Journal of Infrastructure, Policy and Development 2024, 8(7), 5311.
https://doi.org/10.24294/jipd.v8i7.5311

Article

Customers’ emotional impact on star rating and thumbs-up behavior towards food delivery service Apps

Le Li[1,2], Noor Azlin Ismail[1], Choo Wei Chong[1], Peng Sun[3,*], Mst. Dilara Pervin[4], Md Shamim Hossain[5]

[1] The School of Economic and Management, Universiti Putra Malaysia, Serdang 43400, Malaysia
[2] The School of Management and Engineering, Anhui Institute of Information Technology, Huainan 232002, China
[3] Department of Business Management, School of Management, Jinan University (JNU), Guangzhou 510632, China
[4] Department of Statistics, Hajee Mohammad Danesh Science and Technology University (HSTU), Dinajpur 5200, Bangladesh
[5] Department of Marketing, Hajee Mohammad Danesh Science and Technology University (HSTU), Dinajpur 5200, Bangladesh
*** Corresponding author:** Peng Sun, 2787387705@qq.com

CITATION

Li L, Ismail NA, Chong CW, et al. (2024). Customers’ emotional impact on star rating and thumbs-up behavior towards food delivery service Apps. Journal of Infrastructure, Policy and Development. 8(7): 5311. https://doi.org/10.24294/jipd.v8i7.5311

ARTICLE INFO

Received: 19 March 2024
Accepted: 1 April 2024
Available online: 31 July 2024

Abstract: This study explores the intricate relationship between emotional cues present in food delivery app reviews, normative ratings, and reader engagement. Utilizing lexicon-based unsupervised machine learning, our aim is to identify eight distinct emotional states within user reviews sourced from the Google Play Store. Our primary goal is to understand how reviewer star ratings impact reader engagement, particularly through thumbs-up reactions. By analyzing the influence of emotional expressions in user-generated content on review scores and subsequent reader engagement, we seek to provide insights into their complex interplay. Our methodology employs advanced machine learning techniques to uncover subtle emotional nuances within user-generated content, offering novel insights into their relationship. The findings reveal an inverse correlation between review length and positive sentiment, emphasizing the importance of concise feedback. Additionally, the study highlights the differential impact of emotional tones on review scores and reader engagement metrics. Surprisingly, user-assigned ratings negatively affect reader engagement, suggesting potential disparities between perceived quality and reader preferences. In summary, this study pioneers the use of advanced machine learning techniques to unravel the complex relationship between emotional cues in customer evaluations, normative ratings, and subsequent reader engagement within the food delivery app context.

Keywords: machine learning; sentiment analysis; emotional features; food delivery service apps; user evaluations; thumbs-up behavior

1. Introduction

The advent of the Internet and widespread accessibility to smartphones has led to a significant surge in the popularity of food delivery services (Ramesh et al., 2023; Su et al., 2022). Online food ordering not only offers convenience and time-saving benefits to consumers but also provides businesses with easier access to new customers through delivery solutions (Annaraud and Berezina, 2020). Online food delivery apps through timely delivery contribute significantly to upholding food quality standards. Moreover, these apps enhance customers’ dining preferences by providing a vast array of restaurant options. With the ability to explore diverse menus, read reviews, and view ratings, customers can make well-informed decisions aligned with their specific preferences (Chandrasekhar et al., 2019; Hossain and Rahman, 2023a). These platforms offer an extensive selection of cuisines, encompassing local favorites as well as international delicacies, catering to a wide range of tastes and culinary preferences. Additionally, food delivery apps empower restaurant companies to cater to the evolving expectations and preferences of a rapidly expanding customer base, allowing them to deliver a personalized and enhanced dining experience (Ramesh et al., 2023; Suhartanto et al., 2019). As a result, the utilization of food delivery apps has become instrumental in meeting the growing demands of customers and facilitating seamless interactions between consumers and food establishments (Chandrasekhar et al., 2019; Ramesh et al., 2023).

Online food delivery services have become a cutting-edge business model globally due to disruptive innovation in information and communications technologies (ICT) and the rise of the sharing economy (Chen, 2023). Online food orders are predicted to produce $466 billion in revenue globally by 2027, up from $296 billion in 2021 (Yaiprasert and Hidayanto, 2023). This represents an almost 60% increase. In several nations, on-demand meal delivery services provided by app-based platforms like DoorDash, UberEats, Seamless, Postmates and Grubhub have become extremely popular. Customers can use the platform to place online food orders from their preferred eateries and have their meals delivered right to their front door (Liu and Li, 2023). Online food delivery apps simultaneously broadened the reach of restaurants by gathering online customers' orders from different customers and hiring delivery services to deliver meals to them (Maimaiti et al., 2018; Wang et al., 2022). People are embracing food delivery apps due to their busy schedules and convenient services. It is simple to understand why ordering food online is growing in popularity given its many advantages (Yaiprasert and Hidayanto, 2023). The market for food delivery has expanded as a result of a number of causes, including the development of digital technology and the expansion of on-demand services. Additionally, the COVID-19 pandemic has had a considerable influence on the market for food delivery services (Pandey et al., 2021) because many eateries and customers have switched to online ordering to minimize direct contact and the danger of contracting the virus.

Including food delivery app organizations, the necessity for all businesses to monitor user-generated material about them and their competitors as well as themselves is expanding along with the customer base in order to manage competition and evaluate the business' competitive climate (Trivedi and Singh, 2021). One of the most well-known user-generated materials that can offer crucial information about what customers are thinking as well as other insightful observations is customer evaluations. App reviews offer an abundance of feature-related data that might assist requirement engineering tasks. App reviews are written comments from users that are enhanced with a star rating that users can provide to other App Store users and app developers regarding their experiences with certain apps. This feedback can assist developers in learning how users view their app and in identifying the needs and preferences of those users (Al-Subaihin et al., 2019). Research conducted on software developers has revealed that the identification of user feedback regarding specific app features holds significant importance for developers (Dąbrowski et al., 2022). This information influences various software engineering activities, ranging from requirements engineering to testing, system maintenance, and evolution.

Sentiment analysis is one of the most popular techniques that has been employed in many recent researches to extract the important insights from customer evaluations (Hossain and Rahman, 2023a; Pashchenko et al., 2022). Sentiment analysis uses artificial intelligence (AI) technologies that involve natural language processing (NLP) to analyse textual texts and identify attitudes and opinions (Elahi et al., 2023). The opinions and actions of customers towards a certain good or service may therefore be understood using these statistics, which can also be used to spot areas that could be improved upon and brand-new prospects for innovation (Li et al., 2023). Businesses can connect this data with decisions about what to buy or other behaviours by analysing the polarity of users' textual inputs (Pashchenko et al., 2022). With the aid of NLP, machine learning (ML), and text analysis tools, sentiment analysis entails categorising and mining subjective information from review text data (Hossain and Rahman, 2022). To ascertain if a review's expressed sentiment is neutral, positive, or negative, sentiment analysis of customer reviews entails analysing the review's content.

