



Quality Perception of São Paulo Transportation Services: A Sentiment Analysis of Citizens' Satisfaction Regarding Bus Terminuses

Donizete Beck¹ Marco Teixeira² Juliana Maróstica³ Marcos Ferasso⁴

Abstract

Purpose: To explore citizens' satisfaction with all Bus Terminuses (BTs) in São Paulo City, Brazil.

Method: This study performed a Sentiment Analysis of citizens' perception of 32 BTs of São Paulo, composed of 8,371 user comments on Google Maps.

Originality/Relevance: This study highlights the role of Sentiment Analysis as an optimal tool for Stakeholder Analysis in the Urban Context.

Findings: First, Sentiment Analysis is a valuable source for stakeholder-oriented urban management. Second, sentiment Analysis provides detailed information about citizen satisfaction, providing valuable cues for urban managers to improve public service quality. Third, Smart Sustainable Cities can provide multiple and massive quantities of data that all kinds of urban stakeholders can use in decision-making processes, which helps perform Sentiment Analysis. Fourth, Sentiment Analysis is helpful for BT managers to improve BT services based on the users' feelings. Finally, further studies should explore sentiment classification in Sentiment Analysis of the critical aspects unfolded in this study as well as for exploring responsiveness of municipal public services.

Methodological Contributions: This study demonstrated that Sentiment Analysis can be a method for scrutinizing stakeholders' opinions and perceptions about governmental services at the city level.

Practitioner Contributions: Urban Planners, Transportation Policy Makers, and Urban Managers can use Sentiment Analysis to foster stakeholder-oriented management, which in turn fosters democracy and urban performance.

Keywords: Smart Sustainable Cities; Stakeholder Theory; Urban Mobility; Sentiment Analysis; Urban Transportation Quality.

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¹ Postdoctoral Researcher. Arq.Futuro Cities Lab, Insper Institute of Education and Research. São Paulo, SP - Brazil. donizetefb@insper.edu.br

² PhD Candidate. Graduate School of Administration, Nove de Julho University. São Paulo, SP - Brazil. mteixei01@uni9.edu.br

³ Master. Graduate School of Smart Sustainable Cities, Nove de Julho University. São Paulo, SP - Brazil. rodrigues.marostica@gmail.com

⁴ Assistant Professor. Escola de Ciências Económicas e das Organizações, Universidade Lusófona. Lisboa, Portugal. And Associate Researcher Grupo de Investigación de Estudios Organizacionales Sostenibles, Universidad Autónoma de Chile. Santiago, Chile. admmarcosferasso@gmail.com ; marcos.ferasso@uautonoma.cl



Percepção da Qualidade dos Serviços de Transporte de São Paulo: Uma Análise de Sentimento da Satisfação dos Cidadãos em relação aos Terminais de Ônibus

Resumo

Objetivo: Explorar a satisfação dos cidadãos sobre todos os terminais rodoviários (TRs) da cidade de São Paulo, Brasil.

Método: Este estudo realizou análise de sentimentos da percepção dos cidadãos de 32 TRs de São Paulo, composta por 8.371 comentários de usuários no Google Maps.

Originalidade/Relevância: Este estudo destaca o papel da análise de sentimentos como uma ferramenta ideal para a análise de stakeholders no contexto urbano.

Resultados: Primeiro, a análise de sentimentos é uma fonte valiosa para a gestão urbana orientada aos stakeholders. Segundo, a análise de sentimento fornece informações detalhadas sobre a satisfação do cidadão, fornecendo dicas valiosas para os gestores urbanos melhorarem a qualidade do serviço público. Terceiro, as Cidades Inteligentes e Sustentáveis podem fornecer quantidades múltiplas e massivas de dados que todos os tipos de stakeholders urbanos podem usar na tomada de decisão, o que fornece subsídios para realizar a análise de sentimentos. Quarto, a análise de sentimentos é útil para gestores de TRs melhorarem os serviços de TRs com base nos sentimentos do usuário. Finalmente, estudos futuros devem explorar o método classificação de sentimentos na análise de sentimentos dos aspectos críticos desdobrados neste estudo, bem como para explorar a responsividade dos serviços públicos municipais.

Contribuições metodológicas: Este estudo demonstrou que a análise de sentimentos pode ser um método para escrutinar as opiniões e percepções de stakeholders sobre os serviços governamentais municipais

Contribuições aos profissionais: Planejadores urbanos, formuladores de políticas de transporte e gestores urbanos podem usar a análise de sentimentos para promover uma gestão orientada aos stakeholders, que por sua vez promove a democracia e o desempenho urbano.

Palavras-chave: Cidades Inteligentes e Sustentáveis; Teoria dos Stakeholders; Mobilidade Urbana; Análise de sentimentos; Qualidade do Transporte Urbano.

Percepción de la Calidad de los Servicios de Transporte en São Paulo: Un Análisis del Sentimiento de la Satisfacción de los Ciudadanos en Relación con las Terminales de Autobuses

Resumen

Propósito: Explorar la satisfacción de los ciudadanos sobre todos los terminales de autobuses (TR) en la ciudad de São Paulo, Brasil.

Método: Este estudio realizó un análisis de sentimiento de la percepción de los ciudadanos de 32 TR en São Paulo, que consta de 8.371 comentarios de usuarios en Google Maps.

Originalidad/relevancia: Este estudio destaca el papel del análisis de sentimientos como una herramienta ideal para el análisis de las partes interesadas en el contexto urbano.

Resultados: Primero, el análisis de sentimientos es una fuente valiosa para la gestión urbana orientada a las partes interesadas. En segundo lugar, el análisis de sentimientos brinda información detallada sobre la satisfacción de los ciudadanos, brindando valiosos consejos para que los administradores urbanos mejoren la calidad del servicio público. En tercer lugar, las ciudades inteligentes y sostenibles pueden proporcionar cantidades múltiples y masivas de datos que todos los tipos de partes interesadas urbanas pueden usar en la toma de decisiones, lo que proporciona subsidios para realizar análisis de sentimientos. En cuarto lugar, el análisis de



opiniones es útil para que los administradores de RT mejoren los servicios de RT en función de las opiniones de los usuarios. Finalmente, los estudios futuros deberían explorar el método de clasificación de sentimientos en el análisis de sentimientos de los aspectos críticos desarrollados en este estudio, así como explorar la capacidad de respuesta de los servicios públicos municipales.

