

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

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ABSTRACT

Passenger feedback is a critical indicator for evaluating the effectiveness of transit improvement programs, with social media emerging as an important data source. This study develops a novel framework by linking unstructured social media posts to specific transit improvement programs, which are corresponding to our pre-defined transit service quality dimensions. We first conduct a text matching to align passenger feedback with program objectives, which includes a Latent Dirichlet Allocation (LDA) and Term Frequency-Inverse Document Frequency (TF-IDF) to identify latent themes from social media posts and a neural embedding for semantic matching. The matched data enables us to evaluate and quantify program impacts. Specifically, we begin by employing Interrupted Time Series Analysis (ITSA) to quantify the sentiment trends before and after program implementation, distinguishing short-term impacts from sustained improvements while controlling for seasonal patterns and temporal autocorrelation. The proposed framework is validated in a case study using 88,253 Weibo posts related to Shenzhen Metro services collected between January 2019 and July 2023. Results reveal statistically significant differences and shifts in public opinion in the targeted dimensions of several service improvement programs. Our approach can be applied to transit program evaluation in other cities beyond our case study area. This is

¹ 1. Introduction

² Public transportation plays a crucial role in urban mobility systems, offering an essential ser-
³ vice that contributes to sustainable development goals by reducing congestion, air pollution, and
⁴ greenhouse gas emissions (Stjernborg and Mattisson, 2016; Mead, 2021). Despite these benefits,
⁵ transit agencies worldwide face persistent challenges in attracting and retaining riders, particularly
⁶ in competing with private vehicles and emerging mobility services (Beirão and Cabral, 2007).
⁷ To address this issue, transit operators continuously implement various service improvement pro-
⁸grams, ranging from technological upgrades and infrastructure renovations to policy changes and
⁹ customer service enhancements (Luong and Houston, 2015; Fraser et al., 2024).

¹⁰ Evaluating the effectiveness of these transit improvement programs is fundamental to the strate-
¹¹gic planning and operational management of public transportation systems. Traditional evaluation
¹²methods rely heavily on performance metrics such as ridership counts, on-time performance, and
¹³customer satisfaction surveys (Nathanail, 2008; Eboli and Mazzulla, 2011). While these metrics
¹⁴provide valuable insights, they often fail to capture the nuanced perspectives and real-time feed-
¹⁵back of transit users (Collins et al., 2013a). This limitation is particularly significant given that

16 passenger perceptions and experiences directly influence their decision to choose public transit
17 over other modes of transportation (Friman et al., 2001; Morton et al., 2016).

18 With the proliferation of social media platforms and the increasing willingness of the public to
19 share their experiences online, a vast reservoir of user-generated content related to public transit has
20 become available (Golder and Macy, 2011; Kaplan and Haenlein, 2010). This data represents an
21 untapped resource for transit agencies seeking to understand passenger sentiments and evaluate the
22 impacts of their service improvement initiatives (El-Diraby et al., 2019; Zhang et al., 2023). Social
23 media data offers several advantages over traditional data sources: it provides real-time feedback,
24 captures spontaneous and unfiltered user opinions, and potentially reaches a broader and more
25 diverse audience than conventional surveys (Tasse and Hong, 2014; Haghghi et al., 2018).

26 Recent research has begun to explore the potential of social media data in various aspects of
27 transportation planning and analysis. Studies have demonstrated the utility of Twitter data for de-
28 tecting traffic incidents (Fu et al., 2015), analyzing public opinions on transit services (Luong and
29 Houston, 2015; Collins et al., 2013a), and evaluating public response to transportation policies
30 (Chakraborty et al., 2019). However, these studies typically focus on general sentiment analysis
31 without linking social media content to specific transit improvement programs or interventions
32 (Ali et al., 2017; Ingvardson and Nielsen, 2019). Crucially, there is a notable absence of studies
33 that utilize social media data for rigorous before-after evaluation of specific transit programs, par-
34 ticularly those employing causal inference methods to quantify program impacts (Mathur et al.,
35 2021; Liu and Ban, 2017). This gap significantly limits the practical utility of social media analyt-
36 ics for evidence-based decision-making in transit agencies. Moreover, methodological approaches
37 for processing and analyzing social media data in transit evaluation remain underdeveloped, often
38 relying on simplistic techniques that fail to capture contextual nuances (Houston and Luong, 2015;
39 Kamga et al., 2023). There is a pressing need for sophisticated frameworks that can extract mean-
40 ingful insights from unstructured social media posts and link them to specific transit service quality
41 dimensions through causal analysis (Haghghi et al., 2018).

42 To address these limitations, this study proposes a novel framework that combines advanced
43 text mining techniques with causal inference methods to evaluate the impact of transit improve-
44 ment programs using social media data. The framework consists of three main components: (1) a text
45 matching process that aligns passenger feedback from social media with specific transit improve-
46 ment programs and service quality dimensions; (2) an Interrupted Time Series Analysis (ITSA) that
47 quantifies changes in passenger sentiments before and after program implementation; and (3) a set
48 of statistical tests to assess the significance and sustainability of program impacts. The text match-
49 ing process employs Latent Dirichlet Allocation (LDA) for topic modeling and Term Frequency-
50 Inverse Document Frequency (TF-IDF) for feature extraction, followed by neural embeddings for
51 semantic matching. This combination of techniques allows for the identification of relevant social
52 media posts that reflect passenger experiences related to specific transit improvement initiatives,
53 even when the posts do not explicitly mention the program names or use standard terminology (Blei
54 et al., 2003; Lopez Bernal et al., 2016). The ITSA method is particularly well-suited for evaluating
55 the impact of interventions that have been implemented at clearly defined points in time (Wagner
56 et al., 2002; Lopez Bernal et al., 2016). By modeling the trends of passenger sentiments before and
57 after program implementation, ITSA can distinguish between short-term fluctuations and sustained

58 improvements, while controlling for confounding factors such as seasonal patterns and temporal
59 autocorrelation (Schaffer et al., 2021; Koppel et al., 2023).