Additionally, in order for organisations to gain insight into the current state of offered products and services, Hossain and Rahman (2022) argue that review text, emotional components of reviewer text reviews, and review readers' reactions (empathy reactions) to reviews are crucial. According to Pashchenko et al. (2022), reviewer star ratings (normative elements of reviews) are a crucial role in determining the valuable insight into what customers think about the offered goods and services. Hossain and Rahman (2022) noted that various customer review styles can trigger various emotional reactions. According to the appraisal theory of psychology, emotions are cognitive-motivational-relational configurations that alter based on how well a person is connected to their environment and how they are perceived (Qi and Li, 2021). According to Weiss and Cropanzano (1996) and Ashton-James and Ashkanasy (2008), affective events and environmental signals can cause emotions, which in turn can alter actions. Humans are capable of experiencing emotions in relation to a variety of situations, whether they are directly impacted or not (Pashchenko et al., 2022). According to Hossain and Rahman (2022) and Pashchenko et al. (2022), some empathic emotional experiences can cause people to experience the same emotions as the other person. Because of this, consumers of customer reviews may feel empathy for the reviewer (Hossain and Rahman, 2023b). Prior research (Coombs and Holladay, 2007; Qi and Li, 2021) has shown that emotional responses can change behavioural goals.

Previous research by Hossain and Rahman explored the correlation between emotional aspects and empathy reactions, while Pashchenko et al. (2022) delved into the relationship between emotional aspects and star rating behavior. However, there hasn't been a study examining the influence of emotional aspects on both star ratings and empathy behavior simultaneously. Furthermore, existing studies have not adequately described how star ratings affect empathy reactions. The present study aims to address these gaps by investigating the impact of emotional aspects on both star ratings and empathy behavior while elucidating the influence of star ratings on empathy reactions. In the context of food delivery service apps. By analyzing customer reviews and applying sentiment analysis techniques, this research will provide valuable insights into the factors influencing user perceptions and engagement with food delivery apps. The findings will contribute to enhancing the app development process, improving user experiences, and guiding strategic decision-making for app developers and service providers. Furthermore, the research will shed light on the role of emotional aspects and normative elements in shaping users' reactions to app reviews, highlighting the importance of managing user sentiment effectively. Thus, using machine learning (ML) techniques, this study aims to achieve several objectives. Firstly, it seeks to analyze users' sentiments towards food delivery service apps by extracting and categorizing emotional features from their text reviews. This will be accomplished through the application of lexicon-based unsupervised machine learning approaches, which will enable the identification and calculation of eight types of customers' emotions expressed in their reviews. Secondly, the study aims to explore the linkages between these emotional features, the normative ranks assigned by users (e.g., star ratings), and the thumbs-up behavior of review readers. By examining the relationships between these variables, valuable insights can be gained into the impact of emotional aspects on users' evaluative processes and subsequent engagement with the app. Finally, the research will investigate how reviewers' star ratings influence the thumbs-up reactions of review readers, providing an understanding of how normative elements contribute to the formation of positive user perceptions. By achieving these objectives, this study will contribute to the existing knowledge on the interplay between emotions, star ratings, and users' engagement with food delivery service apps, ultimately enhancing our understanding of user experiences and informing app development strategies.

The subsequent section of the paper outlines its organizational structure. Firstly, we delve into a comprehensive review of the existing literature concerning the emotional dimensions of customer evaluations within the realm of food delivery service apps. Secondly, we provide a detailed exposition of the methodology employed in this study, with a focus on the detection of emotional features in customer reviews using lexicon-based unsupervised machine learning approaches. Following this, we present the results of our analysis in the subsequent section, elucidating the connections between emotional features, normative rankings, and readers' reactions, along with a discussion of the implications of these findings. Finally, we offer concluding remarks, summarize the key insights garnered from our research, and propose avenues for future exploration within this domain.

2. Literature review

2.1. Opinion mining and apps' reviews

Textual Sentiment Analysis (SA) or Opinion Mining (OM) is a growing field within text mining that focuses on algorithmically analyzing the subjectivity, thoughts, and emotional state expressed in review writings (Pashchenko et al., 2022). SA involves the computer investigation of customers' sentiments, thoughts, and attitudes conveyed in texts about a specific subject. The main objective of SA is to identify individuals with strong opinions, detect the emotions they express, and determine the sentiment polarity. Understanding the sentiment of client reviews can assist organizations in enhancing service superiority and client happiness (Hossain and Rahman, 2022). In the tourism industry, tourist reviews posted on social media have emerged as a valuable source of information that influences both reputation and performance (Puh and Bagić Babac, 2022).

SA techniques have been employed in some few prior studies regarding apps reviews, for example, Lin et al. (2021) conducted sentiment analysis of user comments on low-carbon travel apps using deep learning techniques. Their study aimed to analyze sentiments expressed by users and gain insights into their attitudes towards sustainable travel. Diekson et al. (2023) conducted a case study on sentiment analysis for customer reviews of the Traveloka app, providing valuable insights into sentiment patterns and user opinions. In the realm of health-related apps, in a recent study by Wickramasinghe (2023), the emphasis was placed on predicting sentiments and conducting thematic analysis for diabetes mobile apps through the utilization of Embedded Deep Neural Networks and Latent Dirichlet Allocation. Their study aimed to extract sentiments and identify thematic patterns from user reviews to offer insights for developers and healthcare providers in improving the functionality and usability of diabetes management apps. Furthermore, Islam et al. (2023) employed sentiment annotation using BERT and hybridization of RNN and LSTM techniques to determine the true rating of the Zoom Cloud Meetings app, utilizing user reviews obtained from the Google Play Store. Their study demonstrated the effectiveness of these techniques in capturing sentiment and generating accurate ratings.

Sentiment analysis of app reviews is of paramount importance in comprehending customer opinions, emotions, and attitudes towards diverse applications. By delving into the sentiments expressed in these reviews, businesses and developers can gain valuable insights that help them improve their products and services. While several studies have explored sentiment analysis in various contexts related to app reviews, there is still a research gap when it comes to examining readers' emotional elements and thumbs-up empathy reactions specifically towards evaluations and review stars of online food delivery applications. Therefore, further investigation is needed to address this aspect and deepen our understanding of user sentiments in this domain.

Lexicon-based SA

A customer review text is allied with a vocabulary of words that have been recognized as conveying specific sentiments using a lexicon-based approach in consumer sentiment analysis (Pashchenko et al., 2022). Considering the inherent subjectivity involved in sentiment analysis, the presence of sentiment terms in a review text serves as a crucial indicator of sentiment polarity. Sentiment lexicons are commonly employed to identify polarity by associating the sentiment polarities of phrases in a review text with their lexical emotional polarities. Adjectives with positive connotations, such as, gorgeous, fantastic and dazzling, evoke pleasant sensations, while negative connotation adjectives like terrible, horrible, and disastrous have the opposite effect. Sentiment lexicons play a crucial role in identifying various emotional expressions, and researchers frequently employ sentiment lexicon methods to compile sentiment-related terms (Pashchenko et al., 2022).