Contribuciones metodológicas: este estudio demostró que el análisis de sentimientos puede ser un método para analizar las opiniones y percepciones de las partes interesadas sobre los servicios del gobierno municipal.

Contribuciones para los profesionales: los planificadores urbanos, los responsables de la formulación de políticas de transporte y los administradores urbanos pueden utilizar el análisis de sentimientos para promover la gestión orientada a las partes interesadas, lo que a su vez promueve la democracia y el desempeño urbano.

Palabras clave: Ciudades Inteligentes y Sostenibles; La teoría de las partes interesadas; Movilidad urbana; Análisis de los sentimientos; Calidad del Transporte Urbano.

Introduction

In the digital and highly connected worldwide context, *Smart Sustainable Cities* have emerged to improve the citizens' quality of life and foster sustainability (Bibri & Krogstie, 2017). Also, Smart Sustainable Cities provide many open and accessible Big Data sources through Information and Communications Technology (ICTs) and the Internet of Things (IoT). Much of this data can be used by public managers to improve public services, which is a fundamental contribution of *Smart Governance* (Bibri & Krogstie, 2017; Beck & Conti, 2021). Public managers in cities could also be stakeholder-oriented and formulate *Sustainable Urban Strategies* that embrace value creation for all stakeholders (Beck & Storopoli, 2021). In Smart Sustainable Cities, urban managers can exploit Big Data to foster sustainable urban strategies (Cordella & Bonina, 2012; Bannister & Connolly, 2014; Amankwah-Amoah, 2016; Chatfield & Reddick, 2018; Beck & Conti, 2021; Cavalheiro et al., 2021).

According to Beck and Storopoli (2021), *public transportation* is one of the leading emerging themes in the Sustainable Urban Strategy component of *Stakeholder Theory* in Cities. In this way, analyzing *public service quality* can help formulate sustainable strategies and policies at the local level. Accordingly, focusing on public transportation quality can help urban

managers make sustainable urban strategies oriented to stakeholders based on the Big Data provided by Smart Sustainable Cities.

In this way, *Sentiment Analysis* is an optimal *Natural Language Processing* tool for exploring stakeholder sentiments, scrutinizing stakeholder opinions, and providing an in-depth understanding of stakeholder perceptions about the quality of systems, policies, products, and services (Liu, 2020; Beck & Storopoli, 2021). In short, Sentiment Analysis identifies negative and positive sentiments in a text document using computational methods and lexicons. For example, Sentiment Analysis has been used to explore citizen perception of public libraries, airports, sanitary policies in public transportation, and restaurant customer experience (Thomas & Palfrey, 1996; Lee & Yu, 2018; Mathayomchan & Taecharungroj, 2020; Khan & Loan, 2022; Li et al., 2022; Park et al., 2022). However, there is no research in Urban Studies and Public Administration applying Sentiment Analysis to explore public service quality, as in the case of public transportation. Citizens' satisfaction can be a proxy for public service quality.

Considering that public transportation is critical for sustainable urban strategies, one of the main aspects of sustainable urban mobility is revealed by the quality of bus services at bus terminuses (Ji & Gao, 2010; Miller et al., 2016; Netto & Ramos, 2017). For this reason, *our purpose is to explore citizens' satisfaction in all Bus Terminuses (BTs) in São Paulo City, Brazil*. In this single case study (Yin, 2018), we used Sentiment Analysis of citizens' perception of the existing 32 BTs of São Paulo (SPTrans, 2022). The citizens' perceptions stem from a total of 8,371 user comments about these BTs available on Google Maps.

Theoretical background

This section first introduces an overview of *Stakeholder Theory* in cities by highlighting the role of stakeholder-oriented urban management in *public transportation planning*, which is crucial for developing sustainable urban strategies. After that, we revisited the construct of *Smart Sustainable Cities*, which has a practical approach for this study for two reasons: first, due to the preponderance of stakeholder-orientation in smart governance, and second, because



Smart Sustainable Cities exploit ICTs, IoT, and Big Data for analyzing the service quality of public transportation services, and thus, providing information for better decision-making of urban managers in order to meet the citizens' needs.

Stakeholder Theory in Cities

Stakeholder Theory aims to shed light on the phenomenon of stakeholder networks in businesses, public organizations, and cities (Freeman et al., 2010; Bryson et al., 2011; Harrison et al., 2015; Beck & Storopoli, 2021; Beck & Ferasso, 2023a; Beck & Vigoda-Gadot, in press). This way, the management of these different types of organizations began strategizing their goals and policies based on the multiple stakeholders' needs, expectations, and interests. Stakeholder-orientation is, in turn, a critical element for *Stakeholder Value Creation* (SVC) and a source of competitive advantage for cities and public and private organizations (Freeman et al., 2010; Beck & Storopoli, 2021; Beck & Ferasso, 2023b; Beck et al., 2023; Beck, 2023; Beck et al., in press). SVC is at the corner of Stakeholder Theory, which is defined as "... the sum of all the valuation estimates made by each of that system's essential stakeholder groups for the multiple utilities they receive from participation..." in organizational strategy (Tantalo & Priem, 2014, p. 317). In turn, SVC results from the synergy among stakeholders regarding their expectations and satisfaction with management policies.

According to seminal authors on Stakeholder Theory in cities, Beck and Storopoli (2021), *public transportation* is one of the main emergent themes in *Sustainable Urban Strategy* in which stakeholder engagement is crucial for fostering sustainable development in cities and at the local level (see also: Arvidsson & Pazirandeh, 2017; Ignaccolo et al., 2018; Khreis et al., 2016; Cavalheiro et al., 2021; Mendes et al., 2021). In this way, urban managers and planners should consider "how stakeholders have [used] the public transportation and how to promote stakeholders' engagement and follow their recommendations" (Beck & Storopoli, 2021, p. 5). In sum, stakeholder engagement, perceptions, and expectations should be considered when



urban managers aim to implement sustainable urban strategies and, thus, foster sustainable urban development.

In the case of public transportation, citizens are the most demanding urban stakeholders since they are the primary beneficiaries of public transportation, which is used to commute to their workplaces, leisure facilities, and market stores, among others (Beck & Storopoli, 2021). Therefore, in order to analyze citizens' perceptions of urban and public services, such as public transportation, citizens' satisfaction can be a proxy for public service quality. Much data about citizens' satisfaction can be derived from Smart Sustainable Cities (Beck et al., 2023; Beck, 2023), as discussed in the following subsection.