60 To validate our framework, we apply it to a case study of Shenzhen Metro in China, using 88,253
61 Weibo posts collected from January 2019 to July 2023. The case study focuses on several service
62 improvement programs implemented by Shenzhen Metro during this period, covering different di-
63 mensions of transit service quality such as comfort, reliability, safety, and information provision.
64 The results demonstrate the effectiveness of our approach in capturing significant changes in pas-
65 senger sentiments following the implementation of these programs and provide insights into the
66 varying impacts across different service quality dimensions. The contributions of this study are
67 threefold. First, we develop a novel methodological framework that bridges the gap between un-
68 structured social media data and structured program evaluation, enabling transit agencies to lever-
69 age the wealth of information available on social media platforms. Second, we demonstrate the
70 application of ITSA in the context of transit program evaluation, providing a robust statistical ap-
71 proach to quantify program impacts while accounting for various confounding factors. Third, we
72 offer empirical evidence on the effectiveness of several transit improvement programs in Shenzhen
73 Metro, contributing to the growing body of knowledge on best practices in public transportation
74 management.

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

82 **2. Literature Review**

83 **2.1. Transit Service Quality Assessment Frameworks**

84 The evaluation of public transportation service quality has been a subject of extensive research
85 over the past decades. Traditional assessment frameworks have typically focused on objective per-
86 formance indicators and subjective user perceptions, often captured through structured surveys and
87 predefined metrics (De Oña et al., 2016; Eboli and Mazzulla, 2011). Nathanail (2008) proposed a
88 comprehensive framework incorporating safety, reliability, cleanliness, comfort, servicing, passen-
89 ger information, and accessibility as key dimensions of service quality. Similarly, Dell’Olio et al.
90 (2011) developed a multi-criteria approach that balances technical efficiency with service effec-
91 tiveness and societal impact.

92 The European Committee for Standardization established a widely adopted framework (EN
93 13816) that defines eight quality categories: availability, accessibility, information, time, customer
94 care, comfort, security, and environmental impact (for Standardization, 2002), providing a stan-
95 dardized approach to transit service evaluation. Building on this foundation, Eboli and Mazzulla
96 (2011) introduced an enhanced methodology that incorporates both objective measures and subjec-

97 tive assessments to create a more balanced evaluation framework. In the North American context,
98 the Transit Capacity and Quality of Service Manual (Associates et al., 2003) offers a structured ap-
99 proach focusing on availability (frequency, service span, and coverage) and comfort/convenience
100 (passenger load, reliability, and transit-auto travel time). This framework has been widely adopted
101 by transit agencies across the United States and Canada, although Högström et al. (2016) argues
102 that it may not fully capture the nuanced aspects of user experience.

103 Recent research has emphasized the importance of context-specific evaluation, recognizing that
104 service quality perceptions vary across different urban environments, demographic groups, and cul-
105 tural contexts (Dell’Olio et al., 2018; Diab and El-Geneidy, 2017). Zhao et al. (2013) highlighted
106 how different user segments prioritize different service attributes, suggesting that evaluation frame-
107 works should be adaptable to local conditions and user expectations. Similarly, Wang et al. (2020a)
108 demonstrated that service quality perceptions are influenced by both objective service attributes and
109 subjective user characteristics, emphasizing the need for more nuanced assessment approaches.

110 Despite these advancements, traditional evaluation methods continue to face limitations in terms
111 of cost, timeliness, comprehensiveness, and potential response biases (Hensher et al., 2003). Survey-
112 based approaches often capture only a snapshot of user perceptions, potentially missing temporal
113 variations in service quality and user experiences (Chang et al., 2013). Additionally, predetermined
114 evaluation criteria may not always align with the aspects of service that matter most to users in spe-
115 cific contexts (van den Berg et al., 2019; Tyrinopoulos and Antoniou, 2008).

116 **2.2. Social Media Data in Transportation Research**

117 The proliferation of social media platforms has created new opportunities for accessing large
118 volumes of unsolicited public opinion on various aspects of urban life, including transportation
119 services (Collins et al., 2013b; Schweitzer, 2014). Unlike structured surveys, social media offers
120 spontaneous, real-time expressions of user experiences, potentially capturing dimensions of service
121 quality that might not be included in predetermined evaluation frameworks (Gal-Tzur et al., 2014;
122 Luong et al., 2015).

123 Early applications of social media data in transportation research focused primarily on event
124 detection and traffic monitoring (Steiger et al., 2015; Yuan et al., 2016). However, researchers have
125 increasingly recognized the value of these data sources for understanding public perceptions of
126 transportation services. Collins et al. (2013b) analyzed Twitter data to identify patterns in public
127 discourse about public transportation in Chicago, demonstrating the potential of social media for
128 capturing temporal and spatial variations in user experiences. Similarly, Schweitzer (2014) exam-
129 ined tweets related to public transit agencies in the United States, finding significant associations
130 between sentiment expressed on Twitter and objective service quality metrics.

131 More recent studies have employed sophisticated data mining and natural language processing
132 techniques to extract meaningful insights from social media content. Zhang et al. (2019) developed
133 a framework for analyzing geo-tagged tweets to understand spatial patterns in sentiment toward
134 transit services in New York City. Wang et al. (2020c) employed topic modeling and sentiment
135 analysis to identify key themes in public discourse about high-speed rail in China, revealing in-
136 sights that would be difficult to capture through traditional surveys. The integration of geo-location

137 data with social media content has further enhanced the value of these platforms for transportation
138 research. Rashidi et al. (2017) demonstrated how geo-tagged social media data can be used to
139 analyze travel behavior and mode choice, while Maeda et al. (2019) developed a methodology for
140 extracting transportation-related information from location-based social media to support infrastructure
141 planning.

