ridership, controlling for external factors such as fuel prices and economic conditions.

Advanced causal inference methods, such as difference-in-differences (DiD) and synthetic control methods, have also been applied in transit improvement program evaluation. Hong and Shen (2020) employed a DiD approach to evaluate the impact of transit-oriented development on travel behavior, comparing treated and control areas while accounting for time-invariant unobserved characteristics. Ye et al. (2020) developed a synthetic control framework for assessing the impact of transportation infrastructure investments on economic outcomes, creating a counterfactual scenario from a weighted combination of control units.

The integration of machine learning with causal inference has opened new avenues for transit improvement program evaluation. Athey and Imbens (2017) discussed how machine learning techniques can enhance causal inference by improving the estimation of treatment effects and addressing high-dimensional confounding. Spirtes and Zhang (2016) presented a framework for using causal discovery algorithms to identify potential causal relationships from observational data, which could be valuable for understanding complex interactions in transportation systems.

Despite these methodological advancements, challenges remain in applying causal inference to transit improvement program evaluation. Imbens and Rubin (2015) highlighted the importance of addressing potential violations of key assumptions, such as the stable unit treatment value assumption (SUTVA) and the parallel trends assumption in DiD designs. Angrist and Pischke (2008) emphasized the need for careful consideration of instrumental variables and potential selection biases in natural experiments. Additionally, Pearl (2009) stressed the importance of explicit causal modeling to clarify assumptions and enhance the interpretability of results.

2.4. Integrated Approaches for Transit Service Evaluation

Recent research has increasingly focused on integrating multiple data sources and methodologies to create more comprehensive approaches to transit service evaluation (Tse et al., 2018; Ma et al., 2018). These integrated approaches aim to leverage the strengths of different data types while mitigating their respective limitations.

Zhao et al. (2013) demonstrated how web-based surveys could be combined with traditional intercept surveys to reach a broader population of transit users and non-users, providing a more comprehensive understanding of service perceptions. Building on this work, Barbosa et al. (2017) developed a framework that integrates passenger surveys with objective performance metrics and operational data to create a multi-dimensional evaluation of transit service quality. The combination of social media data with traditional evaluation methods has emerged as a promising approach. Collins et al. (2013b) proposed a framework for triangulating insights from social media analysis with passenger surveys and operational metrics, demonstrating how these complementary data sources can provide a more nuanced understanding of service quality. Similarly, Wu et al. (2020) developed a methodology that combines sentiment analysis of social media content with passenger flow data to identify critical service issues and prioritize improvements.

Advanced statistical and computational methods have facilitated the integration of diverse data types for transit evaluation. Zhang et al. (2018) employed machine learning techniques to integrate structured operational data with unstructured text data from social media, creating a unified framework for service quality assessment. Jin et al. (2020) demonstrated how deep learning approaches can be used to extract meaningful patterns from heterogeneous data sources, including social media, smart card records, and vehicle tracking data. The spatial dimension of transit service evaluation has also been enhanced through integrated approaches. Gal-Tzur et al. (2014) combined geo-tagged social media data with spatial analysis techniques to identify geographic patterns in service perceptions, allowing for more targeted improvement strategies. Wang et al. (2020a) integrated spatial accessibility measures with sentiment analysis of social media content to examine the relationship between physical access to transit and user satisfaction.

Despite the potential of integrated approaches, several challenges remain in their implementation. Tse et al. (2018) highlighted issues related to data integration and compatibility, noting that different data sources may have varying temporal and spatial resolutions. Nguyen-Phuoc et al. (2016) discussed methodological challenges in combining quantitative and qualitative data types, emphasizing the need for robust analytical frameworks. Additionally, Zhang et al. (2019) pointed out practical challenges related to data access, privacy concerns, and technical requirements for implementing integrated evaluation approaches.

3. Methodology

This section presents our methodological framework for evaluating transit improvement programs using social media data. The framework integrates advanced natural language processing (NLP) techniques with robust causal inference methods to systematically analyze how transit improvement programs influence passenger sentiment. As illustrated in Figure 1, our approach consists of three main components: (1) data preprocessing and semantic matching, (2) sentiment analysis and aggregation, and (3) impact evaluation using interrupted time series analysis.

3.1. Data Preprocessing and Semantic Matching

3.1.1. Latent Dirichlet Allocation for Topic Discovery

The first step in our framework involves processing unstructured social media posts to identify latent themes relevant to transit improvement programs. We employ Latent Dirichlet Allocation (LDA) (Blei et al., 2003), a probabilistic topic modeling technique that discovers hidden thematic structures within text data. LDA models each document as a mixture of topics, where each topic is characterized by a distribution over words.

For preprocessing, we first remove URLs, special characters, and numbers from the text, then segment Chinese text using Jieba (Jiawen and Kanev, 2025), a Chinese text segmentation library. We eliminate stopwords and short words (typically single characters), as they convey minimal semantic meaning. To improve the segmentation quality for transit-specific content, we augment the Jieba dictionary with domain-relevant terms such as metro station names.

