

Public Discourse and Digital Customer Experience in Online Motorcycle Taxi Services: A Multimethod Analysis

Ferel Rizqia Maulana*, Asep Miftahuddin, Eka Surachman, Yoga Perdana, Budhi Pamungkas Gautama, Arciana Damayanti

Faculty of Economics and Business Education, Universitas Pendidikan Indonesia, Bandung, Indonesia.

Corresponding Email: ferelmaulana33@upi.edu

Abstract. The digital technology has transformed the platform-based transportation services and now, digital customer experience is playing a pivotal role in the success of the service. But, there is a constant mismatch between what is expected from the services and what the users experience, which can be seen in the social media discourse. The goal of this study is to analyze the construction of digital customer experience, its communication and its impact on online motorcycle taxi services. The research uses a multi-method design, combining sentiment analysis, social network analysis, text network analysis, emotion classification, and trend analysis on social media discourse to get a comprehensive grasp of user-generated discourse and its complexity. The results show that the digital customer experience is multi-dimensional by nature, sometimes being characterized in a positive way and sometimes in a negative way, and the act of speaking publicly of it is a mixture of positive and negative. Furthermore, the discourse is structured, with the main actors being in the center of opinion formation and dissemination in the digital network. These findings enable the theoretical sophistication of the digital customer experience and the digital public sphere, since they show how individual experiences turn into collective perceptions, as a result of their interaction. For the practice, the study highlights the significance of businesses proactively engaging in digital conversations, enhancing their services, and effectively managing digital communities.

Keywords: Public Discourse, Digital Customer Experience, Online Motorcycle Taxi (Ojek Online), Social Network Analysis, Sentiment Analysis.

1 Introduction

Mobile apps, real-time data and interaction with users have revolutionised the services landscape, particularly in platform-services, which have been digitalised [1]. In this situation, digital customer experience has thus become crucial to service success, affecting the perception of service, its evaluation and interaction with digital systems. Digital customer experience is the customer's perception of the whole created by

various digital touchpoints, such as mobile applications, social media and online service ecosystems [2], [3], [4]. Platform-based services are supposed to provide seamless, efficient, and user-oriented experience to improve user satisfaction and long-term user engagement [5].

But empirical evidence suggests that the digitalisation of the customer experience in platform-based transportation services has not achieved these goals in full [6]. The concerns raised by the public in online discussions often include problems with service reliability, cost, algorithm transparency, provider–user interactions, and service inconsistencies [7]. These are expressed in the users created content through social media in a range of perceptions from satisfaction to dissatisfaction [8]. The state indicates that there is a disconnect between what users experience and what they expect, as well as the need to gain a broader knowledge of how digital customer experience is created and communicated in the real world.

Digital Customer Experience (DCX) is created when customers engage with a number of digital touches along the way, such as mobile apps, online payment platforms, customer service, and driver interactions. In digital platform ecosystems, however, such individual experiences are seldom kept private. People are externalizing their assessments on social media platforms, enabling them to share their experiences with others. In the Digital Public Sphere, these stories are subject to interaction, amplification, endorsement and interpretation by other users, which can transform personal experiences into collective perceptions that impact on the understanding of the quality of the platform [9].

This study combines theory of Digital Customer Experience with the theory of Digital Public Sphere to propose that social media is the mediating space, the private Customer Experience is socially constructed in the shared public sphere. As digital interactions repeat, knowledge spreads through the network and emotions are reinforced, collective assessments of online motorcycle taxi services are formed. Digital Customer Experience is therefore not just a psychological phenomenon and reflection of one person but also a socially negotiated phenomenon that occurs in digital communication networks [10].

There have been a number of previous studies focusing on digital customer experience from different angles, such as the one that has explored the impact of digital customer experience on customer engagement [11], customer satisfaction and loyalty [12] and value creation in digital environments [3]. Other newer research further emphasizes the interconnectedness of customers' experiences in the Social Media context, the ways in which they negotiate them collectively and individually, and the ways in which they echo these experiences [13]. Furthermore, the realtime insights from user-generated content are currently becoming more commonplace by using large data analysis systems such as sentiment analysis and machine learning [14].

But the present studies in the realm of digital discourse are mostly single focused (survey or single method analysis), hence fail to adequately reflect multi-dimensionality of digital discourse [15]. Most of the studies are still centered on structured data, that have less ability to support the dynamics of natural interactions and conversations that take place on social media [16]. Besides, there are hardly any studies integrating more than a single computational approach (e.g., text analysis, network analysis,

sentiment classification and temporal trend analysis) in a single analytical structure [17]. These constraints suggest that there is a lack of understanding concerning the social construction of customer experience through digital interactions as well as the individual process of its construction.

This research propose a new perspective on digital customer experience, combining several analytical approaches to analyze social media discourse. In this research, the word cloud extraction method is combined with the Text Network Analysis (TNA), sentiment classification using the IndoBERT Large P2 model, Zero-Shot Classification, Social Network Analysis (SNA), and trend analysis. This multi-method approach allows for a more in-depth analysis of customer's expressions of their experiences, as well as how they relate to each other and change over time in digital environments [18]. The study is rooted in the Digital Customer Experience framework [2] and underpinned by the idea of the Digital Public Sphere that is used to describe how perceptions are created in digital environments through interaction and discourse [19].

Study's novelty is the integrative methodological approach and the use of a massive amount of social media data to reflect the complexity of digital customer experience. This research is different from previous studies, which mostly used only one computational analysis technique, as it incorporates multiple computational analysis techniques to uncover patterns of sentiment, relationships, themes, emotions and time trends in the public discourse. As such, this study offers a more detailed and holistic understanding of the process of platform-based service ecosystems in which digital customer experience is created, challenged and shared.

In view of this background, the aim of this study is to analyze the Digital Customer Experience in Platform-based Transportation Services using Social Network Analysis and Sentiment Analysis Approach. Specifically, this study will seek to discover dominant themes and narratives in the user's conversation, understand sentiment and emotional patterns within their customer experience, and map the network structure of user interactions as well as understanding the public conversation over time. The study is anticipated to make theoretical and practical contributions to the field of understanding digital customer experience in today's digital service environment through these objectives.

The following research questions are answered in this study:

1. How is public discourse on social media used to create and shape digital customer experience in online motorcycle taxi services?
2. Which sentiment, emotion and theme trends appear from social media discussions regarding online motorcycle taxi services?
3. What are the effects of key actors and network structures on the dissemination and framing of customer experience narratives in the digital public sphere?

2 Methodology

This research is conducted using a Social Network Analysis (SNA) with Sentiment Analysis technique to explore the dynamics of digital customer experience in the platform-based transportation sector in public discourse on a social media platform, namely X (Twitter). This method is selected as it can not only uncover the structure and

interaction between users in digital conversation networks but also expose public sentiments around services discussed within these networks. This study utilizes Social Network Analysis (SNA) approaches to map the relationships between actors, characterize accounts as influencers and/or hubs of information flow, and explore how information about customer experience flows through social networks. Meanwhile, sentiment analysis is applied to assign positive, negative or neutral sentiment to opinions, thereby generating an overview of public perceptions and evaluations of platform-based transport services. This method is chosen because social media is becoming a known source of data that can capture public opinion in real time and at scale. Furthermore, social media is a virtual public place where the users interactively share their experiences, opinions and evaluations of the services they receive [20], [21]. By using SNA and sentiment analysis, this study can not only grasp, but also monitor the way users think about a brand, the reasons behind it, and the way it is being promoted in the digital world.