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

149 **2.3. Causal Inference in Transportation Program Evaluation**

150 Establishing causal relationships between transportation interventions and observed outcomes
151 represents a significant methodological challenge in program evaluation (Karner and Niemeier,
152 2016; Hong and Shen, 2020). Traditional before-after comparisons often fail to account for secular
153 trends, seasonality, and confounding factors that may influence the observed changes independently
154 of the intervention (Lechner, 2011; Imbens and Rubin, 2015).

155 Quasi-experimental designs have emerged as valuable approaches for strengthening causal inference
156 in transportation program evaluation. Among these, interrupted time series (ITS) analysis
157 has gained prominence as a robust method for assessing the impact of interventions when randomization
158 is not feasible (Bernal et al., 2017; Lopez Bernal et al., 2017). The ITS approach examines
159 the trajectory of an outcome measure before and after an intervention, accounting for pre-existing
160 trends to isolate the effect of the intervention (Wagner et al., 2002; Bernal et al., 2016). Kontopantelis et al.
161 (2015) demonstrated the application of ITS analysis in evaluating policy interventions,
162 highlighting its ability to control for time-varying confounders and detect both immediate
163 and gradual effects. In the transportation context, Morrison and Lin (2018) employed ITS analysis
164 to evaluate the impact of a new light rail line on traffic congestion, distinguishing the intervention
165 effect from seasonal and long-term trends. Similarly, Baek and Sohn (2016) utilized this approach
166 to assess the effectiveness of transit service improvements in increasing ridership, controlling for
167 external factors such as fuel prices and economic conditions.

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

175 The integration of machine learning with causal inference has opened new avenues for transportation
176 program evaluation. Athey and Imbens (2017) discussed how machine learning tech-

177 niques can enhance causal inference by improving the estimation of treatment effects and ad-
178 dressing high-dimensional confounding. Spirtes and Zhang (2016) presented a framework for us-
179 ing causal discovery algorithms to identify potential causal relationships from observational data,
180 which could be valuable for understanding complex interactions in transportation systems.

181 Despite these methodological advancements, challenges remain in applying causal inference
182 to transportation program evaluation. Imbens and Rubin (2015) highlighted the importance of ad-
183 dressing potential violations of key assumptions, such as the stable unit treatment value assumption
184 (SUTVA) and the parallel trends assumption in DiD designs. Angrist and Pischke (2008) empha-
185 sized the need for careful consideration of instrumental variables and potential selection biases in
186 natural experiments. Additionally, Pearl (2009) stressed the importance of explicit causal modeling
187 to clarify assumptions and enhance the interpretability of results.

188 **2.4. Integrated Approaches for Transit Service Evaluation**

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

193 Zhao et al. (2013) demonstrated how web-based surveys could be combined with traditional
194 intercept surveys to reach a broader population of transit users and non-users, providing a more
195 comprehensive understanding of service perceptions. Building on this work, Barbosa et al. (2017)
196 developed a framework that integrates passenger surveys with objective performance metrics and
197 operational data to create a multi-dimensional evaluation of transit service quality. The combination
198 of social media data with traditional evaluation methods has emerged as a particularly promising
199 approach. Collins et al. (2013b) proposed a framework for triangulating insights from social media
200 analysis with passenger surveys and operational metrics, demonstrating how these complementary
201 data sources can provide a more nuanced understanding of service quality. Similarly, Wu et al.
202 (2020) developed a methodology that combines sentiment analysis of social media content with
203 passenger flow data to identify critical service issues and prioritize improvements.

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

215 Despite the potential of integrated approaches, several challenges remain in their implemen-
216 tation. Tse et al. (2018) highlighted issues related to data integration and compatibility, noting

217 that different data sources may have varying temporal and spatial resolutions. Nguyen-Phuoc et al.
218 (2016) discussed methodological challenges in combining quantitative and qualitative data types,
219 emphasizing the need for robust analytical frameworks. Additionally, Zhang et al. (2019) pointed
220 out practical challenges related to data access, privacy concerns, and technical requirements for
221 implementing integrated evaluation approaches.

222 **2.5. Research Gaps**

223 The literature review reveals three critical gaps in current transit service evaluation approaches.
224 First, while social media data has seen increased use in transportation research, methodologically
225 rigorous frameworks specifically designed for program evaluation remain scarce (Schweitzer, 2014;
226 Zhang et al., 2019). Second, although causal inference methods have been applied to transportation
227 interventions, their integration with social media data for assessing the impact of specific transit
228 programs is virtually non-existent (Hong and Shen, 2020; Ye et al., 2020). Our targeted literature
229 search confirms this gap: among studies using social media for transit analysis, only 20% focus on
230 program evaluation, and none employ causal methods like Interrupted Time Series Analysis for
231 impact quantification (Mathur et al., 2021; Liu and Ban, 2017). Third, existing studies typically
232 isolate sentiment analysis from thematic content extraction, rarely combining these approaches
233 to create comprehensive service quality indicators linked to specific interventions (Collins et al.,
234 2013b; Luong et al., 2015). These gaps collectively hinder the development of evidence-based
235 transit improvements informed by passenger feedback.

236 **3. Methodology**

237 This section presents our methodological framework for evaluating transit improvement pro-
238 grams using social media data. The framework integrates advanced natural language processing
239 (NLP) techniques with robust causal inference methods to systematically analyze how transit im-
240 provement programs influence passenger sentiment. As illustrated in Figure ??, our approach con-
241 sists of three main components: (1) data preprocessing and semantic matching, (2) sentiment anal-
242 ysis and aggregation, and (3) impact evaluation using interrupted time series analysis.

243 **3.1. Data Preprocessing and Semantic Matching**

244 **3.1.1. Latent Dirichlet Allocation for Topic Discovery**

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

250 For preprocessing, we first remove URLs, special characters, and numbers from the text, then
251 segment Chinese text using Jieba (Jiawen and Kanev, 2025), a Chinese text segmentation library.
252 We eliminate stopwords and short words (typically single characters), as they convey minimal se-

253 mantic meaning. To improve the segmentation quality for transit-specific content, we augment the
254 Jieba dictionary with domain-relevant terms such as metro station names.