Smart Sustainable Cities

With the widespread and massive use of Information and Communications Technologies (ICTs) in organizations and cities, *Smart Sustainable Cities* emerge in a context where Big Data, E-government, and the Internet of Things (IoT) are crucial in urban management, smart governance, and policy-making (Bibri & Krogstie, 2017; Macke et al., 2018; Macke et al., 2019; Michelam et al., 2020; Beck & Conti, 2021; Corsi et al., 2022; Freire et al., 2022). In this context, stakeholders' expectations, stakeholder impact, and stakeholder activities are crucial elements in managing stakeholder-oriented Smart Sustainable Cities (Ibrahim et al., 2017; Carvalho et al., 2021). Accordingly, ICTs and IoT provide detailed information about many socio-spatial, economic, environmental, and demographic data. These data are critical for urban managers to improve the performance of urban services and then public services quality (Cordella & Bonina, 2012; Bannister & Connolly, 2014; Clarke & Margetts, 2014; Amankwah-Amoah, 2016; Bibri & Krogstie, 2017; Chatfield & Reddick, 2018; Storopoli et al., 2019; Guo et al., 2022; among others).

For instance, *many open and accessible sources of urban data are available on the internet for Smart Sustainable Cities*; Google Maps is one publicly recognizable example that provides comments, perceptions, and assessments of people about many places, businesses,





and public facilities, among others (Tao, 2013; Caquard, 2014; Ahad et al., 2020). Some examples of studies using Google Maps are: (1) exploration of the opinion/perceptions of citizens about public libraries and airport service quality (Lee & Yu, 2018; Borrego & Navarra, 2021; Khan & Loan, 2022; Li et al., 2022; Park et al., 2022) as well as in businesses such as restaurants (Mathayomchan & Taecharungroj, 2020); (2) assessment of seismic loss in school buildings (Purwana et al., 2022); and (3) to map city-wide traffic congestion, air pollutants emission, transit-oriented development, and real-time public transportation management (Mohan et al., 2017; Mishra et al., 2019; Phun et al., 2019).

This section provided a solid theoretical framework for discussing the results in light of the multi/interdisciplinary approaches of Stakeholder Theory in Cities and Smart Sustainable Cities in Urban Studies. The following section presents the research design used to achieve the research purpose.

Research Design

This research is characterized as a single case study (Yin, 2018) since the city of Sao Paulo was the case in which public transportation is considered the unit of analysis. The opinions and feelings of the citizens about public services, as in the case of public transportation, are relevant sources of information for urban management (Beck & Storopoli, 2021; Beck & Ferasso, 2023a). For this reason, *Sentiment Analysis*, a *Natural Language Processing* (NLP) technique, is suitable for this study because it “analyzes people’s opinions, sentiments, appraisals, attitudes, and emotions toward entities and their attributes expressed in written text. The entities can be products, services, organizations, individuals, events, issues, or topics.” (Liu, 2020, p. 1). Here, we used Sentiment Analysis to analyze citizens’ opinions about BTs in São Paulo City, exploring the service quality of BTs. This section is divided into four subsections: (1) sample selection; (2) data gathering; (3) data wrangling; and (4) Sentiment Analysis. Each part of this section was built considering the principles of replicability and reproducibility of method and data (Kedron et al., 2021a; Kedron et al., 2021b).

Sample Selection

According to *São Paulo Transporte S/A* (SPTrans, 2022), the municipal organization responsible for managing the public transportation and urban mobility of São Paulo city, there are 32 official BTs in the city. Table 1 presents the list of BTs with their number, name, city region, average user rating (AUR), total assessments (TA), total comments (TC) within the assessments, and the percentage of assessments with comments (%CA).

Table 1

List of Bus Terminuses in Sample

#BT	Name of Bus Terminus	São Paulo City Region	AUR	TA	TC	%CA
1	Terminal Jardim Britânia	Area 1 - Northwest	4.0	16	5	31.25%
2	Terminal Pirituba	Area 1 - Northwest	3.8	494	235	47.57%
3	Terminal Casa Verde	Area 2 - North	4.0	123	62	50.41%
4	Terminal Vila Nova Cachoeirinha	Area 2 - North	4.0	980	479	48.88%
5	Terminal A. E. Carvalho	Area 3 - Northeast	3.8	388	195	50.26%
6	Terminal Aricanduva	Area 3 - Northeast	3.8	239	114	47.70%
7	Terminal Penha	Area 3 - Northeast	3.9	161	85	52.80%
8	Terminal São Miguel	Area 3 - Northeast	3.8	479	243	50.73%
9	Terminal Cidade Tiradentes	Area 4 - East	3.8	319	174	54.55%
10	Terminal Itaquera II	Area 4 - East	4.5	21	8	38.10%
11	Terminal Vila Carrão	Area 4 - East	3.5	250	135	54%
12	Terminal Metropolitano São Mateus	Area 5 - Southeast	3.5	1029	536	52.09%
13	Terminal Sacomã	Area 5 - Southeast	4.0	587	289	49.23%
14	Terminal Sapopemba / Teotônio Vilela	Area 5 - Southeast	4.0	888	401	45.05%
15	Terminal Grajaú	Area 6 - South	3.4	16	9	56.25%
16	Terminal Parelheiros	Area 6 - South	3.3	150	70	46.67%
17	Terminal Varginha	Area 6 - South	3.5	489	275	56.24%



18	Terminal Água Espraiada	Area 7 - Southwest	3.9	713	304	42.64%
19	Terminal Capelinha	Area 7 - Southwest	3.5	517	245	47.39%
20	Terminal Guarapiranga	Area 7 - Southwest	3.9	419	206	49.16%
21	Terminal Jardim Ângela	Area 7 - Southwest	3.2	298	160	53.33%
22	Terminal João Dias	Area 7 - Southwest	3.8	547	236	43.14%
23	Terminal Santo Amaro	Area 7 - Southwest	3.4	1143 ¹	663	58.01%
24	Terminal Campo Limpo	Area 8 - West	3.7	1100	533	48.45%
25	Terminal Amaral Gurgel	Central Area	4.0	37	23	62.16%
26	Terminal Bandeira	Central Area	4.0	455	250	54.95%
27	Terminal Lapa	Central Area	3.6	455	248	54.51%
28	Terminal Mercado	Central Area	3.6	67	43	64.18%
29	Terminal Parque Dom Pedro II	Central Area	3.8	1144 ²	840	73.43%
30	Terminal Pinheiros	Central Area	4.1	31	22	70.97%
31	Terminal Princesa Isabel	Central Area	3.6	240	146	60.83%
32	Terminal Vila Prudente	Central Area	4.2	1140 ³	1138	99.82%

