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A Comparative Text-Mining and Semantic Network Analysis of User Reviews on Traveloka and Trip.com

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Abstract

The global online travel market surpassed US$820 billion in 2024 and is expected to reach US$1 trillion by 2027, fueled by digitalization and the rise of mobile-based bookings. Within this expanding sector, Trip.com and Traveloka stand out as leading online travel agencies (OTAs) that depend heavily on user-generated reviews for service enhancement and competitive positioning. This study employs a mixed-method approach combining text mining, and semantic network (CONCOR) analysis to examine 2,000 user reviews (1,000 per platform) gathered from both OTAs. Using RStudio, UCINET, and CONCOR, the analysis uncovers key linguistic and thematic patterns that reflect users' perceptions of service quality, usability, and issue resolution. Findings reveal four shared thematic dimensions: Platform & Travel Logistics, Complaint & Problem Handling, Travel Experience & Services, and Transaction & Booking Process. However, emphasis differs: Traveloka reviews stress refund processing, reliability, and responsiveness, while Trip.com reviews highlight booking efficiency and trust issues, particularly regarding refunds and cancellations. This research advances the application of big-data text analytics in comparative OTA evaluation and demonstrates how semantic relationships in user reviews uncover service perceptions. Practical implications include improving transparency, refund management, and leveraging AI-driven personalization to enhance customer satisfaction.

Keywords: Online Travel Agency (OTA), eWOM, Traveloka, Trip.com, Customer Experience, Big Data Analytics.

1. Introduction

In 2024, the global online travel market was estimated at over US$640 billion and is expected to grow steadily in the coming years, driven by the increasing dominance of online channels that generated about 70 percent of total travel and tourism revenue (Statista, 2024). More than 70% of travelers worldwide now use online platforms or mobile apps to plan and purchase their trips, and user-generated reviews are among the most influential factors shaping travel decisions (Ana & Istudor, 2019). Within this digital ecosystem, Trip.com (Chen et al., 2024) and Traveloka (Mohanty et al., 2022) have emerged as leading online travel agencies (OTAs), serving millions of users across Asia and beyond.

The expansion of digital technologies has fundamentally reshaped how consumers search for, evaluate, and purchase travel services (Pencarelli, 2020). These platforms integrate flight, accommodation, and activity bookings within unified interfaces, creating seamless travel ecosystems that also function as powerful data engines (Raab et al., 2018). The vast amount of feedback produced through reviews, ratings, and comments provides invaluable insight into customer expectations, satisfaction, and pain points, making online reviews a crucial form of electronic word-of-mouth (eWOM) (Handani et al., 2022).

At the same time, the rise of big data analytics allows firms to transform this user feedback into actionable knowledge (Riswanto et al., 2023). Techniques such as text mining, sentiment analysis, and semantic network analysis reveal patterns in consumer language, uncover latent topics, and guide data-driven decision-making (Giannakis et al., 2022). These tools not only enhance marketing precision but also strengthen customer-centric innovation and service design (Kaartti et al., 2025).

Trip.com and Traveloka represent two contrasting yet complementary approaches to digital competitiveness. Trip.com combines global reach with advanced artificial-intelligence-based personalization (Chen et al., 2024), while Traveloka leverages localized services and user-experience optimization to lead in Southeast Asia (Mohanty et al., 2022). Comparing them provides insight into how platform design, data strategies, and customer perceptions interact in shaping loyalty and satisfaction.

Existing research on online travel agencies (OTAs) has provided valuable insights into service quality, customer satisfaction, trust, and loyalty, largely relying on survey-based models or sentiment analysis of online reviews. While these studies identify important determinants of user behavior, they often focus on single platforms, examine isolated experiential factors, or treat user reviews primarily as inputs for polarity measurement rather than as structured expressions of customer experience. As a result, limited attention has been given to how customer discourse itself reflects competitiveness-relevant capability patterns, particularly in a comparative platform context. This study addresses this gap by adopting a comparative, perception-based approach to examine how users articulate and connect experience dimensions across two leading OTAs, Traveloka and Trip.com, using large-scale review data. By integrating text mining with semantic network (CONCOR) analysis, the study moves beyond frequency counts and sentiment scores to uncover the structural relationships among experience attributes embedded in review discourse.

This study employs a text mining and semantic network, of 2,000 user reviews (1,000 from each platform) to explore how travelers perceive and evaluate these OTAs. The analysis identifies major linguistic patterns, thematic clusters, and strategic differences, offering empirical evidence on how customer feedback drives competitive advantage in the post-pandemic digital tourism landscape.

2. Literature Review

2.1. Online Review

The term electronic word of mouth (eWOM) refers to online reviews (Kwon et al., 2021). Because online reviews strongly influence customer purchasing decisions, they have gained increasing attention in marketing research. Scholars have highlighted that the strength of a reviewer's social network can significantly affect how credible and useful their online evaluations are perceived to be, ultimately shaping consumer decisions (Bilal et al., 2021). Li et al. (2019) conducted a combined sentiment–topic analysis demonstrating how online reviews can impact product sales. Moreover, Guo et al. (2020) observed a bias toward positive emotions in online reviews, suggesting that emotionally expressive feedback tends to influence buyers more effectively than neutral or negative comments. As a result, numerous researchers have recognized the importance of online reviews and explored their effects in various studies.

The online reviews have an impact on the firm level outcomes, such as performance in terms of sales, rate of returns, and brand equity, besides influencing customer behavior. As an example, excessively positive reviews may lead to growing customer expectations and product returns, particularly among first-time buyers (Li et al., 2021). Also, text mining and customer feedback methods demonstrate that the depth, objectivity, and social credibility of reviewers influence the benefits of reviewing (Liu et al., 2015). According to Sotiriadis and Van Zyl (2013), internet reviews and recommendations influence how customers choose services, and word-of-mouth (WOM) significantly influences the subjective norms and attitudes toward a service as well as a customer's propensity to promote it. Therefore, customer feedback through delivery service platforms can be highly valuable for companies to better understand their diverse users and develop strategies to enhance service quality in a highly competitive market.