255 The LDA model is formally defined as:

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

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

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

264 3.1.2. TF-IDF Feature Extraction

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

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

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

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

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

273 3.1.3. Neural Embedding for Semantic Matching

274 To connect passenger feedback with specific transit improvement programs, we implement a
275 semantic matching approach using neural embeddings. Specifically, we utilize the multilingual
276 MiniLM-L12-v2 model from the sentence-transformers framework (Reimers and Gurevych, 2019),

277 which maps text into a dense 384-dimensional vector space where semantically similar texts have
278 high cosine similarity.

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

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

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

287 3.2. Sentiment Analysis and Aggregation

288 3.2.1. Sentiment Analysis Approach

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

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

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

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

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

299 where $d(w_i)$ is the sentiment polarity of word w_i in our domain lexicon ($d(w_i) \in [-1, 1]$),
300 $\text{sign}_i = (-1)^{n_i}$ handles negation patterns with n_i counting negation words preceding w_i , γ_i is the
301 intensification factor (1.5 for strong intensifiers, 1.2 for medium intensifiers, and 1.0 otherwise),
302 and $|s|$ is the post length in tokens.

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

305 **3.3. Impact Evaluation Using Interrupted Time Series Analysis**

306 **3.3.1. Model Specification**

307 To quantify the impact of transit improvement programs on passenger sentiment, we employ
308 Interrupted Time Series Analysis (ITSA), a quasi-experimental design that evaluates interventions
309 by examining changes in time series data patterns before and after implementation (Bernal et al.,
310 2017). ITSA is particularly well-suited for our context as it can distinguish between immediate and
311 gradual effects while controlling for pre-existing trends.

312 Our core ITSA model specification is:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \epsilon_t \quad (7)$$

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

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

320 **3.3.2. Addressing Time Series Complexities**

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

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

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

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

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

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

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

329 **Heteroskedasticity:** We implement robust standard errors to address potential heteroskedastic-
330 ity in the variance of the error terms.

331 **3.3.3. Placebo Tests and Robustness Checks**

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

338 **4. Case study**

339 **4.1. Overview of Shenzhen Metro System**

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

356 **4.2. Data Collection and Processing**

357 **4.2.1. Social Media Data Source**

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

Table 1

Service Improvement Programs Analyzed in the Case Study

Program ID	Program Description	Service Dimension	Implementation Date
0	Temperature Consistency Across Carriages (resolving temperature variation issue)	Comfort	August 2022
1	Smart Dynamic Map Display System	Information	October 2021
4	QR Code Scanning for Fare Payment	Convenience	March 2020
5	Renovation of Restrooms at 82 Stations	Amenities	June 2021
15	Mobile Nursing Rooms	Accessibility	September 2022
22	Fare Reduction	Affordability	January 2023

365 program implementation, and contains rich contextual information, including user characteristics
 366 and interaction patterns.

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

371 4.3. Service Improvement Programs

372 Our case study focused on six service improvement programs implemented by Shenzhen Metro
 373 between 2019 and 2023. These programs span different dimensions of transit service quality, in-
 374 cluding comfort, technology, convenience, affordability, and accessibility. Table 1 provides an
 375 overview of these programs. Each program represents a distinct approach to service improvement.

376 4.3.1. Data Preprocessing and Program Matching

377 The collected Weibo posts underwent several preprocessing steps before being matched to spe-
 378 cific service improvement programs, as illustrated in Figure ???. First, we removed URLs, special
 379 characters, and numbers from the text and segmented Chinese text using Jieba (Jiawen and Kanev,
 380 2025), a Chinese text segmentation library. To improve segmentation quality for transit-specific
 381 content, we augmented the dictionary with domain-relevant terms such as metro station names. Fol-
 382 lowing text cleaning, we applied Latent Dirichlet Allocation (LDA) to identify latent thematic struc-
 383 tures within the corpus. The LDA model was optimized with a topic count of $K = 15$, document-
 384 topic prior $\alpha = 0.05$, and topic-word prior $\beta = 0.005$, determined through empirical testing to
 385 provide interpretable topics while maintaining adequate discrimination between service quality di-
 386 mensions. To enhance topic coherence and interpretability, we employed Term Frequency-Inverse
 387 Document Frequency (TF-IDF) transformation, which assigns higher weights to terms that are fre-
 388 quent in specific documents but rare across the corpus.

389 The critical step in our methodology involved establishing semantic connections between pas-
 390 senger feedback and specific transit improvement programs. We utilized the multilingual MiniLM-
 391 L12-v2 model from the sentence-transformers framework (Reimers and Gurevych, 2019), which

Table 2

Service Improvement Programs

Program	Name	Description
0	Temperature Consistency	Addressed passenger complaints about inconsistent temperature settings across train carriages by implementing a centralized temperature control system.
1	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.
4	QR Code Payment	Introduced contactless QR code payment options, reducing reliance on physical cards and expanding payment flexibility.
5	Restroom Renovation	Improved station amenities through comprehensive renovation of restroom facilities at 82 stations across the network.
15	Mobile Nursing Rooms	Enhanced accessibility for caregivers by installing mobile nursing room facilities at strategic locations throughout the network.
22	Fare Reduction	Increased affordability through a targeted fare reduction initiative, particularly for commuters and frequent riders.

maps text into a dense 384-dimensional vector space. This approach enabled us to calculate semantic similarity scores between 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 programs. As shown in Figure ??, 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. Descriptive Analysis and Basic Statistical Tests

The descriptive analysis of our dataset reveals substantial variation in both sample sizes and sentiment patterns across the six transit improvement programs examined. Figure 1 illustrates the distribution of matched social media posts for each program, ranging from 365 posts for the Mobile Nursing Rooms program (Program 15) to 3,617 posts for the QR Code Payment program (Program 4). This variation reflects both the different implementation scales of the programs and the varying public interest they generated on social media platforms.

