Public Perception of RapidKL Service Using Twitter Sentiment Analysis

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ABSTRACT

This study investigates public perception of the Rapid KL service through sentiment analysis of user-generated content on Twitter. With the increasing reliance on social media as a platform for expressing opinions and feedback, understanding sentiment trends is crucial for service improvement and community engagement. Utilizing advanced sentiment analysis techniques, including machine learning algorithms and natural language processing, this research analyzes a dataset of comments and posts related to the Rapid KL service. The findings reveal significant insights into user satisfaction, areas for improvement, and the overall sentiment landscape surrounding the service. By identifying prevalent themes and sentiments, this study aims to provide actionable recommendations for stakeholders to enhance service delivery and foster positive community relations. The implications of this research extend to broader applications in public service management and social media engagement strategies.

Keywords: public perception, public transport, sentiment analysis, machine learning

INTRODUCTION

Public transportation plays a crucial role in the urban landscape of Kuala Lumpur, Malaysia, particularly as the district grapples with rapid urbanization and increasing reliance on private vehicles. The significance of public transport in Johor can be understood through various dimensions, including its impact on urban sustainability, economic development, and social inclusivity. This literature review aims to synthesize existing studies and research findings related to Rapid KL buses's performance, service quality, and public perception. Rapid KL bus is a public transportation initiative aimed at enhancing urban mobility in Kuala Lumpur, Malaysia. This service is part of a broader strategy to address the increasing traffic congestion, and environmental concerns associated with private vehicle use in metropolitan areas. The initiative is particularly relevant given the projected surge in private vehicle ownership, which is expected to exacerbate road incidents and deteriorate air quality in the region.

The Rapid KL bus system serves as a crucial component of public transport in Malaysia, particularly in the Klang Valley region. This system exemplifies an effort to enhance urban mobility while promoting sustainability and accessibility. The integration of such public transport systems is essential for reducing traffic congestion, lowering greenhouse gas emissions, and improving overall urban livability.

One of the primary advantages of the Rapid KL bus system is its role in facilitating a shift from mobility- oriented to accessibility-based transport planning. This transition is vital for creating sustainable urban environments where public transport options are prioritized over private vehicle use. Tiboni et al. emphasize that urban regeneration processes can foster this shift, thereby enhancing accessibility for all users [17]. Furthermore, the integration of a multilevel transport system model, as discussed by [14], can significantly improve the effectiveness of urban mobility planning, which is crucial for the successful implementation of systems like Rapid KL [14].

Simultaneously, social media platforms offer opportunities for users to express opinions on politics, public affairs, and disseminate information widely [39]. The use of Twitter as a social media platform in Malaysia has evolved significantly, particularly in the political sphere. Twitter has emerged as a vital tool for political

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communication, allowing politicians, activists, and citizens to engage in discourse and disseminate information rapidly.

The ability of Twitter to foster interaction and debate among citizens without fear of political repercussions has been noted as a critical aspect of its role in Malaysian politics. This trend is corroborated by a survey indicating that 71% of Malaysian internet users engage in cyber social activities for more than one hour daily [19]. Therefore, this study aims to use social media, namely Twitter (now known as X) as a benchmark to understand people's sentiment of the service.

In conclusion, Twitter serves as a multifaceted platform in Malaysia, facilitating political discourse, influencing language use, and shaping youth engagement in politics. Its role in fostering public debate and participation is crucial, yet it also presents challenges related to language representation and the potential for ideological polarization. As social media continues to evolve, understanding its impact on Malaysian society and politics will remain a vital area for future research.

Based on the objectives stated, the research question are as follows:

What is the overall sentiment of Twitter users towards Rapid KL buses' services?

What are the strengths and weaknesses of Rapid KL buses' services as perceived by the public?

LITERATURE REVIEW

Public Transportation in Kuala Lumpur

Public transportation in Kuala Lumpur plays a crucial role in the urban mobility landscape, significantly influencing the daily lives of its residents. The city's public transport system comprises various modes, including buses, light rail transit (LRT), and monorail services, which collectively aim to alleviate traffic congestion and provide efficient travel options for commuters. However, the effectiveness and quality of these services are often subject to scrutiny and require ongoing improvements.