2.2. Big data

In many aspects of marketing strategy and corporate management, big data analysis has become a game-changer (Sood et al., 2022). Emphasize how big data analytics has revolutionized management techniques and allowed businesses to make data-driven, well-informed judgments (McAfee & Brynjolfsson, 2012). Show how cutting-edge analytical methods, such as latent Dirichlet allocation, may be used to glean strategic marketing insights from enormous amounts of internet user-generated information (Tirunillai & Tellis, 2014).

Big data refers to extremely large, complex, and diverse datasets that cannot be efficiently collected, processed, or analyzed using traditional data management tools (Tao & Kim, 2017). Big data analytics address the challenges of managing vast, unstructured, and rapidly evolving information generated by organizations across business, research, and government sectors (Zakir et al. 2015). Data sets and analytical methods in applications that are so big (terabytes to exabytes) and complex (sensor to social media data) that they require sophisticated and one-of-a-kind data storage, management, analysis, and visualization technologies are referred to as big data and big data analysis (Tao & Kim, 2017).

2.3. Trip.com

Trip.com Group (formerly Ctrip) has built its competitive strength through leveraging digital capabilities, partnerships, and customer-centric services. Chen (2024) analyzes Trip.com's marketing strategies and argues that the company uses SEO, targeted content marketing, and alliances (such as with Booking.com and TripAdvisor) to extend its reach and diversify inventory. The platform's ability to integrate multiple travel services (flights, hotels, tours) into a single ecosystem also reinforces its value proposition, allowing users to plan complete trips in one place (Chen, 2024). Such capabilities allow Trip.com to respond dynamically to demand fluctuations and personalize recommendations, which are central to its ongoing competitive differentiation.

To effectively oversee its high-value partnerships, Trip.com uses a Key Account Management (KAM) strategy, a refined B2B relationship approach that offers tailored support to its top-performing hotel partners (Sagita ,2025). Tourism websites function as marketing platforms that provide essential travel information while highlighting a destination's attractions and the city's ongoing transformation (Huang, 2017).

2.4. Traveloka

Traveloka has distinguished itself in Southeast Asia through a strong orientation toward user experience, localized services, and retention strategies (Tan & Joquiño, 2020). A study of Traveloka's website quality among Indonesian students found that functionality and security/privacy are the strongest predictors of satisfaction, which in turn significantly influence purchase intention (Choirisa, 2021). In the mobile context, Putra et al. (2022) report that application utility and user interface structure are key drivers of continued usage and app loyalty for Traveloka's mobile platform, highlighting the importance of usability in travel e-commerce. Further, a recent examination of Traveloka's digital interaction strategy revealed that both e-service quality and customer experience positively influence customer loyalty, showing that technological and experiential improvements can bolster retention (Ramdani & Wardi, 2024).

In terms of perceived service quality and loyalty, several studies confirm that service quality and brand image contribute meaningfully to customer satisfaction and loyalty. Bunga and Sopiah (2024) reveal that service quality has both direct and indirect positive effects on user satisfaction via trust, which underscores the importance of reliability and integrity in Traveloka's operations. Similarly, Bimantaka and Muthohar (2024) find that service quality, brand image, and customer satisfaction each positively influence loyalty among Traveloka users, reinforcing that a positive brand perception and consistent service performance are central to long-term retention. On the behavioral side, Ripandi and Murni (2020) examine Indonesian users' repurchase intention for flight tickets and conclude that ease of use, promotional offers, and price significantly affect satisfaction, which in turn drives repurchase behavior on Traveloka. These findings suggest that Traveloka's strategy of combining usability, promotions, brand strength, and dependable service works synergistically to sustain customer loyalty.

2.5. Text Mining and Semantic Network Analysis

Text mining refers to the process of extracting meaningful and previously unknown information from textual data by applying natural language processing (NLP), information extraction, and retrieval techniques (Gaikwad et al., 2014). As illustrated in Figure 1, the initial phase of text mining involves data collection, followed by preprocessing where text data are segmented into morpheme units and grammatical errors are corrected. After preprocessing, the extracted words are analyzed based on frequency, centrality, and clustering, which help identify key themes and relationships within the dataset (Kim et al., 2020).

Semantic network analysis, on the other hand, focuses on identifying and examining the relationships between words to understand the structure and meaning within a network of terms (Drieger, 2013; Ban & Kim, 2019). For example, Shim et al. (2011) applied semantic network analysis to interview data to explore how social media and smartphone users consume digital content. This approach relies on analyzing the network structure, interconnections among major terms, and frequency of keyword occurrences to reveal patterns of information flow (Kim, 2017).

In recent years, the integration of semantic web analytics into information analysis has gained increasing attention. For instance, Kim (2017) utilized text mining and semantic network analysis to identify the most frequently mentioned terms from a large dataset collected at a culinary exhibition. Semantic network analysis enables researchers to examine how words co-occur within the same context, thereby uncovering semantic patterns and conceptual associations without depending on nominal classifications (Shim et al., 2011). Overall, semantic network analysis serves as a powerful method for understanding the structure and flow of web-based content (Tao et al., 2017).