The LDA model is formally defined as:

$$p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) p(w_n|z_n, \beta) \tag{1}$$

where θ represents the document-topic distribution, $\mathbf{z}$ denotes the topic assignments, $\mathbf{w}$ represents the observed words, and α and β are the hyperparameters for the Dirichlet priors on the document-topic and topic-word distributions, respectively.

To enhance model robustness, we optimize the LDA hyperparameters through multiple initializations with different random seeds, selecting the model with the lowest perplexity score. For our implementation, we set the number of topics $K = 15$, document-topic prior $\alpha = 0.05$, and topic-word prior $\beta = 0.005$, which we determined through empirical testing to provide interpretable topics while maintaining adequate discrimination between service quality dimensions.

3.1.2. TF-IDF Feature Extraction

After topic modeling, we employ Term Frequency-Inverse Document Frequency (TF-IDF) transformation to identify the most distinctive terms for each topic. The TF-IDF score for a term t in document d within corpus D is computed as:

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D) \tag{2}$$

where $\text{TF}(t, d)$ is the frequency of term t in document d, and $\text{IDF}(t, D)$ is calculated as:

$$\text{IDF}(t, D) = \log \frac{|D|}{|\{d \in D : t \in d\}|} \tag{3}$$

This transformation assigns higher weights to terms that are frequent in a specific document but rare across the corpus, which helps identify the most characteristic words for each topic. We apply TF-IDF transformation to the word-document matrix before fitting the LDA model, which helps improve topic coherence and interpretability (Ming et al., 2014).

3.1.3. Neural Embedding for Semantic Matching

To connect passenger feedback with specific transit improvement programs, we implement a semantic matching approach using neural embeddings. Specifically, we utilize the multilingual MiniLM-L12-v2 model from the sentence-transformers framework (Reimers and Gurevych, 2019), which maps text into a dense 384-dimensional vector space where semantically similar texts have high cosine similarity.

For each transit improvement program, we create a document that describes its objectives and features, then compute the embedding vector for this description. Similarly, we compute embedding vectors for each processed social media post. The semantic similarity between a transit improvement program p and a post s is calculated as:

$$\text{sim}(p, s) = \frac{\mathbf{v}_p \cdot \mathbf{v}_s}{||\mathbf{v}_p|| \cdot ||\mathbf{v}_s||} \tag{4}$$

where $\mathbf{v}_p$ and $\mathbf{v}_s$ are the embedding vectors for the transit improvement program description and social media post, respectively. We establish a similarity threshold based on empirical testing, which balances precision and recall in matching relevant posts to transit improvement programs. Posts exceeding this threshold are considered relevant to the corresponding transit improvement program and included in the subsequent analysis.

3.2. Sentiment Analysis and Aggregation

3.2.1. Sentiment Analysis Approach

Given the specificity of transit-related terminology and the Chinese language context, we employ a domain-adapted sentiment analysis approach that combines a pre-trained sentiment model with domain-specific adjustments. For each post s, we compute a sentiment score $f(s) \in [-1, 1]$, where -1 represents extremely negative sentiment, 0 represents neutral sentiment, and 1 represents extremely positive sentiment. The sentiment score is computed as:

$$f(s) = \text{clip}\left(\alpha \cdot f_{\text{base}}(s) + \beta \cdot f_{\text{lex}}(s)\right) \tag{5}$$

where $f_{\text{base}}(s)$ denotes the base sentiment score from a pre-trained model (e.g., BERT), $f_{\text{lex}}(s)$ represents the domain-adapted score from our transit-specific lexicon, α and β are weighting coefficients ($\alpha + \beta = 1$) that balance model prediction and domain knowledge, and $\text{clip}(x) = \max(-1, \min(1, x))$ ensures scores stay within $[-1, 1]$.

The domain-adapted score $f_{\text{lex}}(s)$ accounts for negation patterns and intensifiers:

$$f_{\text{lex}}(s) = \frac{1}{|s|} \sum_{w_i \in s} \gamma_i \cdot \text{sign}_i \cdot d(w_i) \tag{6}$$

where $d(w_i)$ is the sentiment polarity of word w_i in our domain lexicon ($d(w_i) \in [-1, 1]$), $\text{sign}_i = (-1)^{n_i}$ handles negation patterns with n_i counting negation words preceding w_i, γ_i is the intensification factor (1.5 for strong intensifiers, 1.2 for medium intensifiers, and 1.0 otherwise), and $|s|$ is the post length in tokens.

This formulation integrates state-of-the-art deep learning with domain-specific linguistic rules to accurately capture passenger sentiment in the transit context.

3.3. Impact Evaluation Using Interrupted Time Series Analysis

3.3.1. Model Specification

To quantify the impact of transit improvement programs on passenger sentiment, we employ ITSA, a quasi-experimental design that evaluates interventions by examining changes in time series data patterns before and after implementation (Bernal et al., 2017). ITSA is well-suited for our context as it can distinguish between immediate and gradual effects while controlling for pre-existing trends.