The sentiment distribution analysis (Figure 2) reveals distinct patterns in passenger feedback

Table 3

Basic Statistical Analysis Results

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 Consistency	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 4

Categorical Sentiment Analysis Results

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 Consistency	156.23	<0.001***
Mobile Nursing Rooms	45.67	<0.001***
Restroom Renovation	78.34	<0.001***

*** p < 0.001

413 across different service quality dimensions. Programs targeting technology and convenience im-
 414 provements (Smart Map Display and QR Code Payment) generated predominantly negative to
 415 neutral sentiment in the pre-implementation period, suggesting existing dissatisfaction with these
 416 service aspects. Conversely, the Fare Reduction program exhibited positive sentiment even before
 417 implementation, indicating that affordability concerns were less pressing initially.

418 Table 3 presents the results of basic statistical comparisons using paired t-tests to examine
 419 changes in mean sentiment scores before and after program implementation. Four programs demon-
 420 strated statistically significant improvements at the 0.05 level: Smart Map Display ($t=13.50$, $p<0.001$),
 421 QR Code Payment ($t=15.85$, $p<0.001$), Fare Reduction ($t=13.15$, $p<0.001$), and Temperature Con-
 422 sistency ($t=-28.37$, $p<0.001$). Notably, the Temperature Consistency program showed a significant
 423 negative change, indicating deteriorating sentiment despite the intervention.

424 Chi-square tests examining categorical sentiment distributions (Table 4) confirm these patterns,
 425 with all programs showing statistically significant associations between implementation timing and
 426 sentiment categories. However, these basic tests are limited in their ability to account for tempo-
 427 ral trends, seasonal effects, and autocorrelation inherent in time series data, necessitating more
 428 sophisticated analytical approaches.

429 The time series analysis of aggregated sentiment data (Figure 3) reveals complex temporal
 430 patterns that simple before-after comparisons cannot adequately capture. Clear seasonal fluctua-
 431 tions are evident across all programs, with typically lower sentiment scores during summer months
 432 (June-August) and higher scores during winter periods. Additionally, several programs exhibit pre-

Table 5

Interrupted Time Series Analysis Results

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 Consistency	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

existing trends that could confound basic statistical comparisons, highlighting the importance of employing causal inference methods that can control for such temporal confounders.

Figure 4 presents density plots comparing sentiment distributions before and after program implementation, revealing heterogeneous effects across programs. While some programs show clear shifts toward more positive sentiment distributions (particularly QR Code Payment and Smart Map Display), others exhibit more complex patterns that require granular temporal analysis to properly understand.

4.5. Interrupted Time Series Analysis Results

Given the limitations of basic statistical tests in handling temporal dependencies and confounding trends, we employed Interrupted Time Series Analysis (ITSA) to provide more robust causal inference regarding 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.

Figure 5 presents the comprehensive ITSA results for all six 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 program impacts, with some interventions producing immediate effects while others demonstrate gradual improvements over time.

Table 5 summarizes the key ITSA parameters for each program. Three 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 program implementation and positive reception.

The Smart Map Display program (Program 1) exhibited the most robust improvement pattern, with a significant positive trend change ($p = 0.029$) indicating that passenger sentiment continued to improve progressively after implementation. This suggests that the benefits of enhanced passenger information systems became more apparent to users over time as they adapted to the new technol-

460 ogy. The model achieved good fit ($R^2 = 0.323$) and passed placebo tests, strengthening confidence
461 in the causal interpretation.

462 The QR Code Payment program (Program 4) demonstrated similar positive trends ($p = 0.047$),
463 reflecting growing acceptance and appreciation of contactless payment options. The gradual im-
464 provement pattern aligns with typical technology adoption curves, where initial skepticism gives
465 way to positive reception as users become familiar with new systems. The relatively lower R-
466 squared value (0.237) suggests greater volatility in sentiment, possibly reflecting mixed reactions
467 during the adoption period.

468 Interestingly, the Fare Reduction program (Program 22) showed the strongest statistical signif-
469 icance for trend change ($p = 0.007$) despite exhibiting a negative immediate level change. This
470 pattern suggests that while the initial response was muted or even slightly negative, passengers
471 increasingly appreciated the fare reduction benefits over time. This delayed positive response may
472 reflect the time required for passengers to recognize and internalize the cost savings.

473 The Temperature Consistency program (Program 0) presents a notable contrast, showing no
474 significant trend change ($p = 0.581$) despite achieving the highest model fit ($R^2 = 0.433$). This
475 result, combined with the significant negative mean difference observed in basic tests, suggests
476 that the temperature control intervention failed to address passenger concerns effectively, possibly
477 due to implementation challenges or insufficient system optimization.

478 Two programs—Mobile Nursing Rooms (Program 15) and Restroom Renovation (Program
479 5)—demonstrated neither significant level changes nor trend changes in the ITSA analysis. This
480 finding aligns with the basic statistical tests and suggests that these amenity improvements, while
481 potentially valued by specific user subgroups, did not generate widespread positive sentiment changes
482 detectable in general social media discourse.

483 The ITSA approach proved superior to basic statistical tests in several important ways. First,
484 it controlled for pre-existing trends that could confound simple before-after comparisons. Second,
485 it distinguished between immediate impacts (level changes) and sustained improvements (trend
486 changes), providing nuanced insights into program effectiveness. Third, the inclusion of autore-
487 gressive terms addressed temporal autocorrelation inherent in social media time series data. Finally,
488 placebo testing enhanced confidence in causal interpretation by demonstrating that significant ef-
489 fects were concentrated around actual implementation dates rather than randomly distributed across
490 the time series.