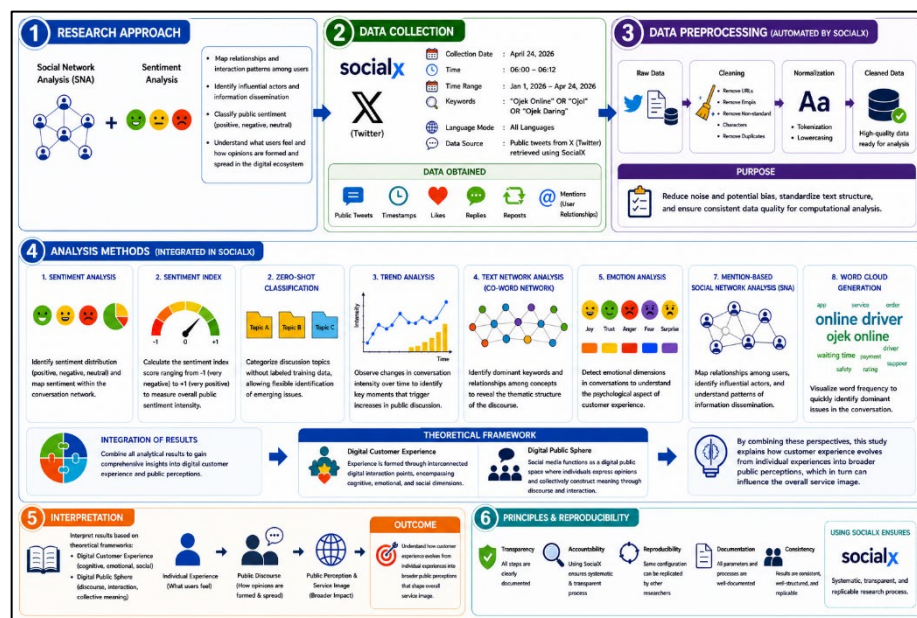


Fig. 1. Methodology Framework

The data collection time was set between April 24, 2026, 06:00 and 06:12, the search time was set between January 1, 2026, and April 24, 2026. These include the keywords such as "Ojek Online" OR "Ojo" OR "Ojek Daring." These keywords were chosen to reflect variations of the conversations that are relevant to the experiences users have with transportation through an app [22], [23]. The data gathered are public tweets (mode: all languages), enhanced by critical information generated automatically, like timestamps, mentions of interactions (likes, replies, reposts), etc., or by relationships with other users (relationships based on mentions). The systematic and transparent data

collection process with the use of SocialX upholds the principle of reproducibility in scientific research [24]. Thus, this study can be replicated by other researchers using the same configuration. The next phase is data preprocessing to ensure that the data is of good quality and suitable for analysis. This is done automatically by SocialX and involves removing text from URLs, emoji, non-standard characters and duplicate data. Besides, text normalization process is conducted by tokenizing and lowercasing the text data to standardize the text data structure [25], [26]. In unstructured data research, this process is very important to eliminate noise or possible bias that can impact the analysis outcomes. In the analysis stage, it means that the data analyzed is more consistent and can be processed by various computation methods [27].

The Main part of the study is performed with the help of a few computational analysis approaches, all implemented within the framework of SocialX. First, Sentiment Analysis is used to automatically categorize public opinions as positive, negative and neutral, and to visualize the sentiment distribution in the conversation network [28]. Sentiment classification is carried out by using SocialX sentiment analysis API that uses a language model based on Indonesian RoBERTa/IndoBERTa to process the Indonesian social media data. Because SocialX is a commercial proprietary platform, specific information about the platform architecture of the underlying model, validation processes, and performance metrics are not made publicly available [29]. Hence, the reliability of the language model is substantiated by the previous studies on IndoBERT that has been consistently shown to be state-of-the-art in Indonesian Natural Language Understanding (NLU) tasks. When evaluating the performance of IndoBERT Large on the IndoNLU benchmark [30], the model achieved an average classification score of around 88.43%, which is better than some multilingual transformer models. In addition, recent fine-tuned studies with IndoBERT-BASE-P2 on Indonesian Twitter data have re-reported the accuracy of 84.43% and macro F1-score of 84.33% for sentiment and text classification on social media data [31] which shows the effectiveness of transformer-based language models for sentiment and text classification on informal Indonesian social media texts.

In addition, transformer based language models like IndoBERT are particularly suited to extracting the semantic information of the context because they can better identify in-formal language, abbreviations, lexical variations and conversational writing styles common in social media, which are not well captured by conventional machine learning techniques. In model development, elements specific to Twitter (usernames, hashtags, URLs and other types of noisy tokens) are normalized or masked, so that the context is better understood. However, sarcasm, implicit meanings, irony and very context dependent expressions are still difficult for automated systems for sentiment classification. Therefore, the SocialX sentiment labels should be understood not as definitive measures of public opinion but rather as estimates of public opinion based on computation [31].

Second, Zero-Shot Classification, which is used to classify topics without any training data is used, enabling flexible classification of new topics in the dataset [32]. Third, Trend Analysis is applied to track the trends in conversation intensity over time, which helps to identify some moments in time that trigger a rise in the level of public conversation [33]. Fourth, Text Network Analysis (co-word network) can be employed to look

for dominant keywords and relations among the concepts in the text, creating a thematic structure which shows the main position of the discourse.

This makes it easy to get a quick view of public opinion and its trend over time [34], [35], [36]. All the analytical results are then read against the theoretical underpinnings of the Digital Customer Experience and the Digital Public Sphere. Digital Customer Experience is a concept that focuses on the customer experience as a result of the various different aspects of a digital interaction that form the whole experience, cognitive, emotional and social [37]. In the meantime, the idea of the Digital Public Sphere [38] describes how social media becomes a digital public space in which people not only express their opinions, but also engage in the act of collectively building meaning through discourse and interaction. This study integrates both views to illustrate the process of customer experience from personal experiences to public perception, and how the perception of the service image can affect the overall service image [39].

Overall, the research method aims to ensure transparency, accountability and reproducibility in the research process, which is described in a detailed and systematic way. Using SocialX as an analytical tool makes the research process consistent, documented and reproducible by other researchers with the same parameters.

3 Result and Discussion

3.1 Result

The data set in this research was 300 tweets extracted using data mining technique through SocialX platform on April 24, 2026. All posts were pulled from the X (formerly Twitter) feed between January 1, 2026, and April 24, 2026. Data collection was done through posts that are publicly available by searching the key words *Ojek Online*, *Ojol*, and *Ojek Daring*, as well as their corresponding hashtags, to get information regarding online motorcycle taxi services. These were chosen to capture as wide a range of customer experiences and perceptions of the subject as possible as well as the public discourse on the subject.

The final data yielded tweet content, dates, user information, and data on social interactions that occurred with each tweet such as retweets, replies, mentions, likes, and quote tweets enabling both text and network analysis. The data was then cleaned by eliminating duplicate posts, ads, spam, bot-generated content, and irrelevant discussions from the posts that were not associated with online motorcycle taxi services. Only posts with customer opinions, experiences in services or transportation related discussions were posted if the content was not purely promotional or a repost of a news post without customer discussion. The data collection methodology employed the “all languages” option in SocialX and hence, the resulting dataset represents multilingual public discourse which allows a wider representation of online conversations about digital transportation services.

Distributed in time, the activity of the tweets is not evenly spread across the study period. There was a gradual increase in tweets per month: the number of tweets in January was relatively low (only a dozen), in February it was slightly higher, and in March 2026 it was significantly higher (hundreds of tweets). The upward trend appears to

indicate a growing interest in raising awareness about the existing issues as well, including customer feedback regarding their experiences with motorcycle taxi services, Lodge complaints, and community events which attracted large numbers of people, and were covered in the media. This is the same for the daily distribution which saw one or two tweets in some days in January, but had much denser and more regular in March. The temporal structure of the dataset thus establishes the fact that March is the height of discourse dynamics.