3. Methodology

This study utilized two leading online travel agencies (OTAs), Traveloka and Trip.com, operating within the digital travel industry. Both platforms function as multi-service marketplaces that aggregate and broker travel products, including flights, hotels, transportation, and in-destination activities, through mobile apps and web interfaces. In Southeast Asia, Traveloka emphasizes localized services and user-experience optimization, while Trip.com combines broad international reach with data-driven personalization (Mohanty et al., 2022; Chen et al., 2024). Within the broader market context of rapid digitalization and mobile adoption, OTAs have become central intermediaries linking travelers with suppliers and concentrating customer feedback at scale (Pencarelli, 2020; Raab et al., 2018).

Both enterprises rely heavily on user-generated reviews and ratings to surface pain points, guide service recovery, and inform product design. From a capability standpoint, the two firms illustrate distinct strategic logics. Trip.com exploits AI-supported recommendation systems, real-time pricing, and a unified booking ecosystem to scale personalization and operational efficiency (Chen, 2024; Tang, 2023). Traveloka integrates end-to-end lifestyle services and financial features (e.g., insurance, e-payments) to reinforce retention and brand salience across the trip cycle (Tan & Joquiño, 2020; Ramdani & Wardi, 2024). In both models, big-data pipelines enable continuous monitoring of customer discourse and rapid iteration on refund workflows, customer support, and interface design (McAfee & Brynjolfsson, 2012; Tirunillai & Tellis, 2014).

This study treats Traveloka and Trip.com as a comparative case of strategic competitiveness in digital travel, where performance hinges on three interdependent domains: platform usability, transaction transparency (payment, refund, cancellation), and problem resolution. User reviews were collected from publicly available app-store review pages for Traveloka and Trip.com. To ensure temporal relevance, reviews were restricted to the period January 2024 to December 2024. Reviews in all available languages were included in order to capture a broad and representative range of user experiences across different markets. Prior to analysis, non-English reviews were translated into English to allow unified text preprocessing and semantic network construction. Translation was applied consistently across both platforms to minimize systematic bias. Duplicate entries and non-informative reviews (example: blank text or reviews containing insufficient textual content) were removed. A total of 2,000 app-store reviews (1,000 per platform), analyzed text mining, and semantic network analysis (CONCOR) to map thematic structures and derive actionable strategic implications. This design aligns with prior calls to use big-data text analytics to uncover how customer experience narratives shape loyalty and market advantage in OTA ecosystems (Giannakis et al., 2022; Kaartti et al., 2025).

A total of 2,000 reviews were collected, 1,000 from each platform, as shown in Table 1. The reviews were selected to ensure diverse representation across key service areas such as booking, refunds, and travel experiences.

Table 1. Comparison of Total Reviews and Ratings for Leading Travel Apps

No.	App	Total Review	Rating
1	Traveloka	2,060,000.	4.8
2	Trip.com	662,000	4.7

Using text mining techniques in combination with Instant Data Scraper, data were collected and key words with high frequency were identified. The analysis was performed in RStudio and a matrix of the most frequently used words was generated. UCINET was used to evaluate the significance of words, while CONCOR, in combination with text mining techniques and Instant Data Scraper, enabled the analysis of textual data. Word frequency count was done to identify 50 most frequently used keywords for each platform. Following this, UCINET (Borgatti et al., 2002) was used to evaluate the significance of words, and CONCOR was applied to examine the relationships among them.

This technique grouped words into thematic clusters representing distinct areas of customer experience, and identified four major clusters across both platforms, platform & travel logistics, complaint and problem handling, travel experience & services and transaction & booking process. These clusters represent the main dimensions of customer experience and highlight differences in user focus and satisfaction between Traveloka and Trip.com. Figure 1 illustrates the overall procedure of text-mining analysis, including data collection, preprocessing, word extraction, and network analysis.

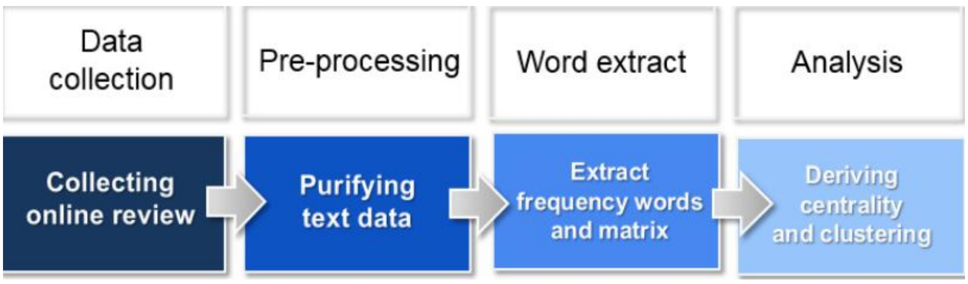

Figure 1. Text-mining process for online review analysis

4. Results

4.1 Big Data Analysis of Traveloka

The text mining analysis of Traveloka's user reviews produced a total of 50 high-frequency words that reflect users' main concerns and experiences with the platform. The most frequently mentioned terms included *app* (677), *traveloka* (594), *refund* (448), *flight* (396), *service* (331), *customer* (326), and *booking* (308), suggesting that customers primarily focused on the platform's functionality, service quality, and booking performance. Words related to financial transactions, such as *refund*, *payment* (137), *money* (140), and *reschedule* (144), appeared frequently, emphasizing users' attention to refund processes and payment management.

Negative terms such as *bad* (146), *problem* (84), *issue* (80), and *worst* (88) indicate recurring dissatisfaction, often linked to technical errors, poor response times, or customer service experiences. In contrast, positive words like *good* (91), *easy* (110), and *help* (92) suggest that some users appreciated the app's usability and convenience. Additionally, temporal expressions such as *time* (224), *wait* (77), and *already* (103) reveal customer frustration regarding delays and system efficiency. Overall, the 50-word frequency analysis indicates that service reliability, refund handling, and platform usability are key determinants of customer satisfaction and perceived value in the Traveloka digital ecosystem. Results can be seen in Table 2.