Our core ITSA model specification is:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \epsilon_t \tag{7}$$

where Y_t represents the mean sentiment score at time t, T_t indicates the time elapsed since the start of the study, X_t is a dummy variable that distinguishes between pre-intervention ($X_t = 0$) and post-intervention periods ($X_t = 1$), $X_t T_t$ serves as an interaction term measuring time since the intervention occurred, and ϵ_t denotes the error term.

In this model, β_0 represents the baseline level, β_1 captures the pre-intervention trend, β_2 indicates the immediate change in level following intervention, and β_3 represents the change in trend after intervention.

3.3.2. Addressing Time Series Complexities

To handle the complexities inherent in time series data, we extend the basic ITSA model to account for:

Autocorrelation: We test for autocorrelation in the residuals using the Durbin-Watson statistic and incorporate autoregressive (AR) terms when necessary:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t \tag{8}$$

where p is the order of the autoregressive process, and ϕ_i are the AR coefficients.

Seasonal Patterns: We incorporate seasonal components to account for cyclical variations in transit usage and social media activity:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \sum_{j=1}^{J} \gamma_j S_{j,t} + \epsilon_t \tag{9}$$

where $S_{j,t}$ are seasonal indicator variables, and γ_j are the corresponding coefficients.

Heteroskedasticity: We implement robust standard errors to address potential heteroskedasticity in the variance of the error terms.

3.3.3. Placebo Tests and Robustness Checks

To strengthen causal inference, we conduct several robustness checks: performing placebo tests by artificially shifting the intervention point to different time periods (expecting the strongest effect at the true intervention point); controlling for variation in the number of social media posts across time periods by including sample size as a covariate; and testing alternative model specifications by varying parameters such as aggregation periods, semantic matching thresholds, and sentiment analysis approaches.

4. Case study

4.1. Overview of Shenzhen Metro System

Shenzhen Metro, operated by Shenzhen Metro Group Co., Ltd., serves as the primary rapid transit system for Shenzhen, one of China's major metropolitan areas in Guangdong Province. Since its first line opened in 2004, the system has expanded significantly to accommodate the city's rapid growth and development. As of 2023, the network comprises 16 operational lines spanning approximately 530 kilometers with 345 stations, making it one of the largest and busiest metro systems in China (Chen et al., 2019). The system serves a diverse population of over 13 million residents and handles an average daily ridership exceeding 7 million passengers (Li et al., 2022). As a technology hub often referred to as "China's Silicon Valley," Shenzhen has integrated numerous technological innovations into its metro operations, including digital payment systems, facial recognition technology, and AI-powered crowd management systems (Guo et al., 2019). Shenzhen Metro has implemented various transit improvement programs in recent years aimed at enhancing passenger experience across multiple dimensions of service quality. These improvements include technological innovations, infrastructure upgrades, policy changes, and customer service enhancements (Deng et al., 2021). The evaluation of these transit improvement programs presents an ideal context for applying our proposed framework, as it allows us to investigate how different types of service improvements affect passenger sentiment and experience.

4.2. Data Collection and Processing

4.2.1. Social Media Data Source

For our analysis, we collected 88,253 Weibo posts related to Shenzhen Metro services between January 2019 and July 2023. Weibo, often described as China's equivalent to Twitter, serves as a major platform for public expression and opinion sharing in China, with approximately 530 million monthly active users as of 2022 (Wang et al., 2020b). This platform offers several advantages for transit improvement program evaluation: it captures spontaneous, real-time passenger feedback outside the constraints of structured surveys, provides access to a larger and potentially more diverse sample of transit users, allows for the analysis of temporal patterns in public sentiment before and after transit improvement program implementation, and contains rich contextual information, including user characteristics and interaction patterns.

The data collection process involved an API-based retrieval using keywords related to Shenzhen Metro, including the system's name in different variations (e.g., "Shenzhen Metro", "Shenzhen Subway") and station names. We implemented comprehensive error handling and rate limiting to comply with platform policies while maximizing data quality.

4.3. Transit Improvement Programs

Our case study focused on six transit improvement programs implemented by Shenzhen Metro between 2020 and 2023. These transit improvement programs span different dimensions of transit service quality, including comfort, technology, convenience, affordability, and accessibility. Table

Table 1
Transit Improvement Programs

Name	Description	Service Dimension	Implementation Date
Temperature	Different temperatures in the same carriage	Comfort	August 2022
Smart Map Display	Enhanced passenger information through dynamic digital maps that update in real-time to show train location, estimated arrival times, and transfer information.	Information	October 2021
QR Code Payment	Introduced contactless QR code payment options, reducing reliance on physical cards and expanding payment flexibility.	Convenience	March 2020
Restroom Renovation	Improved station amenities through comprehensive renovation of restroom facilities at 82 stations across the network.	Amenities	June 2021
Mobile Nursing Rooms	Enhanced accessibility for caregivers by installing mobile nursing room facilities at strategic locations throughout the network.	Accessibility	September 2022
Fare Reduction	Increased affordability through a targeted fare reduction plan, particularly for commuters and frequent riders.	Affordability	January 2023

1 provides an overview of these transit improvement programs. Each transit improvement program represents a distinct approach to service improvement.