In his work, Turney (2001) introduced a lexicon-based sentiment analysis approach that involved calculating the semantic alignment of a phrase by comparing it to two chosen kernel terms, measuring their point-wise similarity. Lexicon-based approaches provide several benefits for evaluating emotions, including the capability to analyze sentiment in reviews that contain distinct elements like conjunctions, capital letters, slang, emoticons, punctuation, and more. These methods are well-suited for analyzing social media posts and demonstrate compatibility across different domains. Additionally, they do not require training samples. In this study, two lexicons were utilized. Valence Aware Dictionary for sEntiment Reasoning (VADER), a lexicon-based Sentiment Analysis tool, revolutionized the detection of sentiments on social media platforms. It employs a combination of a vocabulary and a sparse rule-based evaluator. Notably, VADER was one of the pioneering instruments in effectively capturing sentiment on social media. The VADER emotion lexicon takes into account the prevalent usage of social media gestures, acronyms, emojis, words, and slang, enhancing its accuracy in sentiment analysis (Pashchenko et al., 2022). The VADER framework performed comparably to human raters on Twitter and demonstrated similar or better performance compared to seven sentiment analysis lexicons (Hossain and Rahman, 2022). Therefore, the Vader lexicon was employed in this study to assess its accuracy in detecting various types of consumer thoughts based on review scores.

In 1980, Robert Plutchik introduced the eight-emotion wheel, a comprehensive framework for emotional responses (Plutchik, 1980). This wheel encompasses fear, sadness, surprise, joy, trust, anger, anticipation, and disgust. To identify emotional elements in user reviews of apps, an alternative approach utilizing the NRC human emotion detection lexicon was adopted. Created in 2013 by Mohammad and Turney, this lexicon builds upon Plutchik's eight emotional categories. It includes English phrases along with their associated emotional meanings, covering trust, grief, anticipation, fear, surprise, rage, disgust, and joy. Hossain and Rahman (2023b) explain that human emotion identification or analysis involves determining the emotional state of a review text using lexical algorithms or machine learning techniques. The objective is to understand how individuals express their emotions in reviews and how words can evoke different human emotions. Emotion analysis enables the identification of various emotional aspects exhibited by individuals (Pashchenko et al., 2022).

This study involved assigning review ratings to food delivery apps after evaluating user opinions expressed in their reviews. To validate the effectiveness of this approach, user emotions were re-evaluated using the Vader lexicon, which can detect sentiment variations solely from the review texts, independent of the rating stars. The results from the Vader Lexicon provide online meal delivery service developers with a swift and precise method to assess consumer sentiment. Additionally, the study evaluated the emotional aspects of different sentiment analysis types using the NRC (National Research Council) sentiment lexicon-based measure.

2.2. Emotional experiences

The experience of emotions is a fundamental aspect of human perception (Hossain and Rahman, 2022). Fear, sadness, anger, surprise, disgust, and happiness are universal emotional feelings that exist across cultures. These emotions and sensations are essential to communication because they aid prospective clients in making sense of their environment and streamlining cognitive processes (Chuah et al., 2021). In addition, one's emotional states affect their objectives and behavior (Hossain and Rahman, 2022). Emotional responses can be expressed verbally, indicating that our assessment of a situation can evoke an emotional or affective response. Users' emotional experiences have been found to influence both satisfaction and behavioral intention (Ratnasari et al., 2020). In the midst of the COVID-19 pandemic, Roy and

Sharma (2021) used a text mining technique to get insight into the emotional state of tourists during one-day excursions. Additionally, Pashchenko et al. (2022) discovered a connection between consumers' normative assessments of tourism-related businesses (like star ratings) and the emotional components of those assessments. Hossain and Rahman (2022) explored the impact of various types of consumer sentiment on prospective clients' emotional experiences on social networks in the context of financial service firms. However, previous research has not specifically examined users' emotional reactions to online food delivery app reviews.

The future of service and human-robot interaction emphasizes the power of emotion in shaping customer experiences (Chuah and Yu, 2021). Understanding and analyzing users' emotional responses to online food delivery app reviews can provide valuable insights for enhancing customer satisfaction and improving the overall service quality. This gap in research highlights the need to investigate users' emotional aspects and empathy reactions towards online food delivery app reviews, which can have significant implications for the app developers and the industry as a whole (Hossain and Rahman, 2023b).

2.3. Empathy behavior

Empathy is a fundamental aspect of human interaction and has been extensively studied using both demonstrative and neural methods (Hossain and Rahman, 2022). The term "empathy," coined by Edward B. Titchener in 1909, originates from the German word "einfühlung", which literally means "feeling into" (Hossain and Rahman, 2022). Describing empathy accurately can be challenging, as different criteria have been used in its definition (Longobardi et al., 2020). In an empathic situation, individuals understand and comprehend the emotions of others and focus on those feelings rather than their own as observers (Hossain and Rahman, 2022). Studies have come to appreciate the important connection between prosocial conduct and human empathy (Longobardi et al., 2020). Associated with interpersonal behavior, empathy encourages social participation (Hossain and Rahman, 2022). There is a lot of data showing that prosocial conduct and empathy are related. Additionally, Hossain and Rahman's research from 2022 showed that a person's emotional condition affected how they responded to customer feedback.

In the setting of online food delivery apps, users post reviews through text and star ratings on platforms like the Google Play Store, and other users can express their approval or disapproval through thumbs-up or thumbs-down reactions. However, there is still uncertainty about how consumers behave when rating other users' evaluations of online food delivery apps. To examine users' thumbs-up behavior towards such reviews, this study employs unsupervised and lexicon-based machine learning methods. The study also draws upon appraisal theory, a psychological paradigm that explains how people respond to user feedback. Overall, understanding empathy and users' reactions towards online food delivery app reviews can deliver appreciated insights into user behavior, pleasure, and engagement. Further research in this area can underwrite to improving the complete customer experience and enhancing the effectiveness of app platforms (Hossain and Rahman, 2023b).

Psychological paradigm (appraisal theory)

Systemic Functional Linguistics (SFL) serves as the substance for appraisal theory (psychological paradigm), which examines how verbal expresses positive or negative evaluations and how emotions and attitudes outline personal perspectives and meanings (Pashchenko et al., 2022). Moreover, the psychological paradigm hypothesis elucidates how others people respond to user reviews based on their evaluations (Hossain and Rahman, 2022). Systemic Functional Linguistics (SFL) appraisal theory presents a theoretical framework for categorizing different types of evaluative statements. It views meaning as a series of choices made by speakers or writers and illustrates how these choices are manifested in the lexicon and syntactic structure of evaluative language within the SFL framework.