Table 2. Top 50 Most Frequently Used Words in Traveloka User Reviews

Rank	Word	Freq	Rank	Word	Freq
1	app	677	26	already	103
2	traveloka	594	27	want	103
3	refund	448	28	also	102
4	flight	396	29	like	101
5	service	331	30	need	99
6	customer	326	31	really	96
7	booking	308	32	check	93
8	use	270	33	travel	93
9	hotel	258	34	help	92
10	time	224	35	change	92
11	ticket	187	36	good	91
12	price	175	37	times	90
13	get	163	38	call	90
14	bad	146	39	worst	88
15	can	144	40	order	88
16	reschedule	144	41	give	88
17	money	140	42	always	87
18	payment	137	43	problem	84

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19	never	125	44	tried	81
20	airline	124	45	issue	80
21	now	121	46	process	80
22	experience	120	47	wait	77
23	email	111	48	another	73
24	easy	110	49	system	72
25	make	110	50	please	70

The semantic network visualization of Traveloka user reviews provides an overview of how frequently used terms are interconnected within the dataset. As shown in Figure 2, nodes represent individual words, and the links between them indicate their co-occurrence within the same review. Larger nodes correspond to higher word frequency, illustrating which terms dominate user discussions. The dense network structure reveals strong associations among core terms such as *app*, *refund*, *booking*, *service*, and *flight*, reflecting the centrality of operational performance, refund management, and customer service in shaping overall user perceptions of the Traveloka platform.

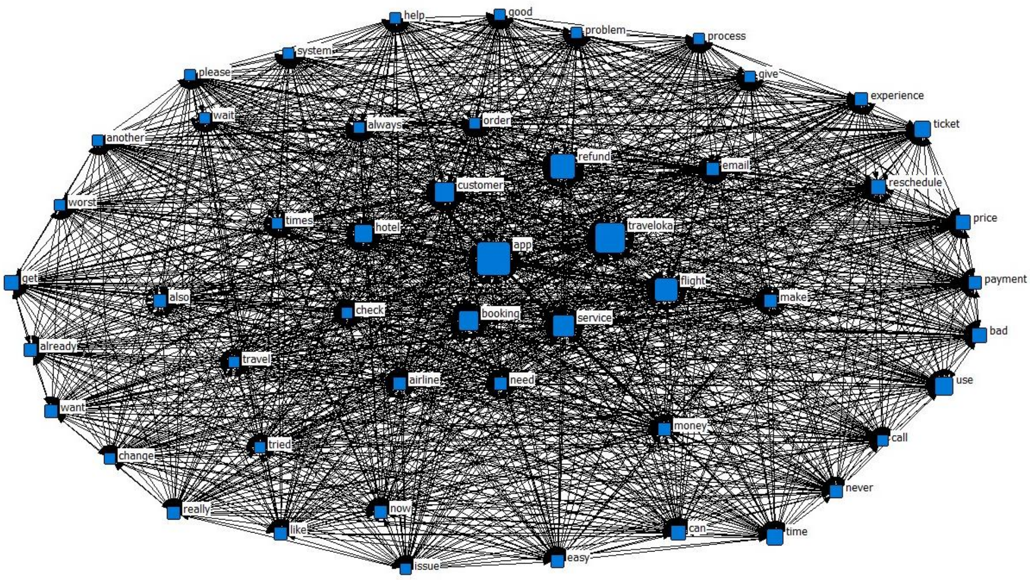

Figure 2. Semantic network visualization showing co-occurrence relationships among high-frequency words in Traveloka user reviews

The CONCOR analysis visualized in Figure 3 reveals four distinct clusters representing major dimensions of user perception toward Traveloka. The first cluster, Platform & Travel Logistics, contains terms such as *app*, *traveloka*, *flight*, *hotel*, and *airline*, emphasizing users' focus on system functionality and the operational core of travel logistics. The second cluster, Complaint & Problem Handling, includes words like *problem*, *issue*, *worst*, *wait*, and *please*, reflecting user frustration regarding service recovery, delays, and communication issues. The third cluster, Travel Experience & Services, links words such as *customer*, *service*, *good*, *experience*, and *help*, capturing positive evaluations related to usability and service support. The final cluster, Transaction & Booking Process, comprises terms like *refund*, *booking*, *ticket*, *payment*, and *price*, signifying attention to the efficiency, transparency, and reliability of monetary transactions.