4.3.1. Data Preprocessing and Transit Improvement Program Matching

The collected Weibo posts underwent several preprocessing steps before being matched to specific transit improvement programs, as illustrated in Figure 2. First, we removed URLs, special characters, and numbers from the text and segmented Chinese text using Jieba (Jiawen and Kanev, 2025), a Chinese text segmentation library. To improve segmentation quality for transit-specific content, we augmented the dictionary with domain-relevant terms such as metro station names. Following text cleaning, we applied Latent Dirichlet Allocation (LDA) to identify latent thematic structures within the corpus. The LDA model was optimized with a topic count of $K = 15$, document-topic prior $\alpha = 0.05$, and topic-word prior $\beta = 0.005$, determined through empirical testing to provide interpretable topics while maintaining adequate discrimination between service quality dimensions. To enhance topic coherence and interpretability, we employed Term Frequency-Inverse Document Frequency (TF-IDF) transformation, which assigns higher weights to terms that are frequent in specific documents but rare across the corpus.

The critical step in our methodology involved establishing semantic connections between passenger feedback and specific transit improvement programs. We utilized the multilingual MiniLM-L12-v2 model from the sentence-transformers framework (Reimers and Gurevych, 2019), which maps text into a dense 384-dimensional vector space. This approach enabled us to calculate semantic similarity scores between transit improvement program descriptions and social media posts, addressing the fundamental challenge of automatically identifying which posts relate to specific service improvements. To determine the optimal similarity threshold for matching, we conducted a systematic evaluation across seven threshold values: 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, and 0.85. Two domain experts independently validated a randomly selected subset of 500 matches at each threshold level, assessing the semantic relevance between matched posts and transit improvement programs. As shown in Figure 3, higher similarity thresholds yielded improved matching accuracy, ranging from 72.3% at threshold 0.25 to 96.8% at threshold 0.85. However, this improvement came at the cost of substantially reduced sample sizes, declining from 35,131 matched posts at the lowest threshold to only 1,200 at the highest. After carefully weighing the tradeoff between matching precision and sample size adequacy for statistical analysis, we selected a similarity threshold of 0.55, which achieved 87.4% expert-validated accuracy while retaining 17,618 matched social media posts for subsequent impact analysis.

4.4. Preliminary Statistical Analysis

Before implementing the more sophisticated Interrupted Time Series Analysis, we conducted basic statistical tests to examine overall patterns in passenger sentiment before and after transit improvement program implementation. Although these preliminary analyses provide initial insights, they reveal important limitations that necessitate more robust analytical approaches.

Figure 4 illustrates the distribution of sentiment scores between the six transit improvement programs, comparing the pre- and post-implementation periods. The visualization reveals heterogeneous patterns across different transit improvement programs. Technology-oriented transit improvement programs (Smart Map Display and QR Code Payment) show predominantly negative sentiment in the pre-implementation period, suggesting existing passenger dissatisfaction with these service aspects. In contrast, the Fare Reduction transit improvement program exhibits positive sentiment even before implementation, indicating that affordability was less of a pressing concern initially.

Table 2 presents the results of the paired t-test examining changes in the mean sentiment scores. Four transit improvement programs demonstrate statistically significant changes: Smart Map Display ($t=13.50$, $p<0.001$), QR Code Payment ($t=15.85$, $p<0.001$), Fare Reduction ($t=13.15$, $p<0.001$), and Temperature ($t=-28.37$, $p<0.001$). Notably, the Temperature transit improvement program shows a significant negative change, suggesting sentiment deterioration despite transit improvement program implementation.

Chi-square tests examining the association between implementation periods and sentiment categories yield contradictory results (Table 3). All transit improvement programs show statistically significant associations ($p<0.001$), including Mobile Nursing Rooms and Restroom Renovation, which demonstrated non-significant results in the t-tests. This inconsistency highlights a funda-

Table 2
T-test results for passenger sentiment analysis

Transit Improvement Program	Pre-Mean	Post-Mean	Mean Diff.	t-statistic	p-value
Smart Map Display	-0.213	-0.123	0.090	13.50	<0.001***
QR Code Payment	-0.215	-0.133	0.082	15.85	<0.001***
Fare Reduction	0.188	0.241	0.053	13.15	<0.001***
Temperature	0.130	-0.088	-0.219	-28.37	<0.001***
Mobile Nursing Rooms	0.682	0.664	-0.018	-1.32	0.186
Restroom Renovation	0.397	0.357	-0.039	-0.85	0.394

*** $p < 0.001$

Table 3
Chi-square test results for passenger sentiment analysis

Transit Improvement Program	Chi-square	p-value
Smart Map Display	112.71	<0.001***
QR Code Payment	142.87	<0.001***
Fare Reduction	89.45	<0.001***
Temperature	156.23	<0.001***
Mobile Nursing Rooms	45.67	<0.001***
Restroom Renovation	78.34	<0.001***

*** $p < 0.001$

mental limitation of these basic approaches when applied to complex time series data.