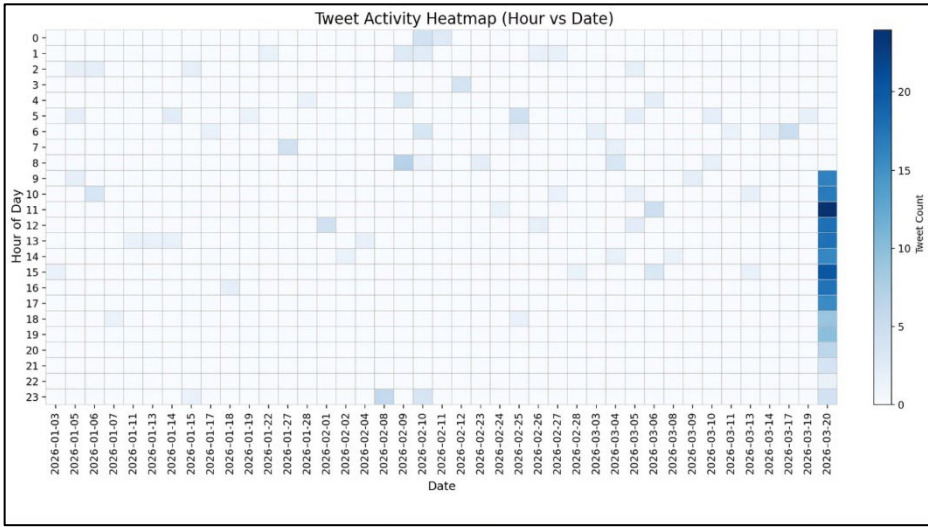


Fig. 2. Tweet Activity Heatmap (Hour vs Date)

Additional information about the daily activity rhythms is provided by the Tweet Activity Heatmap (Hour vs Date) which shows activity by time and date. The heatmap reveals that the highest activity period is from 12:00 to 18:00, where darker colors correspond to higher numbers of tweets. Conversely, the early morning (00:00-06:00) has very low levels of activity indicating that the most productive time for public conversation is during the daytime and afternoon. The fact that the dominant color segmentation in March is again in the first phase of the study frame, which is the most active, further confirms this analysis.

Overall, the heatmap illustrates the uniformity of the public conversation rhythms throughout the day as well as any regular temporal behavior patterns of the users. It is deemed sufficient to capture the structure of public discourse on online motorcycle taxis in the digital sphere, as the number of posts, the intensity of these posts in each hour of the study, and the nature of interaction within the public discourse gave enough room for further analysis, such as mapping the social network, analyzing the nature of sentiment within it, and examining the dynamics of issues throughout the study.

3.1.1 Wordcloud Analysis

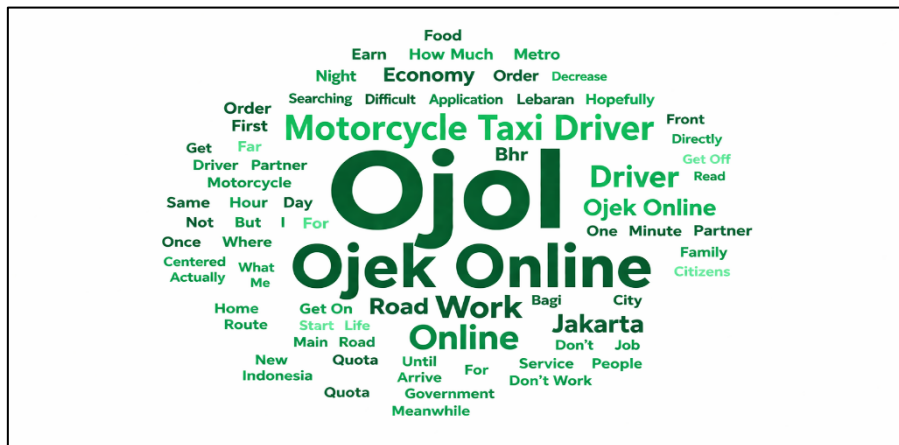


Fig. 3. Wordcloud Analysis

The public discussion of online motorcycle taxi (ojek online/*ojol*) service on the X (Twitter) platform resulted in a Word Cloud Analysis as presented in figure X. The visualization focuses on the word that occurs most often in the data set, words that are bigger have a higher occurrence count, making them more pertinent in the discourse. *Ojol* and “Ojek Online” are the most dominant words, used in large fonts, at the center of the word cloud. This is a confirmation that they are very relevant to the evolvement of online motorcycle taxi services discussion and they stand a central topic of public discussion. These keywords are most prominent, suggesting that there is a strong need for users to refer to transportation services through the internet using the abbreviated keyword ‘*ojol*’ or the full expression ‘ojek online’.

Some other words often appear in the dataset, like “Motorcycle Taxi Driver”, “Driver”, “Work” and “Online”, which tend to focus on drivers' activities. The salience of public discourse, which recognize the importance of the driver, also extends to the persons delivering the service. Not only does this reveal that drivers are a vital piece of the digital customer experience but it also demonstrates that user perceptions can often be effected first-hand by the driver.

In addition, the phrases “Jakarta” “City” “Government” “Economy” and “Service”, also show more contextually related discussion in relation to mobility aspects in urban developments, public policy or economy related to online transportation. These terms appear in this context, indicating that motorcycle taxis service is often mentioned in different social and economic issues that impact urban populations.

The word cloud also includes terms like “Application”, “Order”, “Route”, “Quota”, “Partner” and “Job”, highlighting areas related to the running of platform transportation services. The keywords highlight issues that users have with service accessibility, the functioning of the platform, working conditions, and between platforms and drivers. Additionally, the words “Don't,” “Hopefully,” “Decrease,” and “Difficult” indicate some fears, frustrations, and/or hopes of improvement are present in some

conversations. A positive meaning of these terms is that not all views of public opinion are positive and users often talk about problems and issues with the service. But you will see some words that are related to everyday life experiences, community activities and delivery services, such as “Family,” “Citizens,” and “Food.”

Overall, the results of the Word Cloud Analysis suggest that the public discourse on online motorcycle taxi services was multidimensional, with concerns about the activities of the drivers, the experiences of the passengers, the operations of the service, urban mobility, the economic consequences, and the political implications. The dominance of the driver and service-related keywords indicates that the digital customer experience is tightly linked to service quality as well as to the customer-service interaction with the driver. These results give a preliminary idea of the general aspects of the topics that were discussed by the public as a basis for more in-depth analyses, such as sentiment analysis and text network analysis, as well as social network analysis [35].

3.1.2 Sentiment Analysis

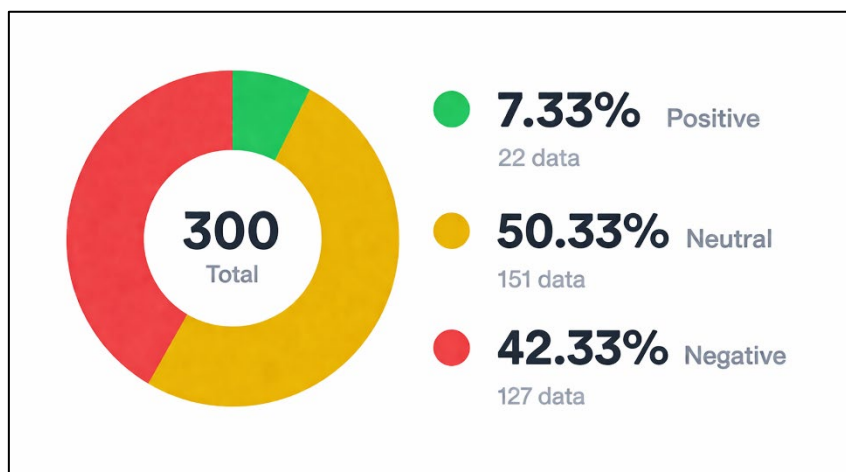


Fig. 4. Sentiment Analysis

Based on the sentiment analysis of 300 tweets, public discussion of online motorcycle taxi (*ojol*) services on the X/Twitter platform can be seen as having a neutral sentiment, with 151 of them or 50.33% having a neutral sentiment. This moderate percentage is relatively high, indicating that most users use informative and descriptive language and/or report factual experiences with little emotional expression. Neutral tweets are usually trip reports, service mentions or brief comments to not include emotional opinions. This means that *ojol* has entered into everyday language, but does not always lead to polarization.