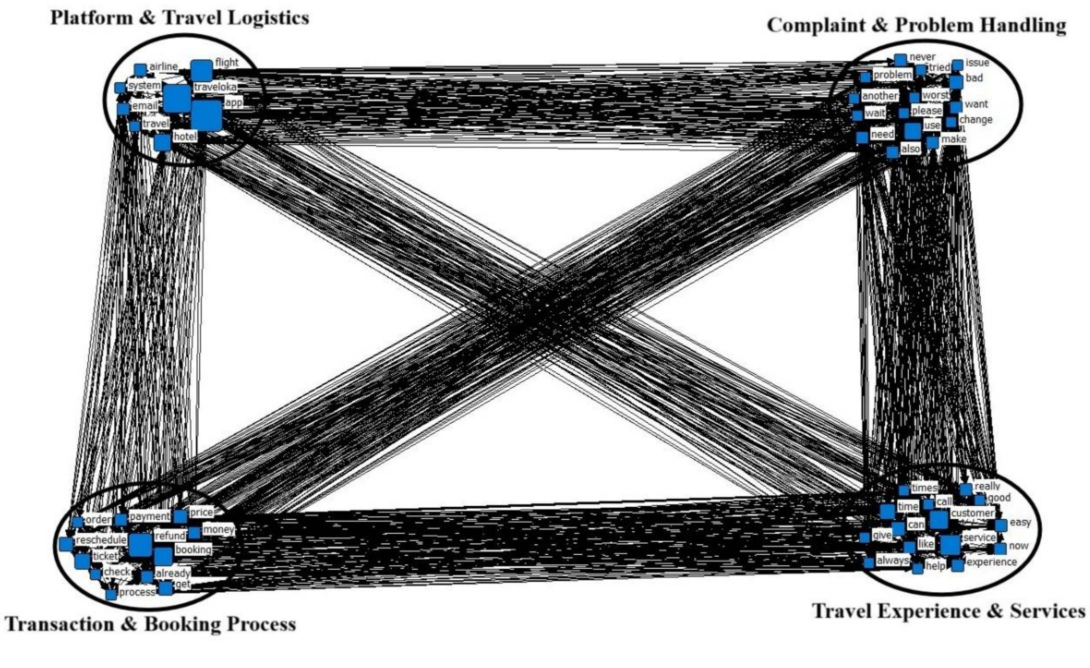

Figure 3. CONCOR Cluster Map of Traveloka User Reviews

The dense interconnections among clusters indicate that Traveloka users perceive their experiences as highly integrated, problems in one area (such as refund handling) often influence perceptions of overall service quality. This suggests that customer satisfaction is not determined by isolated attributes but by the interdependence between platform operation, service responsiveness, and transaction reliability. Collectively, these findings illustrate how text-mining-based CONCOR analysis can uncover the structural patterns of consumer discourse within a digital travel platform ecosystem.

The significant words for each cluster are summarized in Table 3, highlighting the key linguistic patterns that define each dimension of user feedback. The dense interconnections among clusters indicate that Traveloka users perceive their experiences as highly integrated-problems in one area (such as refund handling) often influence perceptions of overall service quality. This suggests that customer satisfaction is not determined by isolated attributes but by the interdependence between platform operation, service responsiveness, and transaction reliability. Collectively, these findings illustrate how text-mining-based CONCOR analysis can uncover the structural patterns of consumer discourse within a digital travel platform ecosystem.

Table 3. Significant Words in CONCOR Analysis

	Extracted Words	**Significant Words**
Platform & Travel Logistics	app//traveloka/airline/flight/ system/email/travel/hotel	app/traveloka/flight/hotel/airline
Complaint & Problem Handling	never/problem/tried/issue/ bad/another/worst/wait/ please/want/change/make/ need/also/use	problem/issue/worst/wait/please
Travel Experience & Services	times/call/really/good/ customer/travel/easy/give/can/ like/service/always/help/ experience/now	customer/service/good/experience/help
Transaction & Booking Process	order/payment/price/money/ refund/booking/ticket/check reschedule/already/get/process	refund/booking/ticket/payment/price

4.1 Big Data Analysis of Trip.com

The text-mining results for Trip.com identified the fifty most frequently used words across user reviews, highlighting customers' primary concerns and experiences with the platform. As shown in Table 4, the most prominent words include *app* (781), *flight* (607), *ticket* (428), *use* (388), *booking* (385), and *price* (297), indicating that users are highly focused on the platform's core travel functions: particularly flight and ticket booking efficiency. Terms such as *refund* (185), *payment* (84), and *cancel* (170) emphasize the importance of transaction management and service reliability, while *customer* (181), *service* (230), and *support* (59) suggest that user satisfaction is strongly linked to post-booking assistance and communication quality.

Positive expressions like *good* (124), *great* (116), and *easy* (135) point to favorable user experiences related to the app's convenience and usability. However, negative or cautionary terms: *bad* (69), *issue* (67), and *scam* (100), indicate persistent challenges with refund processing, ticket changes, and perceived trustworthiness. Temporal and transactional terms such as *hours* (49), *first* (73), and *many* (54) further imply user concerns about timing, responsiveness, and service volume. Overall, the frequency distribution reflects that Trip.com users primarily evaluate the platform through three lenses: booking functionality, payment and refund management, and service responsiveness, each of which directly influences user trust and loyalty toward the platform.

Table 4. Top 50 Most Frequently Used Words in Trip.com User Reviews

Rank	Word	Freq	Rank	Word	Freq
1	app	781	26	payment	84
2	flight	607	27	check	79
3	ticket	428	28	email	75
4	use	388	29	company	75
5	booking	385	30	first	73
6	price	297	31	buy	71
7	service	230	32	bad	69
8	hotel	229	33	direct	68
9	trip	212	34	website	68
10	refund	185	35	issue	67
11	customer	181	36	need	67
12	cancel	170	37	different	66

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13	get	164	38	train	63
14	change	145	39	help	63
15	airline	140	40	card	62
16	easy	135	41	recommend	59
17	good	124	42	support	59
18	can	120	43	best	58
19	great	116	44	want	56
20	try	110	45	made	55
21	like	104	46	many	54
22	scam	100	47	available	54
23	travel	98	48	another	52
24	experience	87	49	new	51
25	real	87	50	hours	49

The semantic network visualization of Trip.com user reviews demonstrate the interrelationships among frequently mentioned terms within the dataset. As shown in Figure 4, each node represents a keyword, and the connecting lines indicate co-occurrence within the same review. Larger nodes correspond to higher frequency, emphasizing the central importance of terms such as app, flight, booking, ticket, and refund. The dense web of connections suggests that users' discussions center on the booking process, payment reliability, and service responsiveness. Overall, the visualization highlights that Trip.com users evaluate the platform primarily through the efficiency of its core travel functions and the effectiveness of post-booking support and refund handling.