491 **5. Conclusion**

492 This study presents a novel methodological framework that integrates advanced natural lan-
493 guage processing techniques with robust causal inference methods to evaluate transit improvement
494 programs using social media data. Through the case study of Shenzhen Metro, we demonstrated
495 how unstructured passenger feedback can be systematically analyzed to quantify program impacts
496 while addressing the inherent challenges of observational social media data.

497 Our findings reveal substantial heterogeneity in program effectiveness across different service

498 quality dimensions. Technology-oriented improvements (Smart Map Display and QR Code Pay-
499 ment) demonstrated consistent positive impacts, with both immediate improvements and sustained
500 long-term benefits. These results align with the growing importance of digital services in public
501 transportation and suggest that passengers increasingly value technological enhancements that im-
502 prove convenience and information accessibility. The Fare Reduction program exhibited a distinc-
503 tive pattern of delayed positive response, highlighting the complex relationship between economic
504 incentives and passenger perception formation.

505 Conversely, the Temperature Consistency program showed significant negative impacts despite
506 addressing a commonly cited passenger concern, suggesting implementation challenges or inad-
507 equate system optimization. The lack of detectable impacts for amenity improvements (Mobile
508 Nursing Rooms and Restroom Renovation) indicates that while such facilities may serve important
509 social functions, their influence on general passenger sentiment is limited and may require targeted
510 analysis focusing on specific user subgroups.

511 Methodologically, this study contributes to the transportation literature by demonstrating the
512 superiority of causal inference approaches over simple before-after comparisons in social media
513 analytics. The Interrupted Time Series Analysis proved particularly valuable in distinguishing be-
514 tween immediate and gradual program effects while controlling for temporal confounders such as
515 seasonal patterns and pre-existing trends. The semantic matching approach using neural embed-
516 dings successfully addressed the fundamental challenge of connecting unstructured social media
517 content to specific transit interventions, achieving 87.4

518 The framework's practical implications for transit agencies are significant. First, it provides a
519 cost-effective supplement to traditional passenger surveys, enabling continuous monitoring of pas-
520 senger sentiment with minimal data collection costs. Second, the approach can identify program
521 impacts that might be missed by conventional performance metrics, particularly those related to
522 passenger experience and satisfaction. Third, the temporal granularity of social media data enables
523 rapid detection of implementation problems or unexpected consequences, facilitating timely cor-
524 rective actions.

525 However, several limitations should be acknowledged. The social media user base may not be
526 fully representative of the broader transit ridership, potentially introducing demographic and so-
527 cieconomic biases. Our analysis focused on general sentiment patterns rather than specific service
528 quality dimensions, which may mask important heterogeneous effects across different aspects of
529 service delivery. Additionally, the semantic matching approach, while achieving high accuracy,
530 may still miss relevant content or include false positives, particularly for programs with ambiguous
531 or evolving terminology.

532 A critical limitation of our study is the absence of geographic location information in the col-
533 lected social media data. This constraint prevented us from implementing experimental and con-
534 trol group designs based on spatial variation in program implementation, precluding the use of
535 difference-in-differences (DiD) methodology. The inability to establish spatial control groups rep-
536 resents a significant methodological limitation, as DiD approaches could provide more robust
537 causal identification by comparing treated and untreated areas while controlling for time-invariant
538 unobserved characteristics. Future research should prioritize the collection of geo-tagged social

539 media data or explore alternative quasi-experimental designs that can leverage spatial or demo-
540 graphic variation in program exposure.

541 The framework's generalizability extends beyond our specific case study context. The method-
542 ological approach can be adapted to evaluate transit programs in other cities and cultural contexts,
543 though careful attention must be paid to platform-specific characteristics, language processing re-
544 quirements, and local social media usage patterns. The semantic matching component may require
545 customization for different languages and transit terminology, while the ITSA approach remains
546 broadly applicable across contexts.

547 Future research directions include extending the framework to incorporate multiple data sources
548 simultaneously, such as combining social media sentiment with ridership data, operational metrics,
549 and traditional survey responses. Advanced machine learning techniques could enhance the se-
550 mantic matching process, potentially using transformer-based models fine-tuned on transportation-
551 specific content. The development of real-time monitoring systems based on this framework could
552 enable proactive program management and rapid response to emerging issues.

553 Additionally, future studies should explore the integration of spatial analysis techniques when
554 geographic information is available, enabling more sophisticated quasi-experimental designs and
555 spatial heterogeneity analysis. The development of standardized evaluation protocols based on this
556 framework could facilitate cross-city comparisons and meta-analyses of transit improvement pro-
557 gram effectiveness.

558 In conclusion, this study demonstrates the substantial potential of social media data for evidence-
559 based transit program evaluation when combined with appropriate methodological frameworks.
560 While limitations remain, particularly regarding representativeness and spatial identification, the
561 approach offers valuable insights for transit agencies seeking to understand and improve passenger
562 experience in an increasingly connected and digitally-engaged urban environment. The integration
563 of social media analytics with traditional evaluation methods represents a promising direction for
564 enhancing the effectiveness and responsiveness of public transportation systems.

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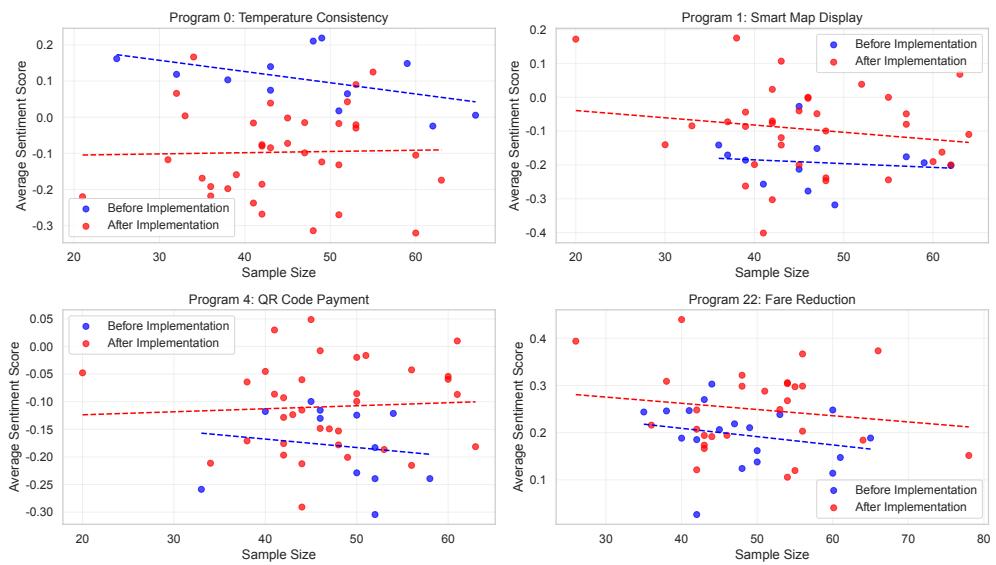