The introduction of public transportation in Kuala Lumpur has been a critical aspect of urban planning and development, particularly in response to the city's rapid urbanization and increasing traffic congestion. The establishment of an efficient public transport system is essential for enhancing mobility, reducing reliance on private vehicles, and promoting sustainable urban living. The Malaysian government has recognized the importance of public transportation as a key component of its National Key Economic Area (NKEA) initiatives, which aim to improve urban infrastructure and service quality across the country [22].

The effectiveness of public transportation in Kuala Lumpur is also influenced by service quality and passenger perceptions. Research indicates that positive evaluations of service quality can enhance passenger involvement and encourage greater use of public transport [17;27]. Factors such as travel intention, personal norms, and subjective attitudes towards public transport significantly affect travel behavior [27]. Furthermore, the design and accessibility of public transport facilities play a crucial role in attracting users, particularly among vulnerable groups such as persons with disabilities [33].

In conclusion, the introduction and development of public transportation in Kuala Lumpur are integral to the city's urban strategy. While significant progress has been made in enhancing the public transport network, ongoing efforts are necessary to improve service quality, accessibility, and public perception to foster a more sustainable and efficient urban mobility system

RapidKL Bus Services

Public transportation in Kuala Lumpur (the capital city of Malaysia) serves the daily commuting needs of all strata of society. To meet the ever-increasing needs of reliable public transport in and around the capital city, the Rangkaian Pengangkutan Integrasi Deras Sdn Bhd (RapidKL) has been established. RapidKL is owned by

Prasarana Berhad, a government-owned company. It was established in 2004 as a provide solution to public transport woes affecting Kuala Lumpur and its surrounding cities.

Today, RapidKL operates 165 bus routes within the Klang Valley which consist of 10 City Bus routes, 85 Local Bus routes, 63 Trunk Bus routes and 3 Express Bus routes. It currently has 11 bus depots spreading across the Klang Valley with 908 buses in operation. Every day, RapidKL transports over 140,000 passengers.

To continuously encourage the use of public transport and to provide services to the general public, RapidKL is also studying new bus routes with the arrival of more new buses. The company is also evaluating all bus routes in the Klang Valley inclusive of all areas without public transport.

Rapid KL bus services represent a vital component of the public transport landscape in Kuala Lumpur and the Klang Valley. Their structured operations, integration with other transport modes, and positive socio-economic impacts underscore their importance in promoting urban mobility. Addressing existing challenges and embracing future opportunities will be crucial for enhancing the effectiveness and sustainability of Rapid KL services.

Social media as a measure of public sentiment

Social media serves as a valuable tool for gauging public opinion by providing a platform for individuals to express their views, engage in discussions, and share sentiments on various topics. Journalists utilize social media to reflect public opinion, especially after significant events like debates [24]**.** Social media platforms offer opportunities for users to express opinions on politics, public affairs, and disseminate information widely [39]. Sentiment analysis has shifted towards analyzing social media texts from platforms like Twitter and Facebook, indicating the importance of social media in understanding public sentiment [23].

Furthermore, social media has become a significant space for public opinion formation and expression, influencing the democratic process by facilitating online social interaction and political engagement [15]. The use of social media data by journalists to infer and report public opinion highlights the increasing reliance on social media for understanding public sentiment [5]**.** Sentiment analysis on social media is widely used to identify the beginning of public opinion across various fields of life, emphasizing the role of social media in capturing and analyzing public sentiments.

Moreover, social media platforms are leveraged for the expression of public opinion, with users participating in discussions, expressing views, and commenting on various topics. Finkel examines how social media platforms facilitate civic education during critical political moments, suggesting that these networks can significantly motivate democratic [9]. The use of sentiment analysis and opinion mining on social media aids in tracking sentiments towards different concepts, allowing for the assessment of positive, negative, or neutral opinions [11].

In conclusion, social media serves as a valuable tool for gauging public opinion by providing a platform for individuals to express their views, facilitating discussions, and enabling sentiment analysis to track public sentiments across various domains.

Social Media Sentiment Analysis

Social media sentiment analysis is a crucial area of research that involves analyzing and understanding the sentiments expressed in social media content. Various studies have highlighted the significance of sentiment analysis in social media, especially during crises and public health emergencies like COVID-19 [38]. Sentiment analysis tools such as VADER have been widely used to extract sentiments from social media posts in multiple languages [42]. These tools help in detecting public sentiment and providing valuable insights into people's opinions and emotions [26].