127 or 42.33% of tweets are negative. This is a fairly high percentage as many people voice complaints, criticism and negative experiences about *ojol* services. Signs of negative sentiment are typically related to safety, comfort, cost, delays and how they

interact with drivers. The prominence of negative sentiment indicates that public discourse tends to be more critical in nature than appreciative.

However, positive sentiment only accounts for 7.33% or 22 tweets. Although relatively small, this portion indicates that some user express appreciation and satisfaction with *ojol* services. Generally, positive tweets are related to nice experiences, feeling safe, or appreciation for friendly and professional drivers. The presence of positive sentiment is important, since it means there is still space for positive stories even if they are in minority to negative sentiment.

Overall, it is concluded that the sentiment pattern of the public discourse on *ojol* is primarily critical and negative, followed by neutral and informational, and has a small proportion of positive sentiments. The outcomes provide a solid foundation for further analysis, such as mapping of the most important challenges to address negative sentiment; identification of factors that enhance customer satisfaction; and development of communication strategies to create positive perception in the digital public sphere in relation to the *ojol* services [32].

3.1.3 Text Network Analysis

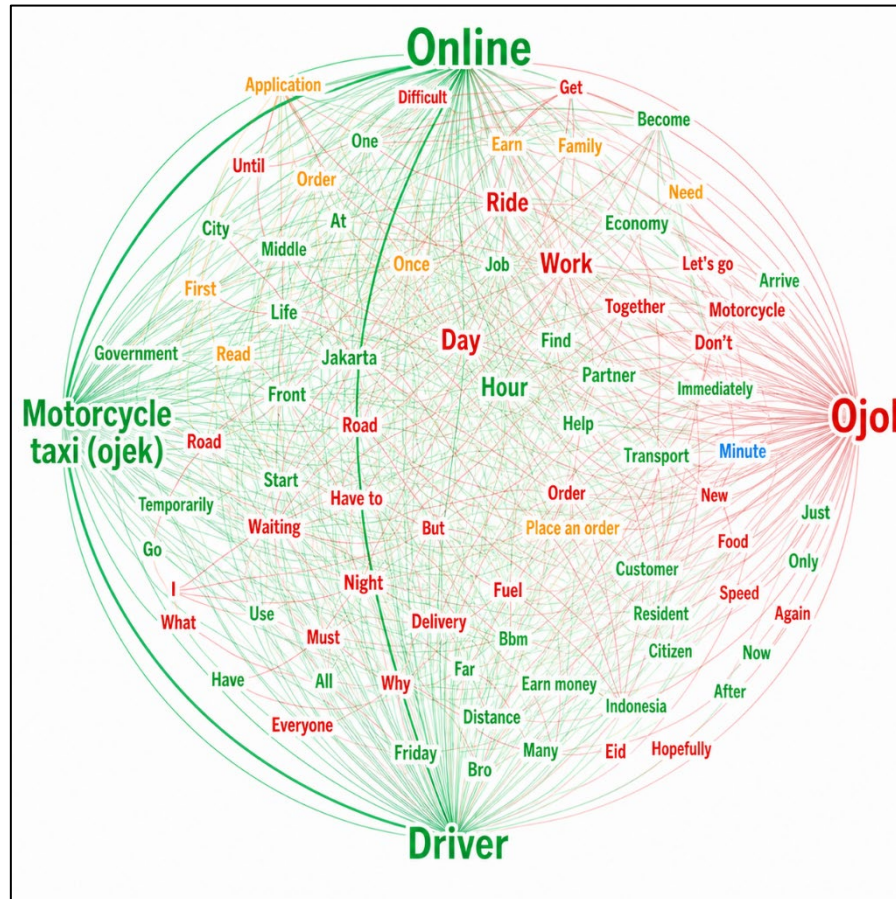


Fig. 5. Text Network Analysis

Results from the analysed data are used to identify the interrelationship of words of the tweets in the network analysis, which reveals the occurrence of certain discourse patterns. The visualization of the network reveals that the terms “ojek”, “*ojol*”, “driver” and “online” have the largest node size and are central to the network, highlighting the fact that they are used much more often than all the other words and at the heart of public discourse around digital motorcycle-based transport services. This network not only illustrates word frequency, but also the co-occurrence of words in the same tweet, creating a number of thematic co-occurrence clusters.

The first group is focused on the words driver and work and the words day, partner and job. The pattern suggests that the topic of drivers' work and daily life is a dominant subject in *qjol* discourse, both in terms of drivers' livelihood and the employment relationship with the platform companies.

The second cluster is the word “driver,” “motorcycle” and “ride” that are associated with words such as “road”, “speed” and “delivery.” This indicates that public dialogue also focuses on users' first-hand experiences, such as their encounters with drivers, the travel method and travel efficiency.

The third cluster focuses on the terms ‘online’, ‘application’ and ‘government’ and addresses the need to digitalise services and the public's perceptions of *ojol* as a solution to urban mobility related to regulation. Find parallels between *ojol* and economic processes, city life, or cultural moments by picking up on nuances and contextual elements such as “economy”, “Jakarta”, and “Eid”.

Additionally, there are ambivalent words like “difficult” and “don't”, and “but” that are found within the network and linked to several of the clusters, representing conversations that include complaints, resistances or negative experiences. This repeats the pattern of previous sentiment analysis, in that although neutral discourse occurs, there is also a significant amount of criticism and evaluation of the *ojol* discourse.

To sum up, this entire wordnet is complex and interwoven, showing that the "discourse system" of public discussion about *ojol* is multidimensional. The network brings together elements of drivers' work, users' experiences, the digitalization of services, the regulation and public appraisal. *Ojol*'s strong word relationship shows that these words complement each other in building a meaningful story of the role of an essential element in modern mobility in Indonesia [40].

3.1.4 Emotion Analysis



Fig. 6. Emotion Analysis

The emotion analysis of 300 tweets indicates that the highest emotion in the data set is “Happy” with 57% or 171 tweets. This positive emotion seems to be dominant, showing that the expression of this emotion is mostly appreciative and optimistic in the discussion of online motorcycle taxi (*ojol*) services on X/Twitter. Tweets that are related to happiness usually occur when there is a positive experience, satisfaction with the service, or a positive interaction with drivers. This indicates that while there is some criticism, there is scope for stories that focus on the positive aspects of using *ojol* in everyday life.

The second most noticeable sentiment is “Anger”, with 20% (60 tweets) of the total. The ratio may indicate that there are a large proportion of public chats of complaints or dissatisfaction such as pricing, safety, delays, or driver behaviour. Across the relatively high proportion of anger, it is possible to see that earlier sentiment analysis results are supported, as criticism of the *ojol* services is an important aspect of public discourse.

Sadness is seen in 16.67% (50 tweets) and is typically related to negative experiences, loss and/or disappointment regarding the service. At the same time, however, “Fear” comes up in 6.33% (19 tweets) and is frequently used when talking about safety in travels, accident risks or regulatory uncertainty. The emotion “Love” is not present at all (0%), meaning that explicit expressions of love are not common in conversations

about *ojol*, but are sometimes implied by pride or appreciation of specific communities of drivers.

In general, the Emotion Analysis results show that there is a mixture of positive and negative emotions expressed in public conversations in the dataset, with the majority of conversations being positive and the negative ones including a high proportion of anger and sadness. This pattern correlates with Sentiment Analysis results, which indicated that the expression of emotion and the polarity of sentiment reveal different content of public discourse and Sentiment Polarity Analysis indicated there was a balance of negative and neutral sentiment, with less of a positive sentiment. It means that the content and opinion of the discourse are ambivalent – positive and gratifying comments are set against critical, concerned and negative comments from the experiences of others, creating dynamics for public discourse that complement one another [41].