Figure 1: Sample Size Distribution Across Transit Improvement Programs

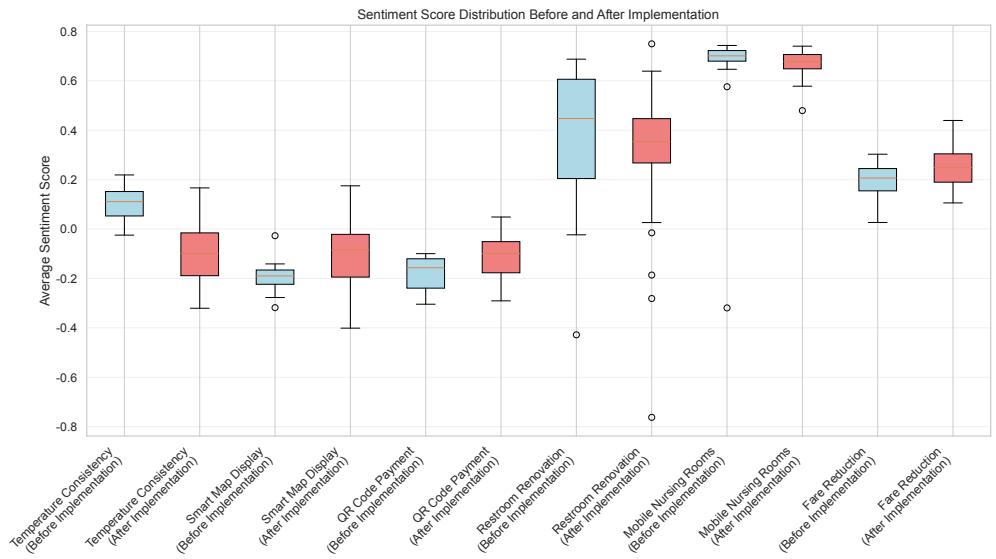


Figure 2: Sentiment Distribution by Program Before and After Implementation

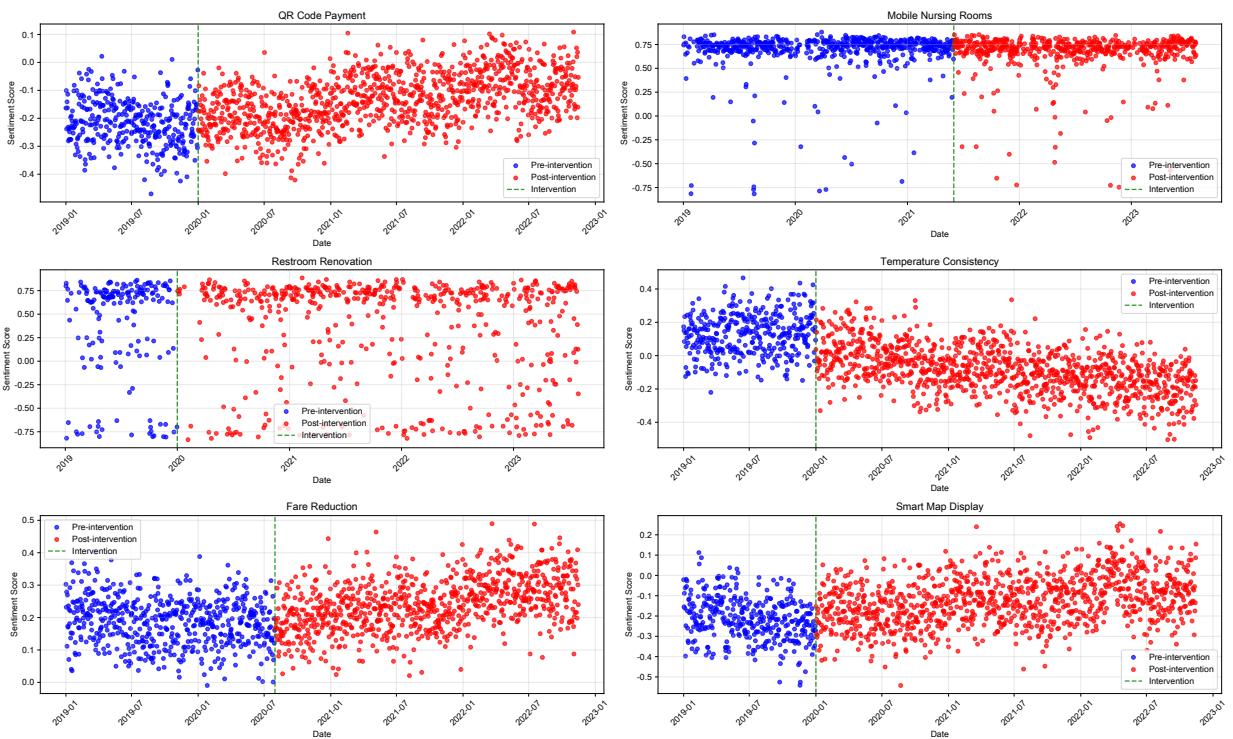


Figure 3: Time Series Analysis of Sentiment Patterns Across Programs