The temporal visualization of aggregated sentiment data (Figure 5) reveals complex patterns that simple before-after comparisons cannot adequately capture. These plots demonstrate substantial variability over time, with apparent seasonal fluctuations and trend changes that occur independently of transit improvement program implementation dates. Such patterns suggest that observed differences between pre- and post-implementation periods may be confounded by underlying temporal trends rather than representing true transit improvement program effects.

Figure 6 presents density plots comparing sentiment distributions before and after implementation. While some transit improvement programs show apparent shifts toward more positive sentiment (particularly QR Code Payment and Smart Map Display), others exhibit overlapping distributions that make it difficult to assess the magnitude and significance of changes without controlling for temporal confounders.

4.5. Interrupted Time Series Analysis Results

Given the limitations of basic statistical tests in handling temporal dependencies and confounding trends, we employed ITSA to provide more robust causal inference regarding transit improvement program impacts. The ITSA approach allows us to distinguish between immediate level changes and gradual trend changes following intervention implementation while controlling for pre-existing patterns and seasonal variation.

Table 4
Interrupted Time Series Analysis Results

Transit Improvement Program	Baseline Level (β_0)	Pre-trend (β_1)	Level Change (β_2)	Trend Change (β_3)	R-squared
Smart Map Display	-0.129	-0.0016	0.008	0.0032**	0.323
QR Code Payment	-0.114	-0.0013	0.030	0.0022*	0.237
Fare Reduction	0.159	-0.000	-0.040	0.0015**	0.256
Temperature	0.109	-0.0010	-0.004	-0.0007	0.433
Mobile Nursing Rooms	0.674	0.0001	0.002	-0.0004	0.189
Restroom Renovation	0.383	-0.0001	0.012	-0.0003	0.156

* $p < 0.05$, ** $p < 0.01$

Figure 7 presents the comprehensive ITSA results for all six transit improvement programs, showing both the observed data points and fitted regression lines for pre- and post-intervention periods. The analysis reveals substantial heterogeneity in both the magnitude and temporal patterns of transit improvement program impacts, with some interventions producing immediate effects while others demonstrate gradual improvements over time.

Table 4 summarizes the key ITSA parameters for each transit improvement program. Three transit improvement programs demonstrated statistically significant positive trend changes following implementation: Smart Map Display ($\beta_3 = 0.0032$, p = 0.029), QR Code Payment ($\beta_3 = 0.0022$, p = 0.047), and Fare Reduction ($\beta_3 = 0.0015$, p = 0.007). These results indicate sustained improvements in passenger sentiment that strengthen over time, suggesting successful transit improvement program implementation and positive reception. The Smart Map Display transit improvement program exhibited the most robust improvement pattern, indicating that the benefits of enhanced passenger information systems became more apparent to users over time as they adapted to the new technology. The QR Code Payment transit improvement program demonstrated similar positive trends, reflecting growing acceptance of contactless payment options with a typical technology adoption curve pattern. The Fare Reduction transit improvement program showed the strongest statistical significance despite exhibiting a negative immediate level change, suggesting that passengers increasingly appreciated the cost savings over time despite an initially muted response.

In contrast, three transit improvement programs showed no significant improvements. The Temperature transit improvement program presents a notable contrast, showing no significant trend change (p = 0.581) despite achieving the highest model fit ($R^2 = 0.433$), suggesting that the temperature control intervention failed to address passenger concerns effectively. The Mobile Nursing Rooms and Restroom Renovation transit improvement programs demonstrated neither significant level changes nor trend changes, indicating that these amenity improvements, while potentially valued by specific user subgroups, did not generate widespread positive sentiment changes detectable in general social media discourse.

The ITSA approach proved superior to basic statistical tests by controlling for pre-existing trends, distinguishing between immediate impacts and sustained improvements, addressing temporal autocorrelation in social media data, and enabling placebo testing to enhance confidence in causal interpretation. This methodology provided nuanced insights into transit improvement program effectiveness by demonstrating that significant effects were concentrated around actual implementation dates rather than randomly distributed across the time series.

5. Conclusion

This study presents a novel methodological framework that integrates advanced natural language processing techniques with robust causal inference methods to evaluate transit improvement programs using social media data. Through the case study of Shenzhen Metro, we demonstrated how unstructured passenger feedback can be systematically analyzed to quantify transit improvement program impacts while addressing the inherent challenges of observational social media data. Our findings reveal substantial heterogeneity in transit improvement program effectiveness across different service quality dimensions. Technology-oriented transit improvement programs (Smart Map Display and QR Code Payment) demonstrated consistent positive impacts, while the Temperature transit improvement program showed negative impacts despite addressing a commonly cited passenger concern. The ITSA proved valuable in distinguishing between immediate and gradual transit improvement program effects while controlling for temporal confounders, with the semantic matching approach achieving 87.4% accuracy in connecting social media content to specific transit interventions.