In accordance with the SFL appraisal theory, our evaluations of actions can elicit diverse emotional responses from prospective consumers. Essentially, our assessment of a situation triggers an emotional or affective reaction based on that assessment (Hossain and Rahman, 2022). Analyzing the syntactic structure of evaluations can be complex, but it can be approached from the perspective of local grammar, which considers various overlapping factors that are not explicitly addressed by appraisal theory. Local grammars capture the patterns formed by random linguistic occurrences in a text and utilize different linguistic tools to express them. The behavior of an evaluative statement can be defined through a combination of local grammar and appraisal theory (Hossain and Rahman, 2022). Appraisal theory facilitates the mediation of interpersonal relationships by conveying the writer's or speaker's stance on specific subjects. It predicts empathy as one potential outcome of the appraisal process, indicating that other users may experience emotions after reading evaluations based on the sentiments expressed by the reviewers. These emotions can be conveyed through language (Chuah et al., 2021). Expanding upon the framework of appraisal theory, Hossain and Rahman (2022) conducted a study to investigate how readers respond to various types of reviews. The study examined the emotional aspects of app reviews and explored how users demonstrate empathy by providing thumbs-up reactions, employing the appraisal theory as the theoretical basis. In summary, the integration of systemic functional linguistics and appraisal theory provides valuable insights into how language conveys evaluations, emotions, and attitudes in interpersonal interactions. By understanding these mechanisms, researchers can better comprehend how users respond to reviews and the role of empathy in shaping their reactions.

2.4. Theoretical framework

Sentiment analysis has gained significant popularity as a sub-field of text analytics over the past two decades. It involves computationally analyzing subjectivity and opinions expressed in text (Sazzed and Jayarathna, 2021; Yadav et al., 2020). Sentiment analysis focuses on extracting and classifying sentiments expressed by individuals in text documents, such as positive, neutral, or negative sentiments (Sazzed and Jayarathna, 2021).

Previous studies have explored the association between the length of customer reviews and their emotions. Customer sentiment in text reviews refers to the neutral, negative, or positive feelings conveyed by customers (Geetha et al., 2017). Customers tend to express negative emotions, such as anger or sadness, when they have unsatisfactory experiences with a product or service, and they may leave negative reviews to share their dissatisfaction with others (Hossain and Rahman, 2022). Hossain and Rahman (2022) found an opposite connection between the length of a review on social media platforms and positive emotions.

Based on these findings, the current study hypothesizes that longer reviews of food delivery service apps would be associated with negative consumer sentiment, while shorter reviews would be associated with positive sentiment. In addition, Robert Plutchik's eight-emotion wheel, which includes fear, joy, trust, disgust, sadness, anticipation, surprise, and anger, is often used to represent different emotions (Plutchik, 2001). Hossain and Rahman (2022) employed machine learning (ML) techniques to assess emotional components in reviews and found that different types of sentiment had varying effects on emotional aspects. Therefore, it is hypothesized that various emotional characteristics have different impacts on reviewers' star rating behaviors toward food delivery service apps.

Furthermore, Hossain and Rahman (2022) demonstrated that reviewer sentiments expressed on social media platforms influence readers' internal emotive states, which, in turn, influence their empathetic responses to customer reviews. Based on this, it is assumed that the emotional aspects and star ratings of reviews regarding food delivery service apps will impact reviewers' thumbs-up reactions, as depicted in **Figure 1**. Overall, the study aims to examine the relationship between review characteristics, emotional aspects, star ratings, and reviewers' empathetic behaviors in the context of food delivery service apps.

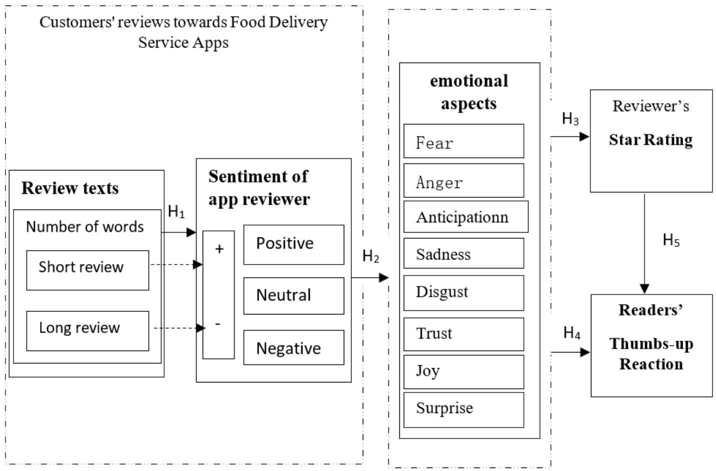

Figure 1. Proposed framework.

2.5. Study's hypotheses formation

2.5.1. App users' review length and sentiment

Based on previous conceptual and empirical studies in the field (Hossain and Rahman, 2022; Jiménez-Zafra et al., 2017; Pashchenko et al., 2022), it has been observed that consumer attitudes expressed in text reviews can vary from negative to neutral to favorable. Several factors have been identified to influence the sentiment conveyed in reviews, including review length and the presence of negative experiences.

For example, Rajeswari et al. (2020) found that longer reviews tend to have lower sentiment scores. Furthermore, Lai et al. (2021) established a connection between reviewer attitude and hotel ratings, indicating a higher likelihood of negative emotions in social consumption situations. Dissatisfied customers are also more inclined to engage in negative word-of-mouth (Hossain and Rahman, 2022), and negative experiences tend to generate more discussion among customers compared to positive experiences (Jiménez-Zafra et al., 2017). Additionally, studies by Pashchenko et al. (2022) and Hossain and Rahman (2023b) have revealed a positive correlation between review length and negative emotions, with longer reviews often indicating a negative attitude. Building on these findings, the present study aims to examine the relationship between review length and the diverse attitudes expressed in online food delivery app reviews. Hence, the hypothesis is as follows:

H1: There is an inverse correlation between review length and favorable sentiment in online food delivery app reviews.

2.5.2. User sentiment and emotional experiences in online food delivery Apps

The perception of others plays a significant role in influencing an individual's decision-making process. In the digital era, customer reviews hold considerable sway over prospective consumers when making purchasing decisions (Hossain and Rahman, 2022). Prospective customers frequently rely on online product and service reviews to mitigate risks, reduce uncertainty, and make informed choices (Zhang et al., 2019). Additionally, individuals experience a range of emotions while engaging with these reviews (Li et al., 2020). Beyond the positive or negative valence, each emotion possesses unique evaluative dimensions, such as control, trust, and excitement, which can influence consumer responses. Li et al. (2020) defined emotion as "a mental state of preparedness triggered by cognitive evaluations of events or thoughts." Various consumer scenarios can evoke diverse emotions. For instance, positive evaluations from consumers may elicit feelings of satisfaction among potential customers, whereas negative feedback can lead to anger (Hossain and Rahman, 2022). Drawing upon the aforementioned conceptual and empirical studies, the present study postulates a connection between user attitudes expressed in online food delivery app reviews and the subjective sentiments of review readers. Therefore, the study proposes the following hypothesis:

H2: Different types of user sentiment expressed in online food delivery app reviews have varying effects on their emotional aspects.

2.5.3. Emotional experience of review readers and thumbs-up empathy responses of review readers

The concept of empathy has been extensively studied through various scientific and artistic disciplines, including neuroscience, psychology, social practices, and the arts (Kesner and Horáček, 2017). Empathy plays a central role in understanding and relating to others' emotions (Pashchenko et al., 2022). The way individuals perceive and comprehend the emotions of others can influence their own emotional experiences (Umasuthan et al., 2017). Understanding the sources of one's own emotional experiences is an important aspect of emotional awareness and reasoning (Hossain and Rahman, 2022).