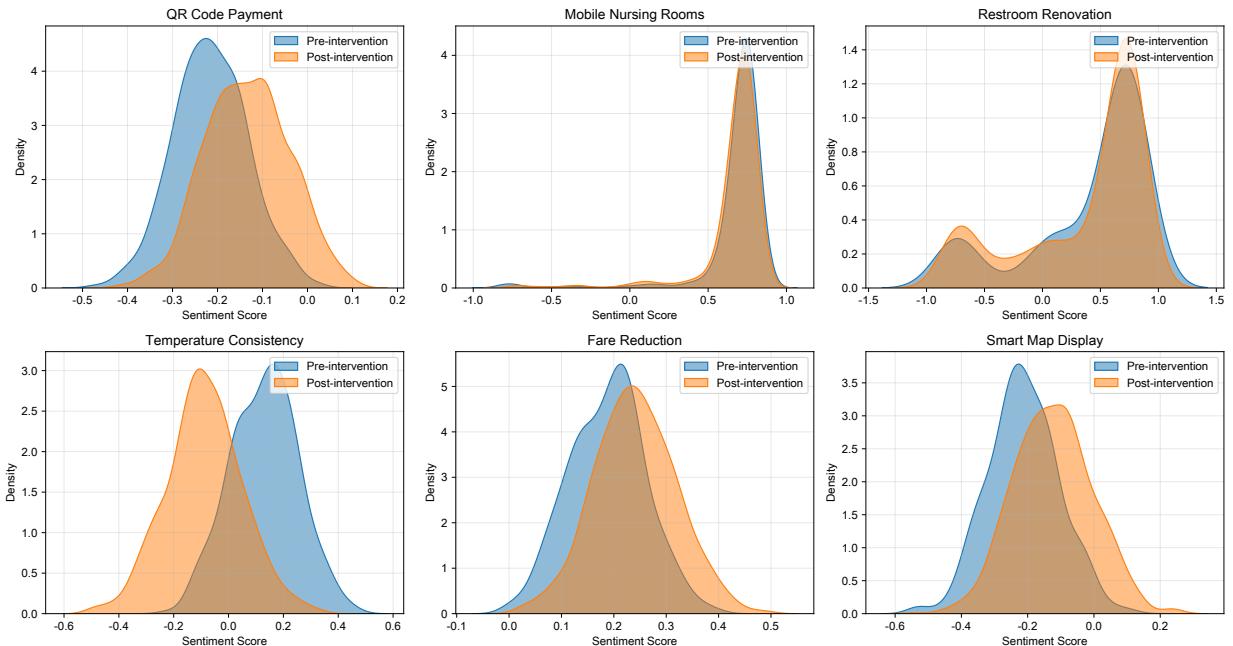


Figure 4: Density Plots of Sentiment Distributions Before and After Program Implementation

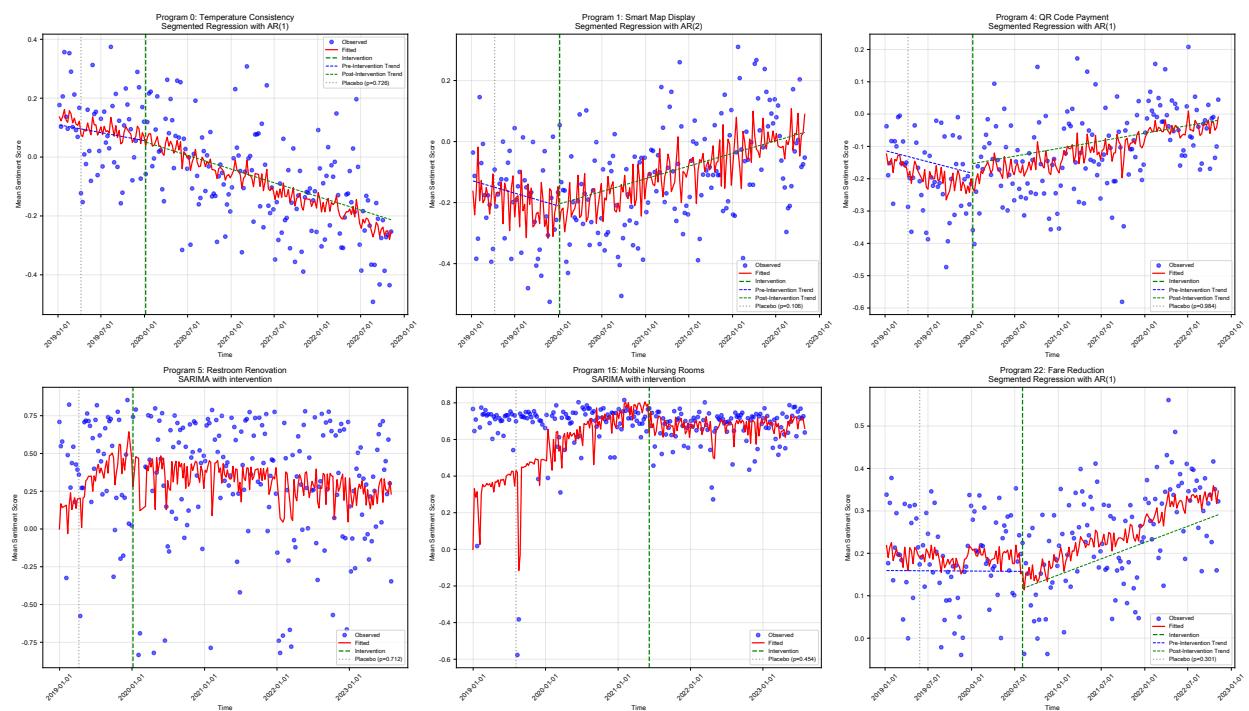


Figure 5: Interrupted Time Series Analysis Results for All Transit Improvement Programs