The framework's practical implications for transit agencies are significant, providing a cost-effective supplement to traditional passenger surveys that enables continuous monitoring of passenger sentiment and rapid detection of implementation problems. However, several limitations should be acknowledged. The social media user base may not be fully representative of the broader transit ridership, potentially introducing demographic biases. A critical limitation is the absence of geographic location information in the collected social media data, which prevented us from implementing experimental and control group designs based on spatial variation. Future research should prioritize the collection of geo-tagged social media data to enable more sophisticated quasi-experimental designs such as difference-in-differences methodology.

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figs/methodological framework.pdf

Figure 1: Data Preprocessing and Transit Improvement Program Matching

figs/Data Preprocessing and Program Matching Workflow.pdf

Figure 2: Data Preprocessing and Transit Improvement Program Matching

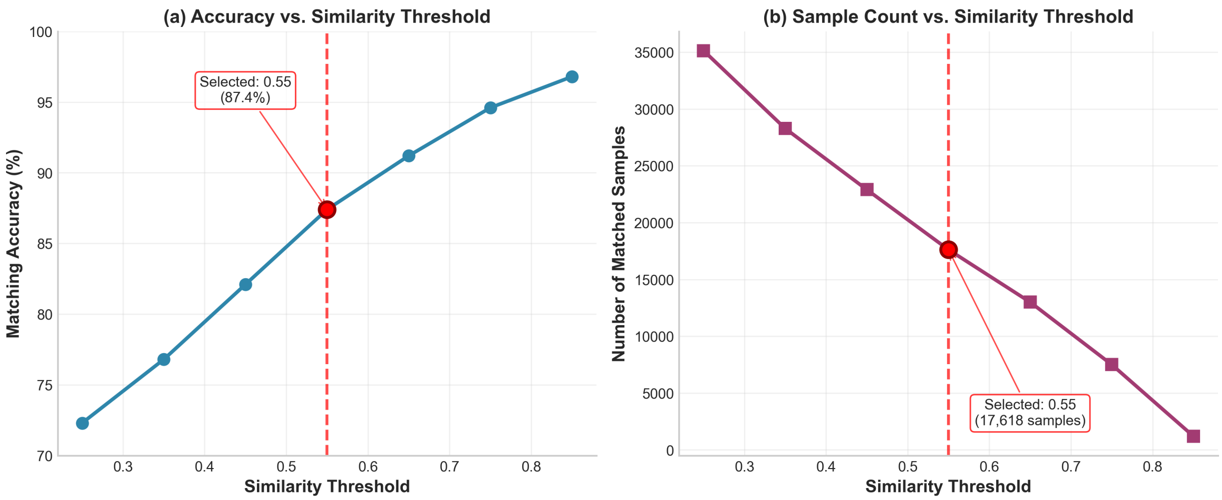

Figure 3: Tradeoff Analysis Between Matching Accuracy and Sample Size Across Similarity Thresholds