Note. Source from SPTrans (2022). *BT* = Bus Terminus. *AUR* = Average User Rating with Stars. *TA* = Total Assessments. *TC* = Total Comments. *%CA* = Percentage of Comments in the Assessments. All the information regarding *AUR*, *TA*, and *TC* were manually collected from Google Maps: first, the data about the BTs 1 to 4 were collected on November 1st, 2022; second, the data about the BTs 5 to 16 were collected on November 2nd, 2022; and third, the data about the BTs 17 to 32 were collected on November 3rd, 2022. The *AUR* ranges from 1 to 5, the highest rating revealing higher user satisfaction; these ratings are the average rating stars of the users for each BT on Google Maps. ¹Although there are 1347 assessments for Terminal Santo Amaro, Google Maps provided only 1143 assessments. ²Although there are 1483 assessments for Terminal Parque Dom Pedro II, Google Maps provided only 1144 assessments. ³Although there are 4969 assessments for Terminal Vila Prudente, Google Maps provided only 1140 assessments.

Thus, we selected all 32 BTs of São Paulo city for the analysis, which were listed in

Table 1 and are based on the official SPTrans (2022) website.

Data Gathering

After selecting the BTs for our sample based on the SPTrans (2022) website, we collected the data of the citizens' opinions and sentiments on Google Maps for each BT. All 32 BTs have their own pages on Google Maps with user ratings and reviews (see *AUR*, *TA*, *TC*, and *%CA* columns in Table 1). The average *AUR* of BTs is 3.8. Therefore, the sample should



consist of 19,307 assessments; however, due to some data restrictions on Google Maps, the sample consists of 14,973 assessments for all TBs. Of these 14,973 assessments, 8,371 have user comments. Thus, *these user comments were the input text used in the Sentiment Analysis*. We manually collected this data by creating a new dataset in Excel sheets (i.e., XLSX format) from Google Maps by sorting it by the most relevant assessments. The data collection process lasted three days:

- On November 1st, 2022, we collected data about *Terminal Jardim Britânia, Terminal Pirituba, Terminal Casa Verde, and Terminal Vila Nova Cachoeirinha*.
- On November 2nd, 2022, we collected data about *Terminal A. E. Carvalho, Terminal Aricanduva, Terminal Penha, Terminal São Miguel, Terminal Cidade Tiradentes, Terminal Itaquera II, Terminal Vila Carrão, Terminal Metropolitan São Mateus, Terminal Sacomã, Terminal Sapopemba / Teotônio Vilela, Terminal Grajaú, and Terminal Parelheiros*.
- On November 3rd, 2022, we collected data about *Terminal Varginha, Terminal Água Espraiada, Terminal Capelinha, Terminal Guarapiranga, Terminal Jardim Ângela, Terminal João Dias, Terminal Santo Amaro, Terminal Campo Limpo, Terminal Amaral Gurgel, Terminal Bandeira, Terminal Lapa, Terminal Mercado, Terminal Parque Dom Pedro II, Terminal Pinheiros, Terminal Princesa Isabel, and Terminal Vila Prudente*.

Due to limitations on Google Maps, it was not possible to retrieve all assessments from the terminuses “Terminal Santo Amaro,” “Terminal Parque Dom Pedro II,” and “Terminal Vila Prudente.” First, from 1,347 assessments of “Terminal Santo Amaro,” Google Maps allowed us to retrieve only 1,143. Second, from 1,483 assessments of “Terminal Parque Dom Pedro II,” Google Maps allowed us to collect only 1,144. Third, from 4,969 assessments of “Terminal Vila Prudente,” Google Maps allowed us to collect only 1,140.



Data Wrangling

After gathering, the data were wrangled and cleaned before performing Sentiment Analysis. First, we translated all the users' reviews to English because it is used in the international scientific community and understood by the lexicon used in Sentiment Analysis (described in the following subsection). The translation was performed with *Google Translator*, a well-renowned machine translation tool widely used by scholars to translate texts for performing sentiment lexicons in English (De Vries et al., 2018; Kaity & Balakrishnan, 2020). Next, the translated texts were inserted in a new column in the same Excel sheets dataset created at the data gathering stage. Our dataset is available on the *Open Science Framework* repository, allowing scholars to share research data anonymously during the peer-review stage, with their names recognizable after the research is accepted for publication (weblink: https://osf.io/hjdbn/?view_only=2edee0aa69014d3591df3af2cbc5edee).

Sentiment Analysis

According to Bing Liu (2020, p. 3), "Sentiment Analysis or opinion mining aims to identify positive and negative opinions or sentiments expressed in text as well as the targets of these opinions or sentiments." Sentiment Analysis is an NLP technique that automatically scans and effectively classifies texts with Big Data (i.e., vast and complex datasets), such as the data used in this study. In order to perform Sentiment Analysis in the dataset collected, we used a knowledge-based approach through the *Bing Lexicon*, which comprises 6.787 English-written words classified by Hu and Liu (2004) as positive or negative sentiments. Also, the Bing Lexicon is the most comprehensive lexicon of positive and negative sentiments (Maas et al., 2011).

We performed the Sentiment Analysis by using the *R programming language* version 4.1.2 (R Core Team, 2021) with the packages *tidytext* version 0.3.2 (Silge & Robinson, 2016), *textdata* version 0.4.4 (Hvitfeldt & Silge, 2022), *readxl* version 1.3.1 (Wickham & Bryan, 2019), *dplyr* version 1.0.8 (Wickham et al., 2022), *stringr* version 1.4.0 (Wickham, 2019), *tibble* version 3.1.6 (Müller & Wickham, 2021), *ggplot2* version 3.3.5 (Wickham, 2016), *wordcloud* version 2.6



(Fellows, 2018), and *reshape2* version 1.4.4 (Wickham, 2007). In order to retrieve the *Bing Lexicon*, we used the *textdata* package with the following exact function: `get_sentiments("bing")`. In short, we removed curse words from the analysis using *stringr* and *dplyr* packages. Also, by using *reshape2* and *wordcloud* packages, we established the maximum number of 400 words as a pattern for all the figures with cloud words of positive/negative sentiments. As for the word cloud without Sentiment Analysis, we used only the *wordcloud* package with a maximum number of 150 words.