According to [26], understanding public sentiments and opinions holds significant importance for transit agencies engaged in data-driven decision-making. The articulation of people's views and concerns regarding transit-related matters serves as a barometer of genuine challenges, particularly in urban settings. These challenges often pertain to either the efficacy of public transit systems or the difficulties individuals encounter while using private vehicles. Social media platforms generate vast quantities of real-time textual data, encapsulating diverse attitudes, opinions, and sentiments across different scenarios and events. In recent years, the influence of social media has manifested in various ways within the realm of transportation, presenting valuable opportunities to inform decision-making processes for agencies.

Researchers have emphasized the importance of considering sentiment-bearing lexical items such as acronyms, emoticons, and slang in sentiment analysis of social media text [13]. This indicates the need for comprehensive sentiment analysis techniques that can capture the nuances of language used in social media platforms. Sentiment analysis not only helps in understanding public sentiment but also aids in political analysis by improving our knowledge of citizens' preferences and opinions [16].

Moreover, sentiment analysis is not limited to textual content but extends to other forms of media such as images related to natural disasters [12]. Analyzing sentiments from images can provide insights into people's emotions and attitudes towards specific events or situations. Social media platforms like Twitter have been particularly useful for sentiment analysis due to the concise nature of tweets, making them suitable for sentiment analysis compared to longer document.

Twitter sentiment analysis has emerged as a critical area of research, particularly due to the platform's role in shaping public opinion and discourse. The analysis of sentiments expressed in tweets can provide valuable insights into various domains, including public health, marketing, and social movements. This synthesis will explore the methodologies, challenges, and applications of sentiment analysis on Twitter data, drawing on a range of studies that highlight the effectiveness of different approaches.

It's a common occurrence for individuals to utilize social media platforms as outlets for expressing their frustrations, anger, and negative sentiments. Consequently, the inclusion of such unfavorable comments without appropriate consideration could potentially skew research findings. [32] demonstrated the significant impact of users' social media usage patterns on the sentiment conveyed in tweets through their analysis of tweets posted in Miami-Dade County during the years 2017 and 2018. Similarly, [20] conducted an analysis of 26,000 comments posted on the Dazhong-Dianping website, focusing on various transportation modes including buses, rail transits, railway stations, and airports in Shanghai. Their study employed different text mining tools to discern the prevalence and distinguishing characteristics of different sentiment classes.

In the context of public transportation service, a study by [29] has presented that they were able to evaluate the sentiment of public transportation passengers by using naïve bayes method based on the collected all feedback from Facebook and Twitter about transportation services. This implies that social media is a valuable source of data for evaluating public sentiment, and methods like Naïve Bayes can effectively analyze this data to provide insights into public opinion on transportation services.

In conclusion, sentiment analysis in social media plays a vital role in understanding public sentiment, political preferences, and responses to various events. By leveraging sentiment analysis tools and techniques, researchers can extract valuable insights from social media content, contributing to a better understanding of societal trends and behaviors.

Gaps in The Literature

While it is known that social media can reflect negative sentiments, there may be a lack of in-depth analysis on the specific drivers behind these sentiments in the context of Rapid KL bus. This paper seeks to bridge this gap by conducting qualitative analyses to identify the root causes of negative sentiments and provide targeted recommendations for improvement.

In summary, the literature review underscores the importance of Rapid KL bus service in Kuala Lumpur’s public transportation system, the historical context of public perception, and ow social media can be a scale as a medium to understand public sentiment, and the evolving factors that may shape public sentiment. These insights provide the foundation for our research on the public perception of Rapid KL bus service using Twitter (known as X) sentiment analysis.

METHODOLOGY

Data Collection

The collection of primary data is conducted via data mining, utilizing social media, Facebook as the method. This approach allows for social media platforms to provide real-time access to public opinions and sentiments. This immediacy allows organizations to quickly gauge public reactions to events, announcements, or changes in services as well as their perceptions and feedback. These insights are instrumental in addressing the research questions.

Data Source

Twitter data was used as the primary data source. Data collection was conducted from January 2023 to August 2024 using tweets with the keyword of 'rapidkl' and 'Rapid KL'. Data mining from Twitter was conducted with a method that scraping from the website.

Tweets data was collected to capture general public sentiment towards Rapid KL bus relevant to the operation of its bus services during the last year, so we can see improvement in public sentiment or vice versa. The data was extracted from hundreds of tweets. Tweets, timestamp info were retrieved. This method is ethical and do not extract any private user data, such as email addresses, gender, or location. It can only extract what the passengers have chosen to share publicly.