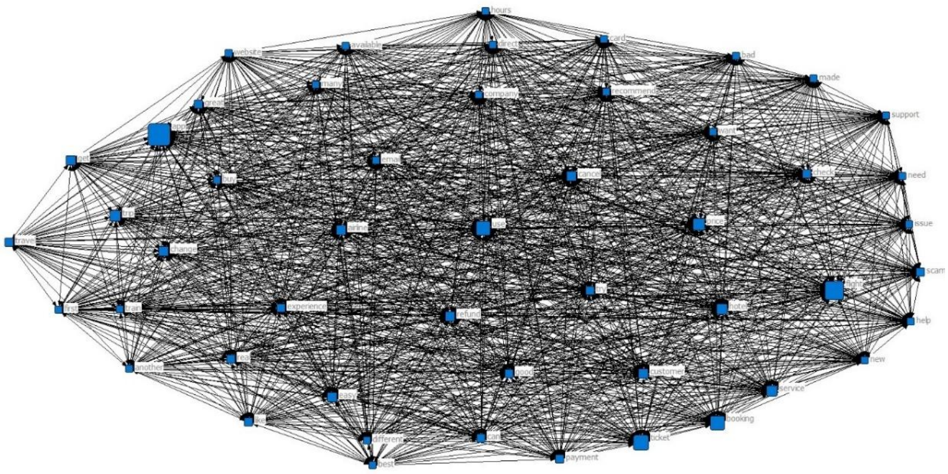

Figure 4. Semantic network visualization showing co-occurrence relationships among high-frequency words in Trip.com user reviews

The CONCOR analysis for Trip.com, illustrated in Figure 2, identifies four primary clusters that represent the structural dimensions of user perception on the platform. The first cluster, Platform & Travel Logistics, includes terms such as app, flight, hotel, airline, and travel, highlighting users' focus on the technical and functional aspects of trip organization and booking integration. The second cluster, Complaint & Problem Handling, features words like issue, scam, bad, cancel, and want, which reveal customer dissatisfaction related to refund disputes, booking errors, or perceived lack of transparency. The third cluster, Travel Experience & Services, encompasses words such as customer, service, good, experience, and help, indicating positive feedback related to service quality, reliability, and user support. Lastly, the Transaction & Booking Process cluster includes key transactional terms such as payment, booking, ticket, refund, and price, signifying that users pay close attention to financial reliability, pricing clarity, and refund efficiency.

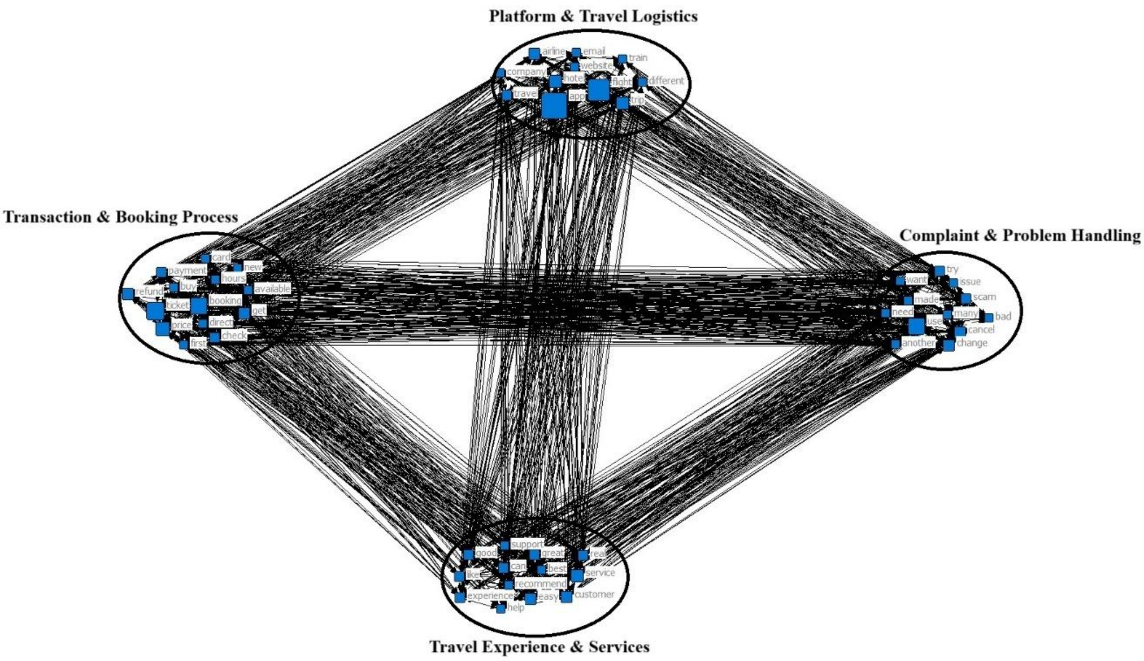

Figure 5. CONCOR Cluster Map of Trip.com User Reviews

The significant words for each cluster are summarized in Table 5, providing detailed evidence of the major themes within Trip.com user reviews. The dense network connections across clusters show that user experiences on Trip.com are multifaceted and strongly interrelated,

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complaints about refunds or booking errors often coexist with evaluations of service quality and pricing fairness. This interconnected pattern suggests that users assess the platform holistically, where operational efficiency, financial transparency, and problem resolution collectively determine overall satisfaction and loyalty.