Instead of performing sentence or aspect sentiment classifications, we performed the document sentiment classification using a knowledge-based approach (based on the *Bing Lexicon*) since we aim to understand the overall sentiments of the users for specific city regions (see the results in subsection 4.1 to 4.9) and the whole city (see subsection 4.10). Sentence sentiment classification is applied for each review and sentence, aspect sentiment classification is based on specific terms, and document sentiment classification considers all the words in one or more documents (Liu, 2020). Accordingly, Sentiment Analysis allowed an in-depth exploration and discussion as unfolded in the following sections.

Results

This section presents the results of the Sentimental Analysis for each specific region of São Paulo City (from subsections 4.1 to 4.9) and the entire city (subsection 4.10).

Bus Terminuses in the Northwest Region of São Paulo City

In this region, cleanness is the top sentiment according to the users' perceptions, which is a positive sentiment with 22 occurrences (around 8.46% of the sentiments). By reading the user comments, we found that users associated cleanness not only with the platforms but mainly also with the toilets. Furthermore, easy accessibility is another critical factor that creates a positive sentiment for users. On the other hand, the users' bad sentiments have been related to experience, mobility, service, and lack of security. From 260 words identified as sentiments, 132 are positive (50.76%), and 128 are negative (49.23%). This result indicates that this



region's negative and positive sentiments are counterbalanced, and positive sentiments slightly outnumber the negative ones. Table 2 lists the most occurring words for the Sentiment Analysis of the Northwest BTs.

Table 2

Most occurring words for the Sentiment Analysis of the Northwest Bus Terminuses

<i>word</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	22
bad	negative	12
easy	positive	11
accessible	positive	8
dirty	negative	7
complain	negative	6
lack	negative	6
excellent	positive	5
love	positive	5
quiet	positive	5
reasonable	positive	5
respect	positive	5
terrible	negative	5

Note. N = Number of occurrences for the word. This table displays only words with five or more occurrences.

Figure 1 illustrates a word cloud of negative and positive sentiments of the users about the Northwest BTs.



Figure 1

Word cloud of Negative and Positive Sentiments about the Northwest Bus Terminuses



Bus Terminuses in the North Region of São Paulo City

Cleanness is again relevant in this region (10% of the sentiments). Users have stated they were happy when they saw a cleaning worker performing their job to keep the platform and buses away from the coronavirus disease. However, although many users find the bathrooms and platforms well-cleaned, there is no consensus since some users think cleanliness should be improved. The word bad is related to bed services, crowded facilities, weak wifi connection, bad



smell in the toilets, lack of signalization, lack of security, rude employee behavior, and time delay of buses; these issues are also related to the feeling of improving as suggested by the users. The positive sentiment of recommending improvements shows *potential cooperation* among the citizens (users/consumers) and the public administration. From 480 words identified as sentiments, 273 are positive (56.87%), and 207 are negative (43.12%). This result indicates that although there are more positive than negative sentiments, many challenges must be overcome. Table 3 lists the most occurring words for the Sentiment Analysis of the North BTs.

Table 3

Most occurring words for the Sentiment Analysis of the North Bus Terminuses

<i>words</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	48
excellent	positive	20
bad	negative	18
improve	positive	15
crowded	negative	14
easy	positive	12
lack	negative	12
accessible	positive	9
nice	positive	8
fast	positive	7
tree	positive	7
quiet	positive	7
delay	negative	6
beautiful	positive	5
dirty	negative	5





poorly	negative	5
respect	positive	5
rude	negative	5
super	positive	5
worst	negative	5

Note. *N* = Number of occurrences for the word. This table displays only words with five or more occurrences.

Figure 2 illustrates a word cloud of negative and positive sentiments of the users about the North BTs.



are divergent about the services provided by the BTs in this region. This rationale is also reflected in data: From 616 words identified as sentiments, 329 are positive (53.40%), and 287 are negative (46.59%). Table 4 lists the most occurring words for the Sentiment Analysis of the Northeast BTs.

Table 4

Most occurring words for the Sentiment Analysis of the Northeast Bus Terminuses

<i>words</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	54
excellent	positive	34
bad	negative	26
fast	positive	23
delay	negative	21
terrible	negative	21
quiet	positive	19
polite	positive	12
accessible	positive	11
super	positive	11
improve	positive	10
poorly	negative	10
dangerous	negative	9
easy	positive	8
lack	negative	8
nice	positive	8
attentive	positive	7
break	negative	7



rude	negative	7
top	positive	7
horrible	negative	6
reasonable	positive	6
respect	positive	6
safe	positive	6
slow	negative	6
congratulations	positive	5
neiprui	positive	5

Note. N= Number of occurrences for the word. This table displays only words with five or more occurrences.

Figure 3 illustrates a word cloud of negative and positive sentiments of the users about the Northeast BTs.



Table 5*Most occurring words for the Sentiment Analysis of the East Bus Terminuses*

<i>word</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	12
excellent	positive	12
terrible	negative	10
bad	negative	9
lack	negative	8
improve	positive	7
complain	negative	6
dirty	negative	6
easy	positive	6
super	positive	6
fast	positive	6
issue	negative	6
nice	positive	6
top	positive	6

Note. N= Number of occurrences for the word. This table displays only words with five or more occurrences.

Figure 4 illustrates a word cloud of negative and positive sentiments of the users about the East BTs.

Figure 4

Word cloud of Negative and Positive Sentiments about the East Bus Terminuses



Bus Terminuses in the Southeast Region of São Paulo City

In this region, lack of organization, structure, management, cleanness, maintenance, and security are several problems for BT users. Conversely, in the other city regions, the negative comments are the vast majority, even though some users argue that the BTs in this



region are excellent and clean. From 1157 words identified as sentiments, 508 are positive (43.90 %), and 649 are negative (56.09%), indicating that this region needs urgent attention from urban managers and transportation policymakers since most citizens are unsatisfied with the services provided by BTs. Crowdedness is another remarkable negative aspect of this region. However, it could be expected since *Terminal São Mateus* is one of the busiest BTs in the city, which connects high-density neighborhoods from the southeast, south, east, and downtown of São Paulo. Table 6 lists the most occurring words for the Sentiment Analysis of the East BTs.