This research used secondary data, especially literature reviews and institutional surveys to enrich the findings. Secondary data was collected from relevant searches on Scopus.

The research method for analyzing public perception of Rapid KL service using twitter sentiment analysis involves several key steps. Firstly, data collection will be carried out by extracting Tweets related to Rapid KL by scraping on twitter. This will include tweets from a defined time frame to ensure temporal relevance. tweets, and user interaction that are related to specified bus services are retrieved. The next step was to store raw data for further processing.

Secondly, the collected tweets will undergo preprocessing to remove noise, such as spam, duplicates, and irrelevant content, and to handle language-specific nuances, including slang and multilingual expressions. Slang removal step is skipped in preparing data for sentiment analysis slang often carries significant sentiment or emotional weight, which can be crucial for accurately understanding public opinion. Removing slang could strip the text of these meaningful expressions, leading to a loss of important contextual information and reducing the accuracy of the sentiment analysis. By retaining slang, the model can better interpret the true sentiment of the data, particularly in informal communication settings like social media, where slang is prevalent.

Then, as most comments were in Bahasa Malaysia, they are translated to English.

Data Analysis

Sentiment Analysis

Sentiment analysis has gained considerable traction due to the proliferation of social media platforms, where vast amounts of user-generated content are available for analysis. This has led to its application in various domains, including e-commerce, public opinion analysis, and mental health assessments [1]. For instance, sentiment analysis can be employed to gauge consumer sentiment towards products or services, thereby informing marketing strategies and product development [36]. Furthermore, the integration of multimodal sentiment analysis, which combines textual, visual, and auditory data, has emerged as a cutting-edge area of research, enhancing the depth of sentiment understanding [41; 37].

Sentiment analysis tools, such as Azure, will be applied to classify the tweets into positive, negative, or neutral sentiments. Azure's Sentiment Analysis service, part of the Azure Text Analytics API, primarily uses machine learning models based on transformer architectures. As of recent updates, the underlying model for sentiment analysis in Azure is often based on BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art model for natural language processing tasks.

The sentiment data will then be quantitatively analyzed to identify overall trends and patterns, and qualitatively examined to uncover recurring themes and specific issues highlighted by users. Additionally, a temporal analysis will be conducted to observe how sentiments change over time, and the findings will be integrated with contextual events or service changes to provide deeper insights. This comprehensive approach will enable a detailed understanding of public sentiment towards Facebook comments, aiding in data-driven decision-making for service improvements. Comments have been mined from the Facebook page of Pengangkutan Awam Johor. About 546 comments have been filtered and prepared for the sentiment analysis phase.

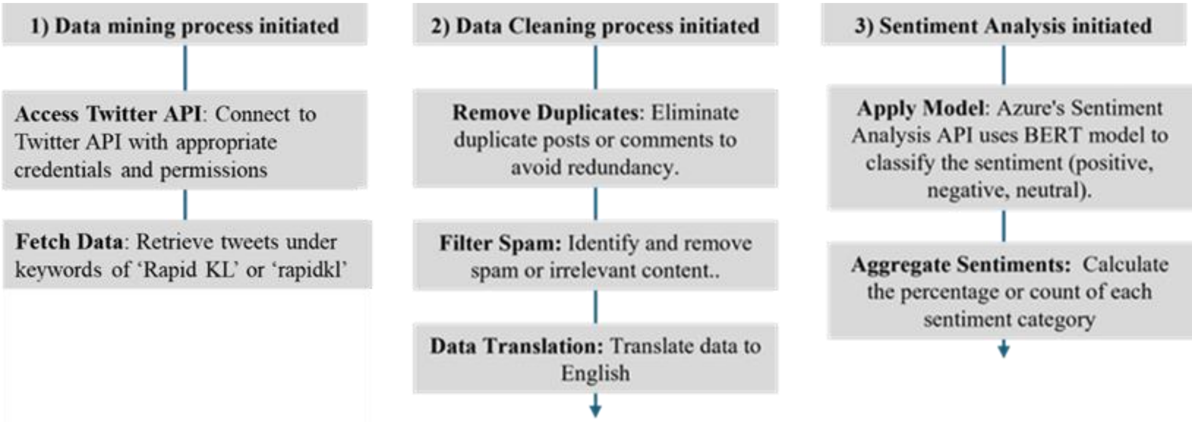

Fig. 1 Sentiment Analysis Process

DISCUSSION

Passengers' perception on Rapid KL bus services on Twitter

A total number of 1,189 tweets were collected based on the crawling criteria explained in the data collection section.