Table 3. Thematic Clusters and Significant Words Identified through CONCOR Analysis of Trip.com User Reviews

	Extracted Words	**Significant Words**
Platform & Travel Logistics	airline/email/website/train/company/ travel/ hotel/app/different/flight/trip	app/flight/hotel/airline /travel
Complaint & Problem Handling	try/want/issue/scam/made/cancel/change/ need/many/bad/use/another	issue/scam/bad/cancel/ want
Travel Experience & Services	good/can/support/recommend/great/best/real easy/customer/service/ like/experience/help	customer/service/good /experience/help
Transaction & Booking Process	card/payment/hours/new/get available/refund/buy/ticket/price/ booking/direct/check/first	payment/booking/ticke t/refund/price

5. Discussion and Conclusion

The results reinforce previous research showing that online reviews are a dominant influence in travelers' purchase decisions (Chong et al., 2018). Both Trip.com and Traveloka exhibit linguistic patterns consistent with prior eWOM studies where service reliability, usability, and emotional tone determined customer trust and satisfaction (Matute et al., 2016). For Traveloka, users emphasized refund processing, booking convenience, and customer service, paralleling the findings of Bimantaka and Muthohar (2024), who highlighted service quality and brand image as the main predictors of loyalty in Southeast Asian travel apps. The negative terms (problem, issue, worst) indicate that technical performance and refund management remain critical pain points, supporting Liu et al. (2015), who found that review usefulness declines when customers perceive service inconsistency.

Trip.com's clusters described the firm's competitive strength in AI-driven personalization and multi-service integration. However, frequent mentions of scam, cancel, and issue suggest that the platform still faces challenges in maintaining transparency and responsiveness, especially in refund processing, issues similarly identified in studies of global OTAs by Sotiriadis and Van Zyl (2013). The CONCOR results also resemble Ban and Kim (2019) and Kim (2017), showing that semantic clusters of service, trust, and experience dominate customer perception networks.

Taken together, these findings extend prior research by demonstrating that user satisfaction on digital travel platforms is not driven by isolated factors but by interconnected experiences across technological, transactional, and service domains. More broadly, the findings suggest that competitive advantage in OTAs does not stem from feature parity but from capability alignment with dominant customer concerns. Text mining and semantic network analysis provide managers with scalable tools to continuously monitor shifting customer priorities and identify emerging capability gaps before they manifest as reputational damage.The integration of text mining and semantic network analysis provides empirical evidence that customer loyalty in OTAs depends on the continuous interaction between usability, transparency, and emotional trust. This complements the strategic insights of McAfee and Brynjolfsson (2012) and Tirunillai and Tellis (2014), confirming that big-data analytics can reveal how digital service ecosystems evolve through consumer feedback loops.

6. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the review sample, 1,000 entries from each platform, represents only a snapshot of user sentiment and may not fully capture seasonal or regional differences. Future research should adopt longitudinal sampling to examine how user perceptions evolve over time or in response to market shocks such as pandemics or regulatory changes. Second, the analysis relied exclusively on text-based data; incorporating star ratings, emojis, and behavioral data (e.g., click-through rates, dwell time) would enable a richer interpretation of user experience.

Third, while CONCOR and frequency analyses identified relational and thematic patterns, they do not reveal causal pathways between satisfaction factors and actual purchase or retention behavior. Subsequent studies could combine machine-learning sentiment modeling or structural equation modeling (SEM) to test how specific linguistic cues predict loyalty. Additionally, comparative research across Western and Asian OTAs, for example, including Expedia, Booking.com, or Airbnb, could determine whether cultural and regional differences moderate how travelers interpret service quality and digital trust.

Finally, future studies could integrate cross-platform big-data frameworks, combining social media posts, app-store reviews, and transaction data to construct a multidimensional model of customer experience in digital tourism. This would advance understanding of how online discourse translates into tangible behavioral and financial outcomes, aligning with calls from recent studies on AI-driven tourism analytics.

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References

Ana, M. I., & Istudor, L. G. (2019). The role of social media and user-generated content in millennials' travel behavior. *Management Dynamics in the Knowledge Economy, 7*(1), 87–104.

Ban, H. J., & Kim, H. S. (2019). Understanding customer experience and satisfaction through airline passengers' online reviews. *Sustainability, 11*(15), 4066.

Bilal, M., Marjani, M., Hashem, I. A. T., Malik, N., Lali, M. I. U., & Gani, A. (2021). Profiling reviewers' social network strength and predicting the "helpfulness" of online customer reviews. *Electronic Commerce Research and Applications, 45*, 101026. https://doi.org/10.1016/j.elerap.2020.101026

Bimantaka, R., & Muthohar, M. (2024). The effect of service quality, brand image, and customer satisfaction on customer loyalty on the Traveloka application. *Jurnal Economic Resource, 6*(1).

Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *UCINET for Windows: Software for social network analysis.* Analytic Technologies.

Bunga, R. S., & Sopiah. (2024). How service quality is able to influence customer satisfaction through the trust of Traveloka application users in Indonesia. *KnE Social Sciences.* https://doi.org/10.18502/kss.v9i4.15071

Chen, J. (2024). Research on the Ctrip tourism market analysis and marketing strategy optimization. *SHS Web of Conferences, 207*, 03003.

Chen, S., Mansor, N. S., Zhou, T., & Lin, Y. (2024). Exploring cultural losses in the tourism website translation: A case study of Trip.com. *Theory & Practice in Language Studies, 14*(3).

Choirisa, S. F. (2021). Traveloka website quality on customer satisfaction and purchase intention for university students in Indonesia. *APIAR Publications, 6*(1).

Chong, A. Y. L., Khong, K. W., Ma, T., McCabe, S., & Wang, Y. (2018). Analyzing key influences of tourists' acceptance of online reviews in travel decisions. *Internet Research, 28*(3), 564–586. https://doi.org/10.1108/IntR-05-2017-0212

Drieger, P. (2013). Semantic network analysis as a method for visual text analytics. *Procedia – Social and Behavioral Sciences, 79*, 4–17.

Gaikwad, S. V., Chaugule, A., & Patil, P. (2014). Text mining methods and techniques. *International Journal of Computer Applications, 85*(17), 42–45.