3.1.5 Social Network Analysis

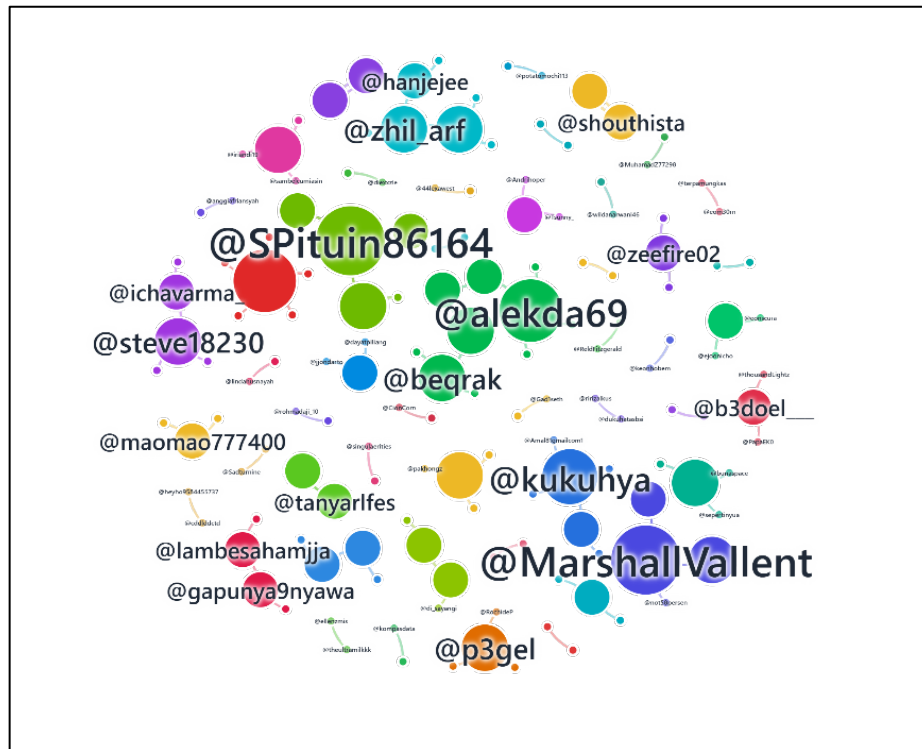


Fig. 7. Social Network Analysis

The conversations around online motorcycle taxis (*ojol*) reveal several important actors that have a significant impact on forming the dynamics of public discourse, as identified through Social Network Analysis (SNA). The most connected users, such as @SPituin86164, @MarshallVallent, and @alekda69, are one of the main sender and

receiver of mentions. These accounts can thus serve as references, or as a source of information, and as cues to start a conversation. They might be community leaders who get involved in conversation, community representatives who share information and/or individuals who have regular opinions and decisionmaking about *ojol* that can affect the direction of community conversation about *ojol*.

Additionally, users like @kukuhya, @zhil_arf, and @steve18230 are used as a “bridge” between clusters. These aren't necessarily the subject of much talk, but they're a key element of the connecting between communities. These types of bridging accounts could enable info flow among groups, without the information silos and maintain an integrated info ecosystem. This bridging is crucial in that it enables the transfer of problems raised in one cluster to another, promotes inter-community communication and create the continuity of the discourse. These key players set a gravitational map in the digital discourses, and the discourse of *ojol* doesn't just happen, but is shaped and focused on certain accounts. They act as the “core” of the network, reinforce the public stories, highlight relevant issues such as pricing, safety and user experience, and help to create a dialogue among the various sections of the community clusters.

this study uses a mention-based SNA (Social Network Analysis) to analyze the interaction among the users and determine the influential actors in the conversation network. The influential users were determined by Degree Centrality, which counts the number of direct links (mentions) each actor has into the network. The selection of Degree Centrality was determined by the goal of this study, which is to find out users who receive the largest number of interactions or who create the most interactions, in order to find out which users are the most central in disseminating information and contributing to forming public opinion about online motorcycle taxi services. The centrality of each actor influences their visibility and influence in the digital public sphere, such that higher degree centrality implies higher visibility and influence as they are connected to more users and can lead to wider dissemination of customer experiences throughout the digital public sphere.

The SNA generally shows that the "*ojol*" discourse in the X platform is coherent, interconnected and collaborative, as for a number of actors, they have become dominant in the building of a complex and multidimensional ecosystem of digital discourse [42].

3.1.6 Trend Analysis



Fig. 8. Trend Analysis

Looking at the historical trend of publications, there is clearly a pattern – tweets are generally lower in January and to mid-March with day to day numbers being rather stable but with intermittent small peaks and troughs. From the second week of March, however, there appears to be a bigger rise in the graph up to March 19, which represents a spike event with almost 200 tweets in one day.

This is not a random event in mid-March but is linked to certain social contexts. This "boom" of public interactions can be a reaction to issues that are occurring, like user experiences using *ojol*, criticism of services, or events that garnered public attention on social media. During the period, it has been seen that the discourse of *ojol* is very sensitive to social momentum and the occurrence of any event can cause a rapid rise in discussion.

Further, the trend of the 7-day moving average is more stable and gradual in an upward trend. This suggests that overall, the public debates on *ojol* have become more intense after late-February and into March, but there are extreme days as well. In other words, user engagement is not just fleeting, but a sustained degree of involvement and interaction.

Therefore, this increase in activity during mid-March can be understood as a consequence of greater interest in information, a user experience and a heightened criticism of the *ojol* services. This trend demonstrates the ability of social dynamics in digital media to directly impact on models of public discussion, particularly in relation to topics that are relevant to daily traffic and the public's interaction with online transportation provision [33].

3.1.7 Zero-Shot Classification

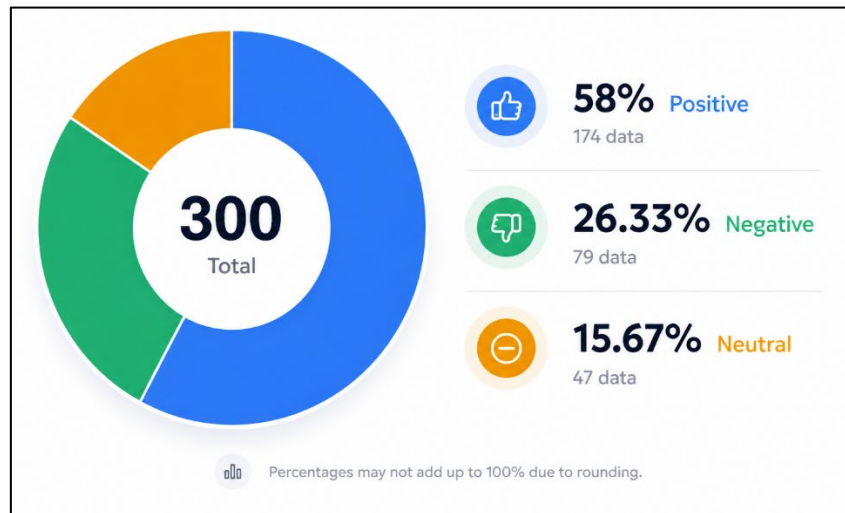


Fig. 9. Zero-Shot Classification Analysis

According to the frequency of the single result of Zero-Shot Classification analysis in 300 tweets, it can be seen that the public attitude towards motorcycle taxi services in Indonesia is mainly positive. Positive sentiment makes up 58% (174 tweets) of public sentiment; the majority of the public tweets are appreciative, supportive and/or satisfied with the *ojol* services. Such positive tweets usually come from pleasant experiences, a sense of safety, or praise for drivers that are perceived as friendly and professional. Positive sentiment overwhelmingly outnumbered criticism, indicating that there is a strong positive discourse about the possibilities of *ojol* in everyday mobility, even in the online public sphere.

Negative But negative sentiment makes up 26.33% (79 tweets), reflecting that there is still a considerable amount of criticism and complaint. The negative tweets are normally associated with the price, driver interactions, safety, or delays. This ratio is indicative that some customers think that the service is not meeting their expectations.

Meanwhile, the neutral sentiment has a proportion of 15.67% (47 tweets). Neutral tweets are usually factual, a description of things, experiences without emotion, or mentions of the *ojol* services in normal settings. *Ojol* has entered into the mundane public discourse, although not always with emotional opinions.