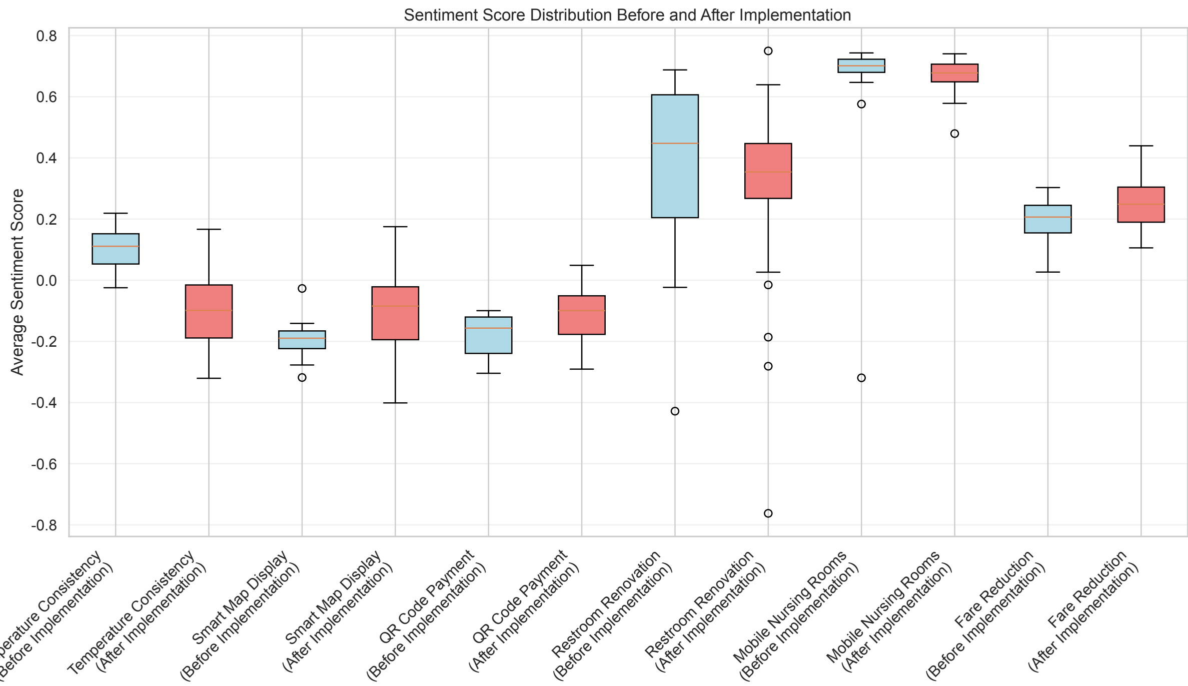

Figure 4: Sentiment Distribution by Transit Improvement Program Before and After Implementation

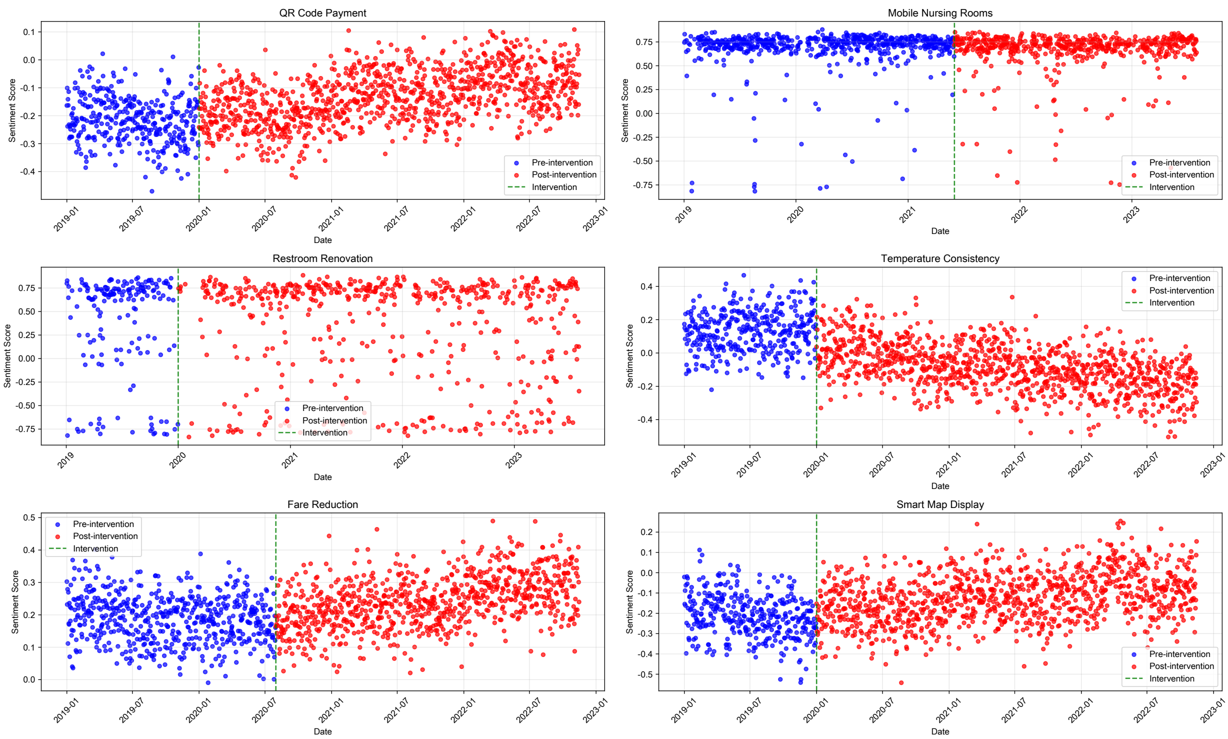

Figure 5: Time Series Analysis of Sentiment Patterns Across Transit Improvement Programs