According to studies, both positive and negative attributes can influence an individual's capacity for perspective-taking and emotional experiences (Pashchenko et al., 2022). Negative emotions have been found to impact behaviors such as compliance, while positive emotions are associated with post-purchase activities like referrals and return visits (Umasuthan et al., 2017). Customer satisfaction with complaint management, as measured by their overall emotional response to service providers, significantly affects the performance of the service sector and fosters strong emotional connections with the business (Hossain and Rahman, 2022). Merely acknowledging customer complaints is not enough; emotional fulfillment plays a crucial role in establishing a strong emotional bond with a company (Umasuthan et al., 2017). However, emotional pleasure alone is insufficient without a deep emotional connection.

Previous studies have identified a range of emotions, including surprise, contempt, anger, fear, anticipation, joy, trust, and sadness, that contribute to empathy (Hossain and Rahman, 2022). Machine learning approaches can be utilized to recognize these emotional components in consumers' emotive experiences. Furthermore, Hossain and Rahman (2022) found that various emotive features derived from social media evaluations had diverse effects on users' empathic behavior. Given the dearth of comparable studies on app reviews, the present study posits a hypothesis that suggests a relationship between a range of emotional sensations resulting from user evaluations and readers' enthusiastic empathic behavior.

Therefore, the hypothesis for the current study is as follows:

H3: Users' thumbs-up empathy behavior is influenced by various characteristics of reviewers' emotional aspects on online food delivery app reviews.

2.5.4. Influence of emotional experience on star rating behavior

Review ratings play a crucial role in assessing the excellence of products or services based on reviewers' involvements (Hossain and Rahman, 2022). These ratings are often presented on a numerical scale, such as a Likert scale ranging from one to five, indicating the complete sentiment of the reviewer towards the product or service (Kim et al., 2021). Consumer research highlights the importance of review ratings in shaping purchase decisions (Ghasemaghaei et al., 2018). With the rise of social media, online ratings have garnered significant attention in understanding customers' involvements (Leung and Yang, 2020). These ratings greatly influence a company's online reputation by representing the level of customer appreciation for their services (Leon, 2019). Studies suggest that personal characteristics of consumers and their desire for attention influence online ratings, drawing from concepts of reasoned act and planned conduct (Hossain and Rahman, 2022).

In addition, customer satisfaction with complaint management, driven by good intentions, has a significant impact on the performance of the service industry, as demonstrated by the overall emotional connection customers feel towards the company (Davidow, 2000). Emotions can be classified into positive and negative components, where positive emotions influence post-purchase behaviors such as repeat visits and recommendations, while negative emotions drive actions related to compliance (Hossain and Rahman, 2022; Sánchez-Franco et al., 2021). Emotionally satisfied customers develop strong emotional bonds with brands, prioritizing the relationship over mere accolades (Umasuthan et al., 2017). However, emotional satisfaction alone is not sufficient without an authentic emotional connection.

Previous research has demonstrated that various emotional factors play a role in star rating behavior, although the specific impact of these emotional dimensions remains unclear. Machine learning approaches have identified eight emotional components, including wonder, anger, horror, sadness, joy, anticipation, trust, and disgust (Kaur et al., 2021). Pashchenko et al. (2022) found that several aspects of reviewers' emotional experiences influence their star rating behavior in hotel and travel company reviews on social media. Additionally, Hossain and Rahman (2022) revealed that clients provide star ratings based on their emotions as reflected in VADER scores during the process of writing reviews.

Based on the empirical evidence linking customers' emotional components to review ratings, the research hypothesis is as follows:

H4: Various aspects of reviewers' emotional experiences on online food delivery apps influence their star rating behavior.

2.5.5. Reviewers star rating and readers' thumbs up behavior

The abundance of information in today's marketplace poses a challenge for consumers who strive to make informed purchase decisions. To alleviate this cognitive burden and minimize search costs, online product reviews provide a valuable heuristic in the form of star ratings, enabling consumers to quickly gauge product quality (Liu and Park, 2015; Peterson and Merino, 2003). Building on this notion, researchers Ramachandran et al. (2021) have delved into the association between the valence of review text and the corresponding product star ratings.

In addition to textual valence, emotional aspects play a significant role in influencing reviewers' star rating behavior (Pashchenko et al., 2022). Moreover, Hossain and Rahman (2023b) have revealed that review readers' reactions can also be shaped by the emotional aspects expressed by reviewers or the emotional experiences they share in their reviews. Consequently, it is apparent that emotions have a pervasive impact on the dynamics of star ratings and readers' responses to reviews.

Recognizing the importance of product reviews in the consumer decision-making procedure, individuals invest considerable time and effort in perusing multiple reviews to gain confidence and make well-informed choices (Sarkar and Ahmad, 2021). Numerous studies have underscored the influential role of product reviews in shaping consumer behavior. For instance, Zhao et al. (2013) found compelling evidence that people glean more knowledge from product reviews than from their own personal experiences, particularly when considering experiential products. McGlohon et al. (2010) highlighted the credibility of consumer recommendations as the most persuasive form of advertising according to a substantial majority of survey respondents. Furthermore, Askalidis and Malthouse (2016) uncovered a remarkable finding that the presence of product reviews significantly enhances purchase likelihood, with low-priced items experiencing a boost of up to 190% and high-priced items witnessing an even more substantial increase of 380%. Notably, users tend to concentrate their attention on the initial reviews when faced with an abundance of feedback. Hu et al. (2014) added that customers tend to rely on numerical ratings during the initial stages of their search and awareness process, gradually placing greater emphasis on text sentiments as they approach the final stage of their purchase decision-making journey. In considering consumer behavior within online platforms, it becomes evident that the platform's characteristics, including the rating system, hold a direct influence over users' actions and choices (Mariani and Borghi, 2018; Mellinas et al., 2016; Parboteeah et al., 2009; Rita et al., 2022). Notably, research has consistently demonstrated the positive effects of customer ratings on firm performance, reinforcing the significance of these ratings as indicators of product quality and consumer satisfaction (Sayfuddin et al., 2021).

Based on the existing literature, we propose the following research hypothesis:

H5: Reviewers' star rating has a positive influence on readers' thumbs-up behavior.

3. Method

3.1. Introduction

In this study, we aimed to investigate the relationship between reviewers' star ratings and readers' thumbs-up behavior within the context of food delivery apps. Our data collection process focused on the top five most popular food delivery platforms in the USA: Doordash, Grubhub, Postmates, Uber Eats, and Seamless, accessed through the Google Play store.

3.2. Data collection

To collect the necessary data, we developed a web scraping Python script tailored to extract key information from the Google Play store reviews. This included details such as the app name, reviewer name, star rating, review date, full review text, and the number of thumbs-up reactions received. Our data collection efforts were exclusively focused on English reviews for the selected food delivery apps.

3.3. Dataset overview

Our data collection process yielded a substantial dataset comprising a total of 1,011,718 reviews across the various food delivery apps. Specifically, we obtained 574,650 reviews for Doordash, 180,474 for Grubhub, 66,139 for Postmates, 37,211 for Uber Eats, and 16,244 for Seamless. This extensive dataset provided a robust foundation for our analysis, allowing for comprehensive insights into the dynamics of reviewers' star ratings and readers' thumbs-up behavior.