In general, the Zero-Shot Classification results reveal that public discussions of *ojol* are multi-faceted, with a majority of positive sentiment, but also include negative criticism and neutral information. This raises the possibility that discussions about *ojol* on social media do not revolve around a single narrative, but follow a range of possible user dynamics. The result could be used as a basis for further analysis, for example, mapping dominant issues in negative sentiment, identifying elements that cause customer

satisfaction and creating communication strategies to build positive sentiment in the digital public sphere [32].

3.1.8 Sentiment Index

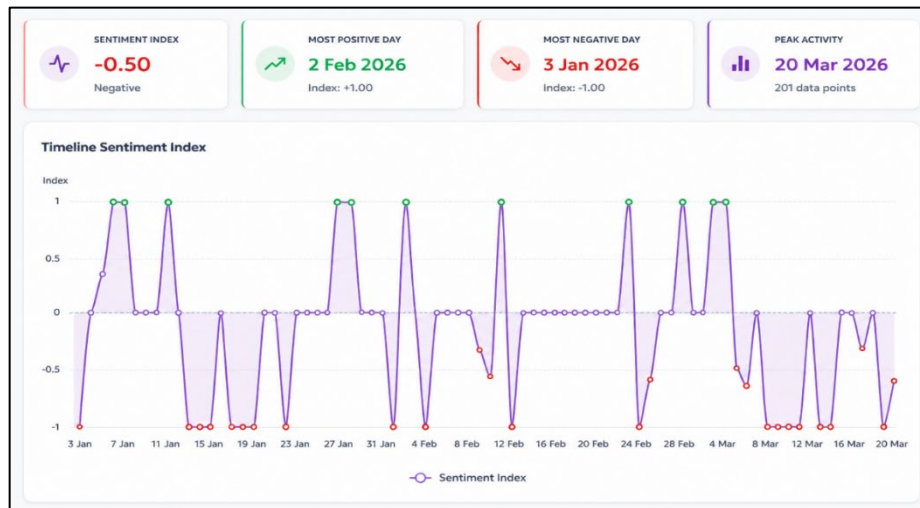


Fig. 10. Sentiment Index Analysis

The sentiment index analysis shows how the public opinion shifted from negative (-1) to positive (+1) over the years. The overall sentiment index is slightly negative: -0.50, meaning that in general, the discussion in the observed period is dominated by negative perceptions. This timeline graph indicates that the public's opinion is active and changes often, with some reading of positive, neutral, and negative sentiment, implying that it is highly dependent on current events or experiences.

The most optimistic sentiment was on February 2, 2026 (+1.00) reflecting a very positive public sentiment. The highest negative sentiment (or disapproval) score is -1.00 on Jan 03 2026, indicating just a lot of dissatisfaction and/or criticism. They demonstrate that for some events or issues, people's opinion may be affected, even resulting in a big change of opinion within a certain period of time.

In addition, there was an increase in public engagement or discussion on March 20, 2026, as evidenced by the 201 data points recorded on that date. One interesting thing to note is that high activity does not always mean positive sentiment – the increased activity can be related to negative factors or controversy. In conclusion, the analysis highlights the need for ongoing sentiment monitoring to gain insights into public opinion and to guide strategic actions to foster trust or mitigate it [28].

3.2 Discussion

While at first this results might seem inconsistent, they do not therefore indicate inconsistencies in the results, but rather differences in the analytical aspects obtained from

different computational methods. The main goal of Sentiment Analysis is to determine the explicit evaluative polarity (positive, negative, neutral) of tweets. However, neutral sentiment should be taken with a pinch of salt because neutral posts do not necessarily mean that customers are having a neutral experience. Many neutral tweets are, however, neutral content that does not necessarily state satisfaction or dissatisfaction, such as factual information, service announcements, traffic updates, transportation news, or other informational content. Therefore, it is necessary to consider neutral sentiment as an informational discourse that is part of the larger framework of the Digital Public Sphere and not as an indicator of customer evaluation.

Emotion Analysis, on the other hand, identifies the person's emotions that are expressed in a conversation, and may occur in parallel with the critique or as part of the information being conveyed. As a result, positive evaluations, such as appreciation towards drivers, empathy, humor, or other positive emotions can be conveyed together with neutral and/or negative evaluative orientations. Similarly, Zero-Shot Classification is based on the ability to see the semantics across contexts, such that positive framing or narratives can be detected even in the absence of explicit positive lexical features.

All these analytical products collectively shows the multidimensionality of the public discourse on online motorcycle taxi services, in which criticism, information sharing, emotional expression, humor and appreciation of service experiences are all included. Thematic analysis also indicates that public discussion is mainly focused on the quality of services, driver related problems, pricing, safety and regulatory questions. Combined, these results indicate that Digital Customer Experience is not limited to functional service attributes (efficiency, reliability, price), but also to the emotional and social aspects (trust, satisfaction, frustration and collective interaction).

Each computational technique provides one of the pieces of the puzzle to understanding Digital Customer Experience, but does not stand alone. Sentiment Analysis reveals the evaluative orientations of customers, Emotion Analysis reveals the psychological dimension of the evaluative orientations of the customers, Text Network Analysis reveals the dominant discussion themes, Social Network Analysis explains how these themes are disseminated through influential actors, and Trend Analysis depicts how the public discourse evolves over time. These analytical approaches collectively yield an explanatory framework for individual customer experiences emerging, developing, circulating and eventually collectively created in the Digital Public Sphere.

Moreover, SNA analysis unearths some users who become central agents in the digital discourse network, as opinion leaders and as connectors of discourse communities. These influential actors are key players in spreading, shaping and enhancing narratives, which helps to create collective perception of online transportation services. This discovery confirms the understanding of Digital Customer Experience as something more than a cognitive or emotional experience – it is a socially constructed and networked experience that is constantly negotiated in public interaction within the digital communication environment.

This study also recognizes that the social media users population is not entirely representative of the population of online motorcycle taxi customers. Active forum users can have different characteristics, level of participation, or amount of service experiences than silent users. Thus, the results should be interpreted as being representative of customer discourse that is publicly expressed and do not necessarily reflect the total customer base. However, social media is still a key source of capturing natural

customers' experience, and has been used widely to understand public opinion as a means of capturing public opinion in digital platform studies.

4. Conclusion

This study aimed to investigate the construction, communication and influence of digital customer experience in online motorcycle taxis with an integrated computational approach, based on social media discourse. The results show that digital customer experience is not a one-dimensional and constant phenomenon, but rather one that is multidimensional and socially constructed in the dynamic process of digital interactions in the public sphere. First, the results address the research question of how digital customer experience is built and is articulated: Customer experience is built collectively through public discourse on social media, in which users talk about and reimagine and negotiate their experiences. They are conveyed in a mix of informational stories, emotional displays and evaluative assessments, suggesting that digital platforms are not just a place where communication occurs but also a location where meaning is being produced. Second, in terms of patterns of sentiment, emotion and thematic clustering, the findings show an ambivalent discourse pattern. The sentiment analysis shows that the sentiment of the majority of the interactions is neutral or negative, which means that there is a high proportion of evaluative discourse and criticism, while the emotion analysis reveals that positive emotions, such as being happy, are still dominant in many of the interactions.

The study can be interpreted as an exemplary theoretical contribution to the notions of "Digital Customer Experience" (DCE) and "Digital Public Sphere" (DPS), suggesting the possibility of changing the perception of individual experiences into the perception of collective experience through networked processes. In terms of methodology, several analysis approaches are adopted to complement each other for a more comprehensive analysis of the complexity of the unstructured data from social media. In a business context, the results reveal that platform-based transportation firms need to go beyond management of their services and be active not only in monitoring but also in the management of digital discourse, because the perception of their service is constantly being constructed and deconstructed as a result of the flow of social media. This means implementing systematic social listening processes and using data to guide decisions in order to identify social problems as they arise, grasp customer expectations and make timely decisions to offset complaints or trending topics. Service quality improvement is still crucial, especially in regards to key areas of dissatisfaction with the service like price transparency, service reliability and safety, which all feature highly on public evaluations and play a strong part in the levels of users' trust in the service. Organizations also have to understand that drivers are the first face their customers encounter and therefore invest in driver training, driver welfare and driver performance management as this investment will impact the customer service. In addition, the fact that influential individuals exist in the digital network means that businesses can more strategically leverage influential members of the online community, opinion leaders, and active users to influence positive brand associations and narratives. This is a move towards network based reputation management, where customer loyalty is developed through interaction instead of being controlled by the company. Organizations should

also have the ability to communicate and respond quickly to a sudden surge in public attention, in addition to crisis management plans to effectively address issues as they arise in a transparent and open way. By using positive customer experiences in their storytelling and user-generated content, companies can also strengthen their trust and emotional connection with the brand.