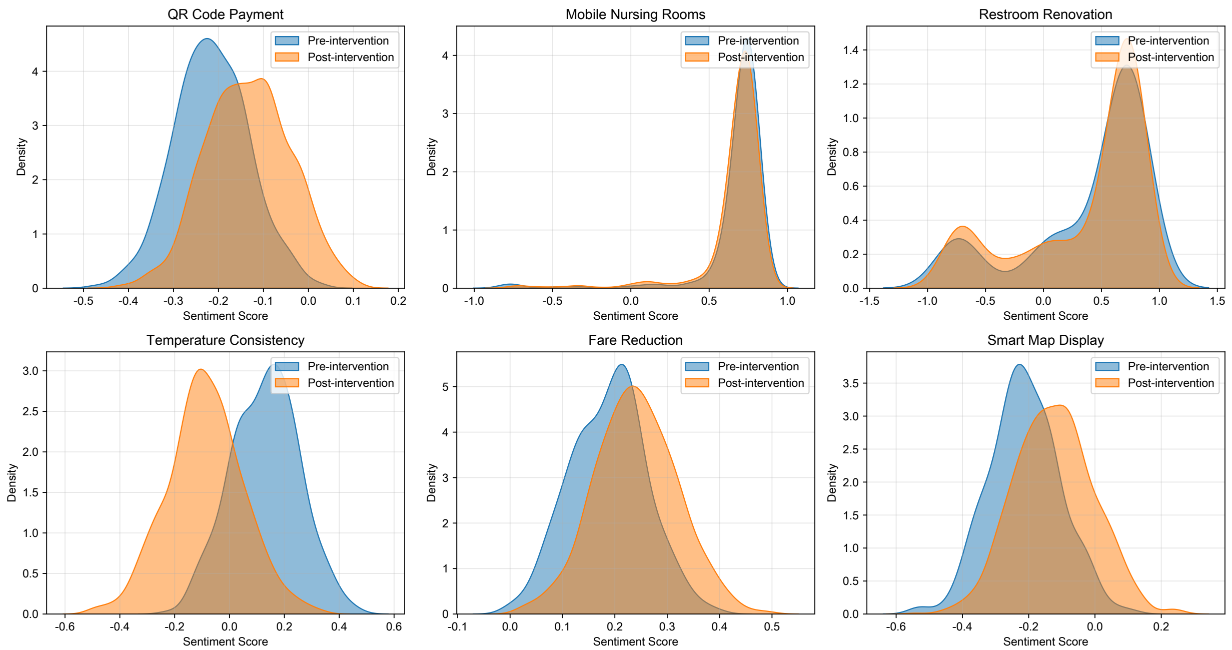

Figure 6: Density Plots of Sentiment Distributions Before and After Transit Improvement Program Implementation

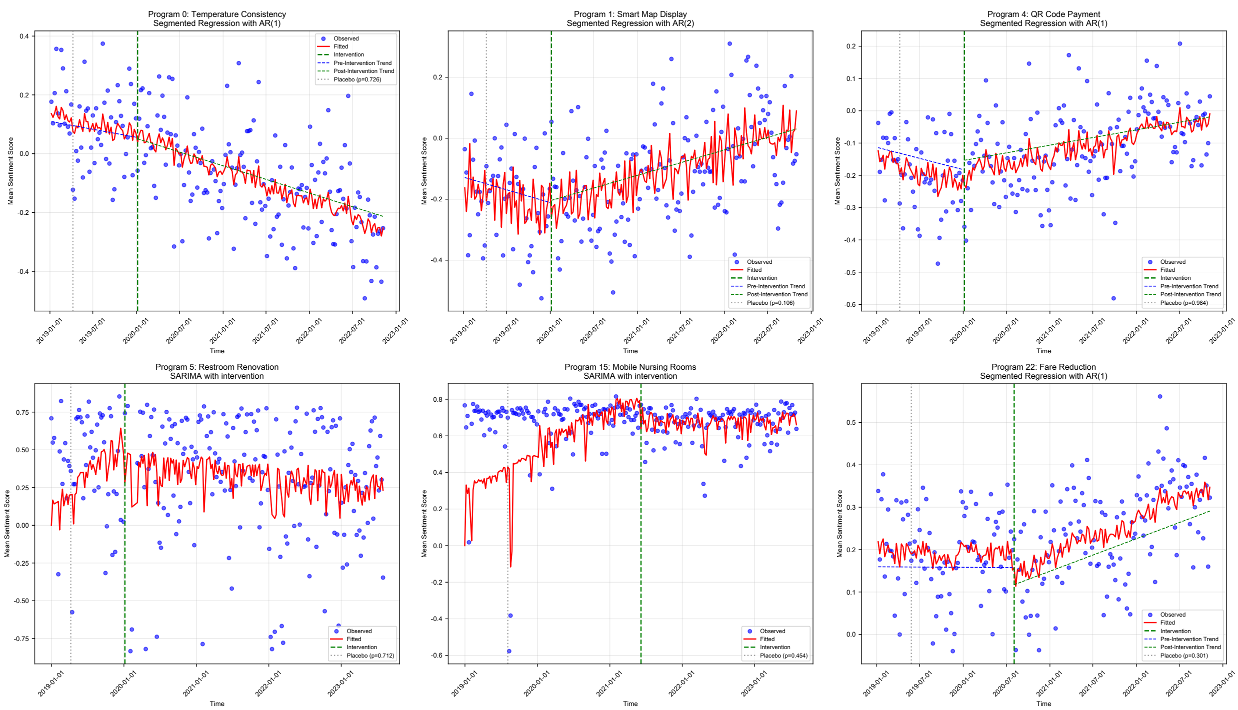

Figure 7: Interrupted Time Series Analysis Results for All Transit Improvement Programs