These comments have undergone Sentiment Analysis using e underlying model for sentiment analysis in Azure is often based on BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art model for natural language processing tasks. The results have been categorized as positive, neutral and negative.

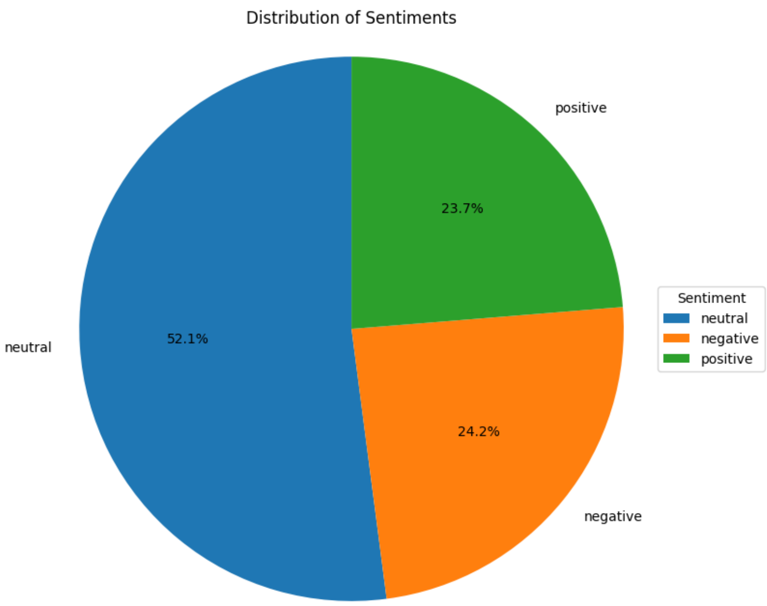

Fig. 2 Distribution of sentiments in the analyzed tweets

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The pie chart illustrates the distribution of sentiments expressed in the analyzed tweets. The largest portion of tweets falls under the neutral sentiment category, accounting for 52.1% of the total. This indicates that over half of the tweets neither express strongly positive nor negative opinions. The negative sentiment category constitutes 24.2% of the tweets, reflecting a significant number of unfavorable opinions. Lastly, the positive sentiment is the smallest group, comprising 23.7% of the tweets. This suggests a relatively balanced mix of sentiment types, though neutrality dominates the dataset.

As this analysis pertains to the bus service, the high positive sentiment is encouraging, but the substantial negative sentiment may highlight areas where improvements are needed. The neutral segment is small, so the focus should be on understanding the factors contributing to both positive and negative sentiments to enhance the positive aspects and mitigate the negative ones.

Examples of Real-Time Tweets

To illustrate the sentiment of users more clearly, a few representative real-time tweets have been included in this analysis. One user expressed strong dissatisfaction by stating:

“What makes it worse is that the lack of buses and bus schedules is shitty as hell... and it's shittier if you live outside campus with no car because of the lack of university buses, forcing you to rely on Grab or RapidKL to get home.”

This tweet was classified as strong negative, with an estimated sentiment breakdown of 95% negative, 5% neutral, and 0% positive.

In contrast, another user shared a positive experience:

“Every day I'm reminded how grateful I am for RapidKL.”

This tweet reflects a strong positive sentiment, with approximately 95% positive, 5% neutral, and 0% negative.

These examples provide insight into the range of public perceptions surrounding RapidKL services, from deep frustration over accessibility issues to expressions of satisfaction and appreciation.

CONCLUSION

In conclusion, the sentiment analysis reveals that the majority of tweets exhibit a neutral tone, suggesting that most users’ express opinions or information without strong emotional bias. The nearly equal proportions of negative and positive sentiments highlight a balanced but polarized response among users, with slightly more negativity. This insight could inform strategies to address concerns or foster more positive engagement within the community.

These findings suggest that while the bus service is well received by many, there is still a notable portion of the user base that experiences issues or dissatisfaction. To improve overall user satisfaction, it would be beneficial to focus on understanding and addressing the specific factors contributing to the negative sentiment. By doing so, service providers can work towards enhancing the quality of the service and potentially converting some of the negative or neutral feedback into positive sentiment.

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