In conclusion, this research confirms that digital customer experience is a dynamic, networked and discourse-based process in which perceptions are continuously negotiated in the digital ecosystem.

4.1 Limitations and recommendations for further research

This study has several theoretical and methodological contributions but there are certain limitations to be noted. First, the results are based on social media content that is publicly available, which may not accurately reflect overall social media discussions among motorcycle taxi users. People who post their own opinions online might not be just as engaged or the same age, experience, or have the same characteristics as those who appear to be silent. Thus the findings are to be understood in terms of the discourse of customers who were present in the public forum, and not in terms of the entire customer population. However, social media is still an excellent platform to record natural user experiences and is a well-used measure of public opinion in digital platform studies.

Second, the data used in this study is relatively small sample size of 300 tweets collected during the observation period. While the dataset and observations here are adequate for the current exploratory study, future research would benefit from more extensive and uniform data and more time in which to observe digital customer experience over time.

Third, the study is conducted on a single social media outlet, namely X (formerly Twitter). Customers' experiences are now shared on several digital platforms, such as Instagram, TikTok, Facebook, online forums, and review platforms. Further studies that investigated digital customer experience from a multi-platform perspective would give a more holistic view of the building and dissemination of digital customer experience in various online contexts.

Fourth, while this study combines several different kinds of computational techniques, such as sentiment analysis, emotion classification, text network analysis, social network analysis, and trend analysis, the study is largely quantitative. Further research should be conducted to integrate the concepts of computation with qualitative research methods, including interview, focus group, and digital ethnography, to gain deeper insights into customer perceptions and experiences.

Fifth, this study does not make platform-specific comparisons, but treats online motorcycle taxi services as a general digital transportation ecosystem. The service features, pricing models, promotion offers, and the type of customers on each platform can all impact the digital customer journey. Comparisons across different service providers, and across regions or countries that have varying cultural, economic and regulatory environments would also give a deeper understanding of digital customer experience.

This study measures neither customer trust nor customer loyalty nor other behavioral outcomes. Thus, the results are not meant to be understood as causal relationships between digital discourse and customer loyalty. Future studies could use survey, experimental, or longitudinal studies to explore the causal relationships between digital customer experience, online public discourse, their implications on customer trust and loyalty, platform usage and organization performance. Furthermore, given the ongoing rapid evolution of digital platforms, recommendation algorithms, and platform governance, ongoing research is required to explore how the future evolution of technologies and policies will affect the digital customer experience.

Acknowledgement

The authors would like to show their sincere thanks to the lecturers and colleagues for their guidance and assistance during the research process and their valuable inputs. Their encouragement and constructive feedback were of great help for completion of this study.

References

- [1] A. Chine, "Digital Transformation in Transport: Enhancing Efficiency and Economic Growth," *Eur. Econ. Lett.*, vol. 14, no. 4, pp. 763–773, 2024, doi: 10.52783/eel.v14i4.2198.
- [2] P. Wagh and A. Shaikh, "DIGITAL TRANSFORMATION AND RELATIONSHIP WITH CUSTOMER EXPERIENCE: A CRITICAL REVIEW OF LITERATURE FROM 1990 TO 2005 FOR PARADIGM SHIFTS IN KNOWLEDGE AND THOUGHTS IN 4-WHEELER CAR SEGMENT," *Int. J. Manag.*, vol. 11, no. 12, pp. 2098–2110, Jan. 2021, doi: 10.34218/IJM.11.12.2020.197.
- [3] M. Weber and C. G. Chatzopoulos, "Digital customer experience: the risk of ignoring the non-digital experience," *Int. J. Ind. Eng. Manag.*, vol. 10, no. 3, pp. 201–210, Sep. 2019, doi: 10.24867/IJIE-2019-3-240.
- [4] P. Klaus, "Towards practical relevance-Delivering superior firm performance through digital customer experience strategies," *J. Direct, Data Digit. Mark. Pract.*, vol. 15, no. 4, pp. 306–316, 2014, doi: 10.1057/dddmp.2014.20.
- [5] R. Sun, "Digital Platforms: Conceptualisation and Practice," the School of Management, Australian National University, 2019. [Online]. Available: [https://openresearch-repository.anu.edu.au/bitstream/1885/203636/2/PhD thesis Ruonan Sun 2020.pdf](https://openresearch-repository.anu.edu.au/bitstream/1885/203636/2/PhD%20thesis%20Ruonan%20Sun%202020.pdf)
- [6] S. Satryawati *et al.*, "Exploration of Customer Satisfaction Factors in the use of Maxim Online Transportation: An Empirical Study in the City of Samarinda," *Asian J. Environ. Res.*, vol. 2, no. 3, pp. 294–303, 2025, doi: 10.69930/ajer.v2i3.590.
- [7] Z. Ning and Y. Qiu, "Will Price Discrimination Affect Customer Satisfaction in the Shared Transportation Market? -A Case Study of Didi," *Adv. Econ. Manag. Polit. Sci.*, vol. 213, no. 1, pp. 120–130, Sep. 2025, doi:

- 10.54254/2754-1169/2024.26691.
- [8] T. Jameel, R. Ali, and K. A. Malik, "Social Media as an Opinion Formulator: A Study on Implications and Recent Developments," in *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, IEEE, Jan. 2019, pp. 1–6. doi: 10.1109/ICOMET.2019.8673509.
- [9] L. Dush, "Nonprofit Collections of Digital Personal Experience Narratives: An Exploratory Study," *J. Bus. Tech. Commun.*, vol. 31, no. 2, pp. 188–221, 2017, doi: 10.1177/1050651916682287.
- [10] M. Waqas, Z. L. Hamzah, and N. A. M. Salleh, "A typology of customer experience with social media branded content: a netnographic study," *Int. J. Internet Mark. Advert.*, vol. 14, no. 2, p. 184, 2020, doi: 10.1504/ijima.2020.10029779.
- [11] S. J. Mohammed, "Digital Marketing and its Role in Customer Engagement," *Am. J. Econ.*, vol. 7, no. 8, pp. 414–422, 2024.
- [12] Yessi Claudia Sianipar, Syafrizal Helmi Situmorang, and Rulianda Purnomo Wibowo, "ANALYSIS OF THE EFFECT OF DIGITAL CUSTOMER EXPERIENCE ON CUSTOMER LOYALTY THROUGH EMOTIONAL MARKETING AND CUSTOMER SATISFACTION FOR INDIHOME CUSTOMERS," *Int. J. Econ. Business, Accounting, Agric. Manag. Sharia Adm.*, vol. 3, no. 4, pp. 1235–1247, Jul. 2023, doi: 10.54443/ijebas.v3i4.1023.
- [13] B. Adisu Fanta and B. Ayman, "Social Media as Effective Tool for Understanding Customer Experience: A Systematized Review," *Mark. Menedzsment*, vol. 55, no. 4, pp. 15–25, Feb. 2022, doi: 10.15170/MM.2021.55.04.02.
- [14] L. Muradkhanli and Z. Karimov, "Customer Behavior Analysis Using Big Data Analytics and Machine Learning," *Probl. Inf. Soc.*, vol. 14, no. 2, pp. 61–67, 2023, doi: 10.25045/jpis.v14.i2.08.
- [15] A. Scalcău, "'Research Methods in Discourse Analysis: Quantitative, Qualitative and Mixed-Methods Approaches'," *Prof. Commun. Transl. Stud.*, vol. 14, pp. 114–122, 2023, doi: 10.59168/krla6949.
- [16] A. Bruns, "Big Social Data Approaches in Internet Studies: The Case of Twitter," in *Second International Handbook of Internet Research*, 2019, pp. 1–17. doi: 10.1007/978-94-024-1555-1_3.
- [17] D. Cogburn, M. Hine, N. Peladeau, and V. Yoon, "Introduction to the Minitrack on Text Analytics," in *Hawaii International Conference on System Sciences*, 2022, pp. 755–757. doi: 10.24251/HICSS.2022.094.
- [18] A. T. S. Wicaksono and S. Sudarmiatin, "Social Media Sentiment Analysis: Customer Perception of Digital Marketing," *Asian J. Appl. Bus. Manag.*, vol. 4, no. 2, pp. 437–450, May 2025, doi: 10.55927/ajabm.v4i2.187.
- [19] M. S. Schäfer, "Digital Public Sphere," *Int. Encycl. Polit. Commun.*, pp. 1–7, 2016, doi: 10.1002/9781118541555.wbiepc087.
- [20] K. Modi and V. B. Patel, "The Role of Social Media in Shaping Public Opinion: A Comprehensive Literature Review," *Int. J. LATEST Technol. Eng. Manag. Appl. Sci.*, vol. 14, no. 10, 2025, doi: 10.70183/ijdlr.2025.v03.133.
- [21] N. G. Alimin, "THE ROLE OF SOCIAL MEDIA IN FORMING PUBLIC OPINION: A CONTEMPORARY SOCIOLOGICAL PERSPECTIVE," 2024, doi: 10.31235/osf.io/d7g89.