Table 6

Most occurring words for the Sentiment Analysis of the Southeast Bus Terminuses

<i>word</i>	<i>Sentiment</i>	<i>N</i>
lack	negative	51
clean	positive	45
easy	positive	38
excellent	positive	37
bad	negative	32
terrible	negative	32
crowded	negative	30
fast	positive	25
dirty	negative	24
delay	negative	23
horrible	negative	23
improve	positive	20
nice	positive	18
garbage	negative	17





accessible	positive	14
rude	negative	13
worst	negative	13
beautiful	positive	12
disorganized	negative	12
free	positive	12
respect	positive	12
congratulations	positive	11
top	positive	11
complain	negative	10
poorly	negative	10
reasonable	positive	10
super	positive	10

Note. N = Number of occurrences for the word. This table displays only words with ten or more occurrences.

Figure 5 illustrates a word cloud of negative and positive sentiments of the users about the Southeast BTs.

sentiments, 147 are positive (36.84%), and 252 are negative (63.15%). Table 7 lists the most occurring words for the Sentiment Analysis of the South BTs.

Table 7

Most occurring words for the Sentiment Analysis of the South Bus Terminuses

<i>words</i>	<i>Sentiment</i>	<i>N</i>
crowded	negative	21
clean	positive	14
lack	negative	14
bad	negative	11
delay	negative	11
improve	positive	11
terrible	negative	11
horrible	negative	10
difficult	negative	8
dirty	negative	8
super	positive	8
smoke	negative	7
worse	negative	7
disorganized	negative	6
fast	positive	6
mess	negative	6
respect	positive	6
worst	negative	6
accessible	positive	5
delays	negative	5

Bus Terminuses in the Southwest Region of São Paulo City

Bad services and lack of quality are the most predominant sentiments of the BTs users in this region. However, the sense of cleanliness ($n = 72$) and dirtiness ($n = 62$) are similar; it indicates that urban mobility-related public managers should address this issue better. From 1830 words identified as sentiments, 747 are positive (40.81%), and 1083 are negative (59.18%). Table 8 lists the most occurring words for the Sentiment Analysis of the Southwest BTs.

Table 8

Most occurring words for the Sentiment Analysis of the Southwest Bus Terminuses

<i>words</i>	<i>Sentiment</i>	<i>IV</i>
bad	negative	85
lack	negative	75
clean	positive	72
dirty	negative	62
excellent	positive	48
crowded	negative	44
terrible	negative	44
easy	positive	42
horrible	negative	42
improve	positive	39
respect	positive	37
delay	negative	36
poorly	negative	24
delays	negative	23
beautiful	positive	21



fast	positive	21
nice	positive	21
worst	negative	20

Note. *N* = Number of occurrences for the word. This table displays only words with twenty or more occurrences.

Figure 7 illustrates a word cloud of negative and positive sentiments of the users about the Southwest BTs.





positive (41.59%), and 285 are negative (58.40%). Table 9 lists the most occurring words for the Sentiment Analysis of this region.

Table 9

Most occurring words for the Sentiment Analysis of the West Region BT

<i>words</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	29
terrible	negative	20
bad	negative	17
lack	negative	17
excellent	positive	16
improve	positive	15
delay	negative	13
complain	negative	11
disorganized	negative	11
horrible	negative	11
easy	positive	10
dirty	negative	9
respect	positive	9
nice	positive	8
crowded	negative	7
delays	negative	7
worse	negative	7
worst	negative	7
garbage	negative	6
ignorant	negative	6



poorly	negative	6
accessible	positive	5
affordable	positive	5
fast	positive	5
improvement	positive	5
rude	negative	5

Note. N = Number of occurrences for the word. This table displays only words with five or more occurrences.

Figure 8 illustrates a word cloud of negative and positive sentiments of the users about the “Terminal Campo Limpo,” the unique BT in the West City Region.



Table 10*Most occurring words for the Sentiment Analysis of the Central Area Bus Terminuses*

<i>words</i>	<i>Sentiment</i>	<i>N</i>
clean	positive	240
dirty	negative	100
easy	positive	100
bad	negative	97
excellent	positive	70
lack	negative	70
improve	positive	60
horrible	negative	51
poorly	negative	51
fast	positive	50
safe	positive	40
beautiful	positive	40
accessible	positive	40
crowded	negative	41
super	positive	41
delay	negative	39
terrible	negative	38
confusing	negative	37
dangerous	negative	30
easier	positive	31

Note. *N* = Number of occurrences for the word. This table displays only words with thirty or more occurrences.

Figure 9 illustrates a word cloud of negative and positive sentiments of the users about the Central Area BTs.

Figure 9

Word cloud of Negative and Positive Sentiments about the Central Area Bus Terminuses





Overall Sentiment Analysis of Bus Terminuses in the Whole City

Before performing the Sentiment Analysis, it is convenient to reveal the most common words of user comments, which are presented in Table 11. It is expected that words such as “terminal,” “bus,” “buses,” “line,” “lines,” “transport,” “station,” and “SPTrans” are common since they are essential elements in the BTs’ management and operation. However, the appearance of the following words reveals the citizens’ concerns and BTs’ issues and characteristics to be considered by managers in BTs’ administration: “time,” “people,” “clean,” “access,” “bad,” “subway,” “lack,” “excellent,” “easy,” “information,” “options,” “employees,” “security,” “minutes,” “location,” “bathrooms,” “terrible,” “improve,” “time,” “hours,” “crowded,” “waiting,” “staff,” “delay,” “hour,” and “horrible.” Overall, the dataset with all BTs has 6,193 different words with more than 54,340 occurrences.