Giannakis, M., Dubey, R., & Yan, S. (2022). Social media and sensemaking patterns in new product development: Demystifying the customer sentiment. *Annals of Operations Research, 308*, 145–175. https://doi.org/10.1007/s10479-020-03775-6

Guo, J., Wang, X., & Wu, Y. (2020). Positive emotion bias: Role of emotional content from online customer reviews in purchase decisions. *Journal of Retailing and Consumer Services, 52*, 101891.

Handani, N. D., Riswanto, A. L., & Kim, H.-S. (2022). A study of inbound travelers' experience and satisfaction at quarantine hotels in Indonesia during the COVID-19 pandemic. *Information, 13*(5), 254. https://doi.org/10.3390/info13050254

Huang, Y. (2017). *Factors influencing choice decision behavior of Chinese tourists on Thai air ticket online booking: A case study of Ctrip.com, Qunar.com, and Elong.com* [Master's thesis, Srinakharinwirot University]. Srinakharinwirot University Institutional Repository.

Kaartti, V., Ojasalo, J., & Wait, M. (2025). Implementing a customer-centric strategy through service design in financial organisations. *International Journal of Bank Marketing, 43*(5), 921–942. https://doi.org/10.1108/IJBM-06-2024-0375

Kim, H. S. (2017). An exploratory study on the semantic network analysis of food tourism through big data. *Culinary Science & Hospitality Research, 23*(4), 22–32.

Kim, S. J., Maslowska, E., & Malthouse, E. C. (2020). Understanding the effects of different review features on purchase probability. In *Electronic word of mouth as a promotional technique* (pp. 29–53). Routledge.

Kwon, H.-J., Ban, H.-J., Jun, J.-K., & Kim, H.-S. (2021). Topic modeling and sentiment analysis of online reviews for airlines. *Information, 12*(2), 78. https://doi.org/10.3390/info12020078

Li, X., Wu, C., & Mai, F. (2019). The effect of online reviews on product sales: A joint sentiment-topic analysis. *Information & Management, 56*(2), 172–184.

Liu, M., Lii, Z., & Shao, M. (2015). The research on the impact factors of perceived online review usefulness. *Canadian Social Science, 9*(6), 36–44.

Matute, J., Polo-Redondo, Y., & Utrillas, A. (2016). The influence of eWOM characteristics on online repurchase intention: Mediating roles of trust and perceived usefulness. *Online Information Review, 40*(7), 1090–1110. https://doi.org/10.1108/OIR-11-2015-0373

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–68.

Mohanty, P., Dhoundiyal, H., & Thomas, A. (2022). Technological innovations in Asian tourism. In *Technology application in tourism in Asia: Innovations, theories and practices* (pp. 69–80). Singapore: Springer Nature Singapore.

Pencarelli, T. (2020). The digital revolution in the travel and tourism industry. *Information Technology & Tourism, 22*, 455–476. https://doi.org/10.1007/s40558-019-00160-3

Putra, P. O. H., Wahyumurti, R. A. W. C. D., & Indra Budi. (2022). Usability factors that drive continued intention to use and loyalty of mobile travel application: A case study of Traveloka. *PMC.*

Raab, C., Berezan, O., Christodoulidou, N., Jiang, L., & Shoemaker, S. (2018). Creating strategic relationships with online travel agents to drive hotel room revenue: An OTA perspective. *Journal of Hospitality and Tourism Technology, 9*(1), 125–140. https://doi.org/10.1108/JHTT-10-2016-0069

Ramdani, R., & Wardi, P. A. (2024). The strategy to enhance Traveloka's digital interaction with customer loyalty by improving e-service quality and customer experience. *ProBusiness: Management Journal, 15*(6), 40–48.

Riswanto, A. L., Kim, S., & Kim, H.-S. (2023). Analyzing online reviews to uncover customer satisfaction factors in Indian cultural tourism destinations. *Behavioral Sciences, 13*(11), 923. https://doi.org/10.3390/bs13110923

Ripandi, M., & Murni, Y. (2020). The analysis of customer satisfaction factors shaping airplane ticket repurchase interest on Traveloka. *International Journal of Economics, Business and Management Research, 4*(10).

Shim, H. J., Kim, Y. C., Shon, H. Y., & Lim, J. Y. (2011). An exploratory usage pattern research of smartphone and social media users through semantic network analysis: Gender and age differences in perception and evaluation of usage pattern. *Korean Journal of Broadcasting, 25*(4), 28–138.

Sood, K., Dhanaraj, R. K., Balusamy, B., Grima, S., & Maheshwari, R. U. (Eds.). (2022). *Big data: A game changer for insurance industry* (Emerald Studies in Finance, Insurance, and Risk Management, Vol. 6). Emerald Publishing Limited.

Sotiriadis, M. D., & Van Zyl, C. (2013). Electronic word-of-mouth and online reviews in tourism services: The use of Twitter by tourists. *Electronic Commerce Research, 13*(1), 103–124.

Statista. (2025, April 10). *Online travel market – statistics & facts.* https://www.statista.com/topics/2704/online-travel-market/#topicOverview

Sagita, P. A. (2025). *Key account management strategies of Trip.com in collaboration with 4- and 5-star hotels in Kuta, Bali* (Doctoral dissertation, Politeknik Negeri Bali). Politeknik Negeri Bali Repository.

Tan, Y., & Joquiño, P. (Eds.). (2020). *Navigating ASEANnovation: The Reservoir Principle and Other Essays on Startups and Innovation in Southeast Asia.* World Scientific.

Tao, S., & Kim, H.-S. (2017). A study of the comparison between cruise tours in China and the U.S.A. through big data analytics. *Culinary Science & Hospitality Research, 23*(6), 1–11.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent Dirichlet allocation. *Journal of Marketing Research, 51*(4), 463–479.

Zakir, J., Seymour, T., & Berg, K. (2015). Big data analytics. *Issues in Information Systems, 16*(2), 81–90.