3.4. Data processing and analysis

All data processing and analysis were performed using Python within a Jupyter notebook environment. Preprocessing techniques, such as punctuation removal, stopwords elimination, and handling missing values, were applied to refine the user reviews. Additionally, we utilized the TF-IDF (Term Frequency - Inverse Document Frequency) vectorizer to convert text data into a numerical format suitable for analysis.

To support our analysis, we leveraged various Python libraries, including pandas, nltk, string, NRCLex, seaborn, vaderSentiment, sklearn, numpy, and matplotlib. Sentiment analysis was conducted based on the star ratings provided by reviewers, with ratings categorized into negative, neutral, and positive sentiments. The VADER sentiment analyzer was employed to validate our sentiment categorization.

3.5. Further analysis

Correlation ratios were computed using Python to explore the relationship between reviewers' star ratings and readers' thumbs-up behavior. Subsequently, data frames were exported and imported into Amos (Version 24) for advanced statistical analysis, including the calculation of direct, indirect, and total impacts of the variables.

3.6. Conclusion

Our methodology encompassed a comprehensive approach to data collection, preprocessing, sentiment analysis, and statistical analysis, enabling us to examine the intricate relationship between reviewers' star ratings and readers' thumbs-up behavior across food delivery apps.

4. Result and discussion

In our analysis of the reviews for food delivery apps, we observed that the majority of the reviews were positive. Specifically, out of the total collected reviews, 640,380 reviews (approximately 63.3%) were positive, indicating that users had a favorable experience with the food delivery apps. On the other hand, 192,268 reviews (approximately 19%) were negative, suggesting that some users had a negative experience or expressed dissatisfaction with the apps. Additionally, we identified 42,070 reviews (approximately 4.2%) that were classified as neutral, indicating that these reviews neither leaned towards positive nor negative sentiments. These findings highlight the overall sentiment expressed by users in their reviews of food delivery apps.

In this study, we utilized the review star (score) provided by reviewers when writing their text reviews to determine the sentiment class for each review. This approach has been validated in previous studies (Hossain and Rahman, 2022; Pashchenko et al., 2022), and our study further reinforces its validity by employing the VADER (Valence Aware Dictionary for sEntiment Reasoning) score calculation. **Table 1** presents the mean values of the VADER scores for different sentiment classes. The sentiment classes include Negative (−1), Neutral (0), and Positive (1). For the Negative (−1) sentiment class, the mean VADER scores are as follows: vader_neg = 0.132408, vader_neu = 0.813429, vader_pos = 0.054161, and vader_compound = −0.216009. For the Neutral (0) sentiment class, the mean VADER scores are: vader_neg = 0.075588, vader_neu = 0.775169, vader_pos = 0.149243, and vader_compound = 0.111033. For the Positive (1) sentiment class, the mean VADER scores are: vader_neg = 0.019615, vader_neu = 0.524554, vader_pos = 0.455832, and vader_compound = 0.489212.

Table 1. Mean value of VADER score towards sentiment classes.

Sentiment	Vader_neg	Vader_neu	Vader_pos	Vader_compound
Negative (−1)	0.132408	0.813429	0.054161	−0.216009
Neutral (0)	0.075588	0.775169	0.149243	0.111033
Positive (1)	0.019615	0.524554	0.455832	0.489212

These mean VADER scores provide insights into the sentiment distribution within each sentiment class. They indicate the average negativity, neutrality, positivity, and overall sentiment intensity of the reviews belonging to each sentiment class. After calculating VADER scores, our study, similar to previous research conducted by Hossain and Rahman (2022) and Pashchenko et al. (2022) (in different fields), confirmed the validity of using the provided star rating (normative aspect of reviews) for sentiment detection in food delivery app reviews. This finding provides a convenient and efficient method for food delivery organizations to detect sentiment without the need for extensive analysis like VADER scores.

In addition to analyzing the sentiment classes, we also calculated VADER scores specifically for each food delivery app. The VADER scores provide a more detailed understanding of the sentiment distribution and intensity for each app. **Table 2** presents the mean values of the VADER scores towards food delivery apps. The apps included in the analysis are Doordash, Grubhub, Postmates, Seamless, and Ubereats. Among these apps, Doordash has the highest vader_compound score, indicating a relatively strong positive sentiment towards this app. It also has the highest vader_pos score, indicating a higher proportion of positive sentiments compared to other apps. Additionally, Doordash has the lowest vader_neu score, suggesting a lower level of neutrality in the reviews, and the lowest vader_neg score, indicating a lower proportion of negative sentiments. On the other hand, Postmates has the lowest vader_compound score, indicating a relatively weaker overall sentiment towards this app. It also has the lowest vader_pos score, indicating the lowest proportion of positive sentiments among the apps. Furthermore, Postmates has the highest vader_neg score, suggesting a higher proportion of negative sentiments, and the highest vader_neu score, indicating a higher level of neutrality compared to other apps. Grubhub, Seamless, and Ubereats fall between these two extremes in terms of their VADER scores, indicating varying levels of positive, neutral, and negative sentiments. These VADER scores provide insights into the overall sentiment towards each food delivery app and highlight the differences in sentiment distribution among them.

Table 2. Mean value of VADER scores towards food delivery apps.

Apps	vader_compound	vader_pos	vader_neu	vader_neg
Doordash	0.353514	0.383728	0.576025	0.040247
Grubhub	0.277726	0.304543	0.640086	0.055371
Postmates	0.132696	0.243540	0.679484	0.076977
Seamless	0.316420	0.314626	0.636943	0.048431
Ubereats	0.248196	0.320012	0.620864	0.059124

After calculating the VADER scores, we proceeded to determine the word count for each review. **Table 3** presents the average values of sentiment, review star (score), thumbsUpCount, and word count for each food delivery app. The sentiment value represents the average sentiment expressed in the reviews for each app, providing an indication of the overall sentiment towards them. Review star (score) reflects the average rating given by reviewers, offering insights into user satisfaction levels. ThumbsUpCount indicates the average number of thumbs-up reactions received for the reviews of each app, reflecting user engagement and agreement with the reviews. Lastly, word count represents the average number of words in the reviews, providing an understanding of the length and level of detail in user feedback.

By examining these mean values, we gain valuable insights into the overall sentiment, user ratings, engagement through thumbs-up reactions, and the length of reviews for each food delivery app. This comprehensive analysis offers a deeper understanding of user perceptions and experiences with the various food delivery services. It is important to note that the values presented in **Table 3** have been calculated based on the data collected and analyzed in the current research study, adding credibility to the findings and supporting the interpretation of the results.

Table 3. Mean value of sentiment, review star, thumbsUpCount, and word count towards each food delivery App.