Table 11

Most common words of user comments about all city BTs (without/before Sentiment Analysis)

<i>vvora</i>	<i>IV</i>	<i>%OAU</i>	<i>vvora</i>	<i>IV</i>	<i>%OAU</i>
terminal	2261	4.16%	station	229	.42%
bus	1495	2.75%	tu	228	.42%
buses	1046	1.92%	takes	227	.42%
time	712	1.31%	city	221	.41%
line	674	1.24%	employees	221	.41%
lines	613	1.13%	security	219	.40%
people	548	1.01%	single	218	.40%
clean	542	1.00%	inside	214	.39%
organized	528	.97%	minutes	196	.36%
service	512	.94%	batnroom	193	.36%
access	509	.94%	public	190	.35%



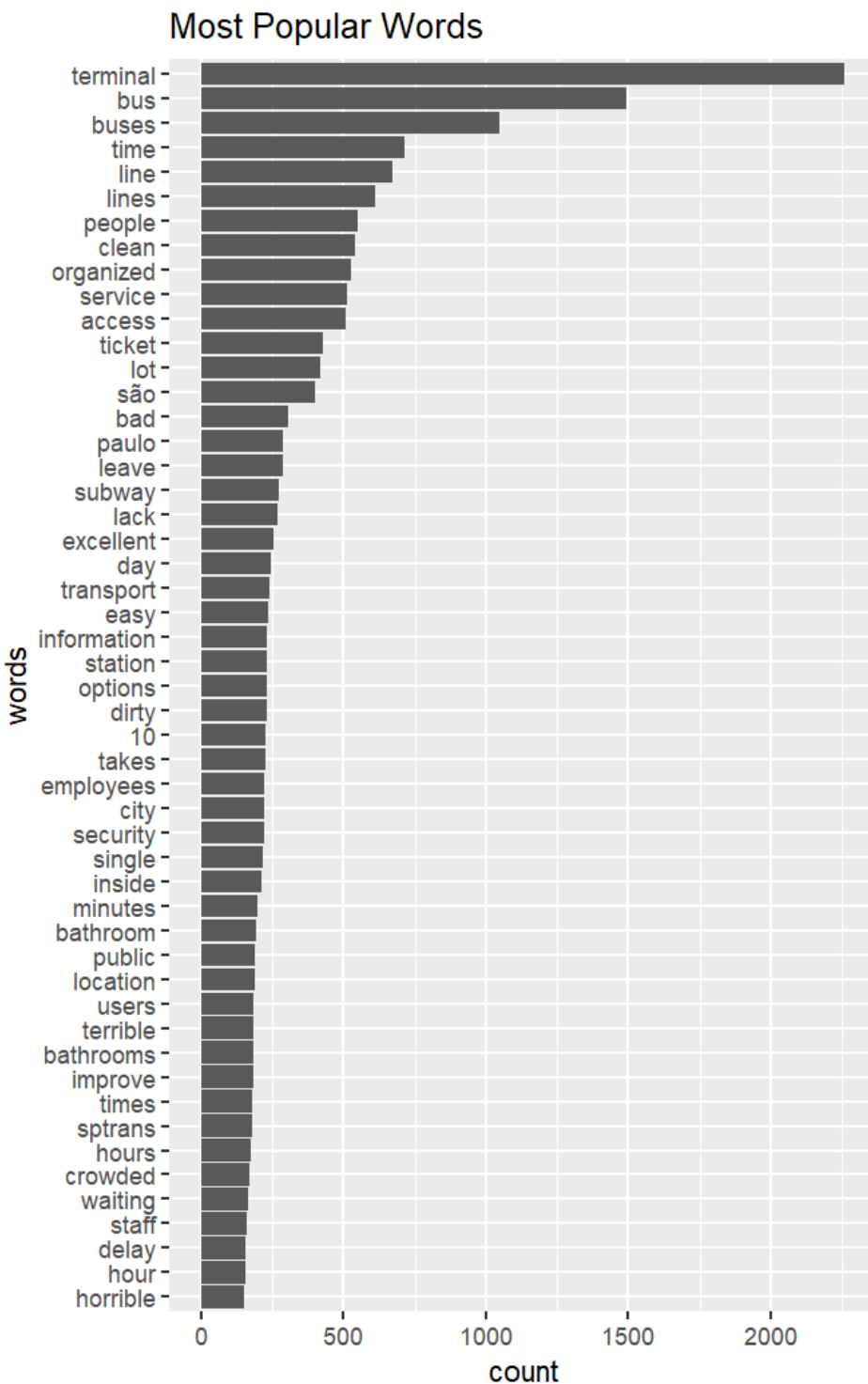
ticket	430	.19%	location	187	.34%
lot	418	.17%	users	186	.34%
sao	400	.14%	batrooms	185	.34%
bad	307	.56%	terrible	185	.34%
leave	288	.53%	improve	183	.34%
pauio	288	.53%	times	181	.33%
subway	275	.51%	sprans	179	.33%
lack	267	.49%	nours	175	.32%
excellent	252	.46%	crowded	171	.31%
day	246	.45%	waiting	167	.31%
transport	242	.45%	staff	158	.29%
easy	236	.45%	delay	156	.29%
information	230	.42%	nour	155	.29%
dirty	229	.42%	horrible	153	.28%
options	229	.42%			

Note. *N* = Number of occurrences for the word. %OAO = Percentage of the number of occurrences in comparison to the overall number of occurrences of all words. This table displays only words with 150 or more occurrences.

Figure 10 illustrates the data presented in Table 10 through a horizontal bar chart.

Figure 10

Horizontal Bar Chart of the Most Popular Words with 150 or more occurrences in the overall analysis



hand, bad, lack, and terrible are other preponderant negative sentiments of BT users. On the other hand, excellent, easy, and improvement are in the positive perspective. Table 12 lists the most occurring words for the Sentiment Analysis of BT services and facilities in São Paulo.

Table 12

Most occurring words in the Sentiment Analysis of Bus Terminuses in the whole city

<i>word</i>	<i>Sentiment</i>	<i>N</i>	<i>%OTSU</i>
clean	positive	542	5.14%
bad	negative	307	3.57%
lack	negative	267	3.10%
excellent	positive	252	2.93%
easy	positive	236	2.74%
dirty	negative	229	2.66%
terrible	negative	185	2.15%
improve	positive	183	2.12%
crowded	negative	171	1.98%
delay	negative	156	1.81%
horrible	negative	153	1.78%
fast	positive	145	1.68%
poorly	negative	117	1.36%
accessible	positive	110	1.27%
respect	positive	107	1.25%

Note. *N* = Number of occurrences for the word. *%OTSU* = Percentage of the Total Sentiments Overall. This table displays only words with 100 or more occurrences.

Figure 12 illustrates a word cloud of negative and positive sentiments of the users about all BTs in the whole city.



proportion of positive/negative sentiments of the users, and define the critical issues and challenges to be overcome in city-specific regions and the whole city. For instance, the feeling of cleanliness versus dirtiness about BTs was one of the citizens' top concerns for most city regions. Other primary concerns were the citizens' perception of the lack/existence of organizing capacity, bad/good employee behavior, and security/insecurity. Therefore, Sentiment Analysis is an optimal instrument when strategizing sustainable urban policies.