- [22] P. A. Carter, "UNDERSTANDING THE RELATIONSHIP BETWEEN DIGITAL TOUCHPOINTS AND CUSTOMER LOYALTY: THE MEDIATING EFFECTS OF ENGAGEMENT AND SATISFACTION," *Int. J. Manag. Bus. Dev.*, vol. 2, no. 3, pp. 1–6, Mar. 2025, doi: 10.55640/ijmbd-v02i03-01.
- [23] W. Xu *et al.*, "An analysis of ridesharing trip time using advanced text mining techniques," *Digit. Transp. Saf.*, vol. 2, no. 4, pp. 308–319, 2023, doi: 10.48130/DTS-2023-0026.
- [24] P. JÜRGENS and A. JUNGHERR, "A TUTORIAL FOR USING TWITTER DATA IN THE SOCIAL SCIENCES: DATA COLLECTION, PREPARATION, AND ANALYSIS," *SSRN Electron. J.*, 2016.
- [25] S. M. Emaduddin, R. Ullah, I. Mazahir, and M. Z. Uddin, "Enhancing Information Preservation in Social Media Text Analytics Using Advanced and Robust Pre-processing Techniques," *Int. J. Media Inf. Lit.*, vol. 7, no. 1, pp. 60–70, Jun. 2022, doi: 10.13187/ijmil.2022.1.60.
- [26] A. R. Lubis and M. K. M. Nasution, "Twitter Data Analysis and Text Normalization in Collecting Standard Word," *J. Appl. Eng. Technol. Sci.*, vol. 4, no. 2, pp. 855–863, 2023, doi: 10.37385/jaets.v4i2.1991.
- [27] V. S. Tomashevskaya and D. A. Yakovlev, "Research of unstructured data interpretation problems," *Russ. Technol. J.*, 2021.
- [28] M. Taboada, "Sentiment Analysis: An Overview from Linguistics," *Annu. Rev. Linguist.*, vol. 2, pp. 325–347, 2016, doi: 10.1146/annurev-linguistics-011415-040518.
- [29] M. A. A. Saputra, A. Alamsyah, D. P. Ramadhani, T. S. Siadari, and H. Fakhruroja, "IndoBERT-Sentiment: Context-Conditioned Sentiment Classification for Indonesian Text," pp. 1–8, 2026, [Online]. Available: <http://arxiv.org/abs/2604.07057>
- [30] S. Cahyawijaya *et al.*, "IndoNLU: Benchmark and Resources for Evaluating Indonesian Natural Language Understanding," *EMNLP 2021 - 2021 Conf. Empir. Methods Nat. Lang. Process. Proc.*, pp. 8875–8898, 2021, doi: 10.18653/v1/2021.emnlp-main.699.
- [31] S. Winarno *et al.*, "Comparative Performance of Fine-Tuned IndoBERT BASE and LARGE Variants for Emotion Detection in Indonesian Tweets," *J. Online Inform.*, vol. 11, no. 1, pp. 14–26, 2026, doi: 10.15575/join.v11i1.1704.
- [32] V. A. and S. S. Sonawane, "Sentiment Analysis of Twitter Data: A Survey of Techniques," *Int. J. Comput. Appl.*, vol. 139, no. 11, pp. 5–15, Apr. 2016, doi: 10.5120/ijca2016908625.
- [33] J. Ziegler and M. Gertz, "Who Is behind a Trend? Temporal Analysis of Interactions among Trend Participants on Twitter," in *Proceedings of the International AAAI Conference on Web and Social Media*, Jun. 2023, pp. 960–969. doi: 10.1609/icwsm.v17i1.22203.
- [34] J. Jussila, M. Boedeker, H. Jalonen, and N. Helander, "Social Media Analytics Empowering Customer Experience Insight," in *Springer Proceedings in Business and Economics*, 2017, pp. 25–30. doi: 10.1007/978-3-319-56288-9_4.
- [35] A. Serna, J. K. Gerrikagoitia, and U. Bernabe, "Discovery and Classification of the Underlying Emotions in the User Generated Content (UGC)," in *ENTER2016. eTourism: Empowering Places. IFITT and ENTER Conferences*

- Connect the global eTourism Community*, 2016. doi: 10.1007/978-3-319-28231-2.
- [36] W. Yen-Jou, N. Yen, and J. C. Hung, "Design of a Multi-Dimensional Model for UGC-Based Emotion Analysis," in *2019 International Conference on Computational Science and Computational Intelligence (CSCI)*, IEEE, Dec. 2019, pp. 1383–1387. doi: 10.1109/CSCI49370.2019.00258.
 - [37] B. Huseynli, "Digital transformation for improving customer experience," in *Handbook of Research on Interdisciplinary Reflections of Contemporary Experiential Marketing Practices*, 2022. doi: 10.4018/978-1-6684-4380-4.ch005.
 - [38] E. Çela, "Social Media as a New Form of Public Sphere," *Eur. J. Soc. Sci. Educ. Res.*, vol. 4, no. 1, p. 195, Aug. 2015, doi: 10.26417/ejser.v4i1.p195-200.
 - [39] K.-M. Tramvalidou and V. G. Vrana, "Customer Experience in Public Organizations: A Multidimensional Analysis," in *1st International Conference on Public Administration 2024*, 2025, p. 9. doi: 10.3390/proceedings2024111009.
 - [40] M. R. Alam, A. M. Sadri, and X. Jin, "Identifying Public Perceptions toward Emerging Transportation Trends through Social Media-Based Interactions," *Futur. Transp.*, vol. 1, no. 3, pp. 794–813, 2021, doi: 10.3390/futuretransp1030044.
 - [41] R. Song, W. Shi, W. Qin, X. Xue, and H. Jin, "Exploring Passengers' Emotions and Satisfaction: A Comparative Analysis of Airport and Railway Station through Online Reviews," *Sustain.*, vol. 16, no. 5, 2024, doi: 10.3390/su16052108.
 - [42] B. Liu, F. Meng, C. Luo, and H. Jiang, "User Interactions in Online Travel Communities: A Social Network Perspective," *J. Hosp. Tour. Res.*, vol. 48, no. 7, pp. 1149–1163, 2024, doi: 10.1177/10963480221141616.