Apps	sentiment	Review star (score)	thumbsUpCount	word_count
Doordash	0.606219	4.101674	0.605572	14.803698
Grubhub	0.409610	3.734388	0.723317	17.763794
Postmates	0.023420	3.024585	2.611923	25.239571
Seamless	0.597082	4.070426	0.490827	15.191024
Ubereats	0.391712	3.704039	0.916208	18.627986

Table 4 presents the mean values of emotional aspects for each sentiment class. The emotional aspects include sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. For the sentiment class −1 (negative), the mean values of the emotional aspects are as follows: sadness (0.055156), fear (0.037401), disgust (0.029896), anger (0.044441), surprise (0.023506), joy (0.066523), trust (0.110402), and anticipation (0.117726). For the sentiment class 0 (neutral), the mean values of the emotional aspects are as follows: sadness (0.037903), fear (0.031028), disgust (0.014656), anger (0.032276), surprise (0.028475), joy (0.069314), trust (0.094332), and anticipation (0.125500). For the sentiment class 1 (positive), the mean values of the emotional aspects are as follows: sadness (0.013932), fear (0.010201), disgust (0.004628), anger (0.010311), surprise (0.020896), joy (0.080358), trust (0.072536), and anticipation (0.090995).

Table 4. Mean value of emotional aspect towards each sentiment classes.

Sentiment	Sadness	Fear	Disgust	Anger	Surprise	Joy	Trust	Anticipation
−1	0.055156	0.037401	0.029896	0.044441	0.023506	0.066523	0.110402	0.117726
0	0.037903	0.031028	0.014656	0.032276	0.028475	0.069314	0.094332	0.125500
1	0.013932	0.010201	0.004628	0.010311	0.020896	0.080358	0.072536	0.090995

Table 5 presents the mean values of emotional aspects for each online food delivery app. The emotional aspects include sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. For the app Doordash, the mean values of the emotional aspects are as follows: sadness (0.022009), fear (0.015746), disgust (0.009227), anger (0.016731), surprise (0.022150), joy (0.076112), trust (0.078942), and anticipation (0.096693). For the app Grubhub, the mean values of the emotional aspects are as

follows: sadness (0.027025), fear (0.018737), disgust (0.012248), anger (0.020906), surprise (0.020715), joy (0.081399), trust (0.085536), and anticipation (0.101147). For the app Postmates, the mean values of the emotional aspects are as follows: sadness (0.032947), fear (0.023536), disgust (0.017299), anger (0.030550), surprise (0.022828), joy (0.074885), trust (0.094539), and anticipation (0.114796). For the app Seamless, the mean values of the emotional aspects are as follows: sadness (0.023688), fear (0.018695), disgust (0.011083), anger (0.017492), surprise (0.016799), joy (0.072803), trust (0.083817), and anticipation (0.082692). For the app Ubereats, the mean values of the emotional aspects are as follows: sadness (0.027743), fear (0.019846), disgust (0.013191), anger (0.021852), surprise (0.022817), joy (0.069930), trust (0.086821), and anticipation (0.092207). These tables provide insights into the emotional aspects associated with different sentiment classes and online food delivery apps. It allows us to understand the presence and intensity of emotions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation in the reviews and how they vary across sentiment classes and apps.

Table 5. Mean value of emotional aspect towards each online food delivery Apps.

Sentiment	Sadness	Fear	Disgust	Anger	Surprise	Joy	Trust	Anticipation
Doordash	0.022009	0.015746	0.009227	0.016731	0.022150	0.076112	0.078942	0.096693
Grubhub	0.027025	0.018737	0.012248	0.020906	0.020715	0.081399	0.085536	0.101147
Postmates	0.032947	0.023536	0.017299	0.030550	0.022828	0.074885	0.094539	0.114796
Seamless	0.023688	0.018695	0.011083	0.017492	0.016799	0.072803	0.083817	0.082692
Ubereats	0.027743	0.019846	0.013191	0.021852	0.022817	0.069930	0.086821	0.092207

In order to examine the relationship between variables within the framework of our study, we utilized Python programming to conduct the necessary calculations. The results, presented in **Table 6**, provide insights into the correlation between sentiment and the number of words used in the reviews of online food delivery Apps. **Table 6** displays the correlation coefficients between sentiment and word count. The coefficient value for sentiment (1.000000) indicates a strong positive correlation with itself, which is expected. Furthermore, the coefficient value between sentiment and word count (−0.512881) reveals a negative correlation. This finding suggests that there is an inverse relationship between the length of reviews, as indicated by word count, and the sentiment expressed by users. The negative correlation indicates that users tend to write longer reviews when expressing negative sentiments, while shorter reviews are more common when users have positive sentiments. This discovery reinforces our hypothesis H1, which proposed an inverse relationship between review length and favorable sentiment in online food delivery app evaluations. Our finding aligns with previous studies conducted by Hossain and Rahman (2022), Jiménez-Zafra et al. (2017), Pashchenko et al. (2022), and Rajeswari et al. (2020). By examining the correlation coefficients, we gain insights into the interplay between sentiment and word count, shedding light on the relationship between user expressions and the length of their reviews. These findings contribute to a deeper understanding of user behavior and perceptions in the context of online food delivery apps, reinforcing the significance of review length as an indicator of sentiment.

Table 6. Correlation between word count and sentiment.

	Sentiment	**Word_count**
Sentiment	1.000000	−0.512881
Word_count	−0.512881	1.000000

Additionally, **Table 7** presents the correlation coefficients between online food delivery app users' sentiment and their different emotional aspects. The table showcases the relationships between sentiment and emotions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation.

Table 7. Correlation between online food delivery app users sentiment and their different emotional aspects.

	Sentiment	**Sadness**	**Fear**	**Disgust**	**Anger**	**Surprise**	**Joy**	**Trust**	**Anticipation**
Sentiment	1.000000	−0.239382	−0.175497	−0.236288	−0.222558	−0.019627	0.047675	−0.118978	−0.061497
Sadness	−0.239382	1.000000	0.376244	0.258997	0.189138	0.031440	−0.091534	−0.051515	−0.061516
Fear	−0.175497	0.376244	1.000000	0.205724	0.191638	−0.015723	−0.070869	−0.036048	−0.043492
Disgust	−0.236288	0.258997	0.205724	1.000000	0.318600	−0.010433	−0.066826	−0.039077	−0.039835
Anger	−0.222558	0.189138	0.191638	0.318600	1.000000	0.015700	−0.040242	−0.011690	−0.017376
Surprise	−0.019627	0.031440	−0.015723	−0.010433	0.015700	1.000000	0.195810	0.181663	0.100686
Joy	0.047675	−0.091534	−0.070869	−0.066826	−0.040242	0.195810	1.000000	0.435412	0.015366
Trust	−0.118978	−0.051515	−0.036048	−0.039077	−0.011690	0.181663	0.435412	1.000000	0.050608
Anticipation	−0.061497	−0.061516	−0.043492	−0.039835	−0.017376	0.100686	0.015366	0.050608	1.000000

The correlation coefficients range from −0.239382 to 0.047675, indicating the strength and direction of the relationships. For example, sentiment shows a negative correlation with sadness, fear, disgust, and anger, implying that as sentiment becomes more negative, these emotional aspects tend to increase slightly. Conversely, there is a positive correlation between sentiment and surprise, joy, and anticipation, suggesting that as sentiment becomes more positive, these emotions may slightly increase. These findings support our hypothesis H2, which posits that different types of user sentiment expressed in online food delivery app reviews have varying effects on their emotional aspects. Our finding aligns with previous studies conducted by Hossain and Rahman (2022), Li et al. (2020), and Zhang et al. (2019). The correlations in **Table 7** demonstrate that the sentiment expressed by users is indeed associated with specific emotional dimensions, albeit with relatively weak relationships. By observing the correlation coefficients, we can infer that users' sentiment in online food delivery app reviews influences their emotional experiences. This implies that the sentiment expressed in the reviews can elicit emotional responses in terms of sadness, fear, disgust, anger, surprise, joy, trust, and anticipation.