Furthermore, Sentiment Analysis could also be applied to urban marketing and other critical emergent themes for sustainable urban strategy implementation, as suggested by Beck and Storopoli (2021), such as housing, municipal solid waste, infrastructure, urban resilience, governance, tourism, and heritage conservation. Accordingly, sentiment analysis is also a promising tool for creating sustainable urban strategies in multiple urban affairs for multiple urban stakeholders, not only in urban mobility and public transportation planning, as explored in this study. In this way, in order to expand the frontiers of knowledge of Stakeholder Theory in Cities with the paradigm of Sustainable Urban Strategies, further studies could use Sentiment Analysis with socio-spatial data about the quality of affordable housing projects as well as the tourist experience in tourist attractions and sites.

Sentiment analysis could provide solid and straightforward information for SVC. In other words, Sentiment Analysis provides a deeper understanding of the stakeholder sentiments about a determined organizational policy (e.g., municipal normative, urban infrastructure, services, and systems), providing valuable information for sustainable urban strategy formulation and implementation. The reason is that understanding stakeholder sentiments reveals answers to questions with what, where, how, and why, of which managers can make a self-analysis of the services or organizational policies. Thus allowing managers to strategize stakeholder-oriented policies. Accordingly, Sentiment Analysis can be a tool for fostering stakeholder synergy and SVC. For instance, the overall results of Sentiment Analysis revealed that the paradigm between cleanliness and dirtiness is the most important topic for BT users in



São Paulo city. In other words, it reveals what should be addressed, and a qualitative reading of the comments related to these issues will reveal the specific BTs (where), highlight the reasons behind them (why), and the best strategies to improve these issues (how).

Therefore, Sentiment Analysis provides detailed information about citizen satisfaction regarding public services and, thus, highlights the main citizen perceptions of the public service that would be useful to improve the public service quality. The data used for Sentiment Analysis stemmed from Smart Sustainable Cities resources, which are based on crowdsourcing services, IoT, Big Data, and ICTs (Bibri & Krogstie, 2017). Thus, the following subsection discusses our findings in light of Smart Sustainable Cities.

Contributions and Implications for Smart Sustainable Cities

Smart Governance is one crucial aspect of Smart Sustainable Cities. According to Beck and Conti (2021, p. 146), Smart Governance is shaped by the sum of three driver forces: "... [First,] an innovative, sustainable, and strategic Public Administration ... [Second,] the use of Information and Communication Technologies to deploy e-government policies and apply the principles of transparency and accountability ... [Third,] the engagement of the actors of this ecosystem within the decision-making process." For this reason, public managers can use ICTs and IoT to exploit Big Data and Quantitative Data Analyses to improve public service quality. In the case of this research, free and open geospatial data available on the internet (i.e., information available on *Google Maps*) can be used by public managers to understand the citizens opinion about public services better and improve citizen experience.

The bottom line is that stakeholders and citizens use many non-governmental and governmental smart applications and smart devices, which are *sources of data* that can be exploited to improve public services, the citizens' quality of life, and public service quality. This study used smart data from *Google Maps*, which has also been used in other studies in Smart Sustainable Cities (Mohan et al., 2017; Lee & Yu, 2018; Mishra et al., 2019; Phun et al., 2019; Mathayomchan & Taecharungroj, 2020; Borrego & Navarra, 2021; Khan & Loan, 2022; Li et al.,





2022; Park et al., 2022; Purwana et al., 2022; among others). However, *Google Maps* is only one of many resources that are free, quickly found, and openly available online.

Therefore, *smart sustainable cities provide massive amounts of data that all kinds of urban stakeholders can use in decision-making processes*. In this context, people can assess public and private places with their perceptions and make decisions based on the opinions of others. Public Services and Facilities can be assessed, and public managers can improve public service quality. Also, businesses, industries, and non-profit organizations can improve their services, goods, and activities based on these data sources. The following subsection discusses the main contributions of this study for BTs, which are the specific urban services analyzed in this study.

Contributions and Implications for Practitioners and Policymakers of Bus Terminuses

This study revealed that Sentiment Analysis is helpful in BT management because it explains the reasons for improving BT quality through understanding the user's feelings. The main contribution of this study for BT management is integrating Stakeholder Theory and Smart Sustainable Cities as tools for improving the quality of the services. For this reason, we recommend practitioners explore Sentiment Analysis in BTs for objective and stakeholder-based analysis. Also, further studies should explore user sentiments in other study cases and contexts.

Conclusion

Through Sentiment Analysis, this study explored citizens' satisfaction regarding all 32 BTs in São Paulo City, Brazil. Our main findings are: (1) Sentiment analysis could provide solid and straightforward information for SVC, stakeholder satisfaction, and Sustainable Urban Strategy formulation, which in turn is a useful source for stakeholder-oriented management as well as for Stakeholder Theory in Cities; (2) Sentiment Analysis provides detailed information about citizen satisfaction on service speed and accuracy, and thus, provides valuable orientations for public managers improve public service quality; (3) Smart Sustainable Cities





provide multiple and massive quantities of data that all kinds of urban stakeholders can use in decision-making processes, which help perform Sentiment Analysis; and (4) Sentiment Analysis is useful for BT managers improve BT services based on the user feelings.

The main limitation of this study is that, as *Google Maps* is a crowdsourcing service, users can comment about other services not related to BTs because they wrongly selected the BT page on Google Maps. Another significant limitation is that reviews evolve and change over time, and this study considered all comments disregarding the time of publication. However, although reviews and user demands grow over time, Sentiment Analysis here aimed to assess the service quality of BTs in all their existing BT pages on Google Maps (i.e., 2005). For this reason, further studies could limit the data of publication to analyze a specific frame or continue using all the data about a BT to understand the users' main topic concerns and feelings.

Finally, further studies should also explore the key terms unfolded by the document sentiment classification. These key terms could be better explored through aspect sentiment classification since it details the terms and contexts associated with the key terms under investigation (Liu, 2020). For public managers, we recommend the replication of the procedures adopted in this research for analyzing other cities' public transportation quality and improving their public management. The procedures implemented by this research can help public management to improve the quality of public services and follow the positive and negative perceptions of public transportation users.

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