The results presented in **Table 7** contribute to a comprehensive understanding of the interplay between sentiment and emotional aspects in the context of online food delivery apps. They provide empirical evidence for the hypothesis H2, shedding light on the varying effects of different sentiment types on users' emotional experiences. These insights can inform app developers and service providers in designing and improving user experiences, catering to the emotional needs and preferences of their users.

Table 8 displays the correlation coefficients between different emotional aspects of review writers and the thumbs-up count received by review readers. The table explores the relationships between thumbs-up count and emotional dimensions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. The correlation coefficients range from 0.006402 to 0.039203, indicating the strength and direction of the relationships. The thumbs-up count shows a positive correlation with emotional aspects such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. This suggests that as the emotional expressions related to these aspects increase, there is a tendency for review readers to give more thumbs-up reactions.

Table 8. Correlation between different emotional aspect of review writer and review reader's ThumbsUpCount.

	Thumbsupcount	**Sadness**	**Fear**	**Disgust**	**Anger**	**Surprise**	**Joy**	**Trust**	**Anticipation**
ThumbsUpCount	1.000000	0.039203	0.031139	0.027758	0.031325	0.010835	0.006402	0.029323	0.017063
Sadness	0.039203	1.000000	0.376244	0.258997	0.189138	0.031440	−0.091534	−0.051515	−0.061516
Fear	0.031139	0.376244	1.000000	0.205724	0.191638	−0.015723	−0.070869	−0.036048	−0.043492
Disgust	0.027758	0.258997	0.205724	1.000000	0.318600	−0.010433	−0.066826	−0.039077	−0.039835
Anger	0.031325	0.189138	0.191638	0.318600	1.000000	0.015700	−0.040242	−0.011690	−0.017376
Surprise	0.010835	0.031440	−0.015723	−0.010433	0.015700	1.000000	0.195810	0.181663	0.100686
Joy	0.006402	−0.091534	−0.070869	−0.066826	−0.040242	0.195810	1.000000	0.435412	0.015366
Trust	0.029323	−0.051515	−0.036048	−0.039077	−0.011690	0.181663	0.435412	1.000000	0.050608
Anticipation	0.017063	−0.061516	−0.043492	−0.039835	−0.017376	0.100686	0.015366	0.050608	1.000000

These findings provide support for our hypothesis H3, which states that users' thumbs-up empathy behavior is influenced by various characteristics of reviewers' emotional aspects in online food delivery app reviews. Our finding aligns with previous studies conducted by Pashchenko et al. (2022) and Umasuthan et al. (2017). The correlations in **Table 8** indicate that the emotional aspects expressed by reviewers have an impact on the thumbs-up count received from review readers. The positive correlations suggest that users' empathy, as demonstrated by their thumbs-up reactions, is influenced by the emotional content expressed by the reviewers. Reviewers who convey emotions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation in their reviews are more likely to receive higher thumbs-up counts, indicating that their emotional expressions resonate with the review readers. These findings contribute to a deeper understanding of the relationship between emotional aspects in reviews and users' thumbs-up empathy behavior. They support the hypothesis H3 by demonstrating that users' engagement through thumbs-up reactions is influenced by the emotional characteristics exhibited by the reviewers. App developers and service providers can leverage these insights to foster a positive emotional environment in their platforms, encouraging users to engage empathetically with the reviews and promote positive interactions among the app community.

Table 9 presents the correlation coefficients between different emotional aspects of review writers and their corresponding star ratings. The table explores the relationships between star ratings and emotional dimensions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. The correlation coefficients range from −0.243543 to 0.046600, indicating the strength and direction of the relationships.

The star ratings show a negative correlation with emotional aspects such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation. This suggests that as the intensity of these emotional expressions increases, there is a tendency for reviewers to assign lower star ratings. These findings provide support for our hypothesis H4, which proposes that various aspects of reviewers' emotional experiences on online food delivery apps influence their star rating behavior. The correlations in **Table 9** indicate that reviewers' emotional expressions play a role in shaping their star rating decisions.

Table 9. Correlation between different emotional aspect of review writer and their score.

	Score	Sadness	Fear	Disgust	Anger	Surprise	Joy	Trust	Anticipation
Score	1.000000	−0.243543	−0.179792	−0.239455	−0.225439	−0.032409	0.046600	−0.127471	−0.069852
Sadness	−0.243543	1.000000	0.376244	0.258997	0.189138	0.031440	−0.091534	−0.051515	−0.061516
Fear	−0.179792	0.376244	1.000000	0.205724	0.191638	−0.015723	−0.070869	−0.036048	−0.043492
Disgust	−0.239455	0.258997	0.205724	1.000000	0.318600	−0.010433	−0.066826	−0.039077	−0.039835
Anger	−0.225439	0.189138	0.191638	0.318600	1.000000	0.015700	−0.040242	−0.011690	−0.017376
Surprise	−0.032409	0.031440	−0.015723	−0.010433	0.015700	1.000000	0.195810	0.181663	0.100686
Joy	0.046600	−0.091534	−0.070869	−0.066826	−0.040242	0.195810	1.000000	0.435412	0.015366
Trust	−0.127471	−0.051515	−0.036048	−0.039077	−0.011690	0.181663	0.435412	1.000000	0.050608
Anticipation	−0.069852	−0.061516	−0.043492	−0.039835	−0.017376	0.100686	0.015366	0.050608	1.000000

The negative correlations imply that reviewers who express emotions such as sadness, fear, disgust, anger, surprise, joy, trust, and anticipation in their reviews are more likely to assign lower star ratings. This suggests that reviewers' emotional experiences influence their perception and evaluation of the food delivery app, leading to lower overall ratings. These findings contribute to a better understanding of the relationship between emotional aspects and star rating behavior in online food delivery app reviews. They support the hypothesis H4 by demonstrating that reviewers' emotional experiences impact their star rating decisions. App developers and service providers can use these insights to identify and address emotional factors that contribute to lower star ratings, thereby improving user satisfaction and the overall quality of the app experience.

Table 10 displays the correlation coefficients between the review writer's star rating (score) and the thumbs-up count given by the review readers. The correlation coefficient for these variables is −0.085561, indicating a negative correlation. This negative correlation suggests that there is an inverse relationship between the review writer's star rating and the thumbs-up count received from readers. As the review writer's star rating increases, there is a significant decrease in the thumbs-up count from readers, and vice versa. These findings contradict our hypothesis H5, which proposes that reviewers' star rating has a positive influence on readers' thumbs-up behavior. Instead, the correlation indicates that higher star ratings are associated with a lower thumbs-up count, and lower star ratings are associated with a higher thumbs-up count.

Table 10. Correlation between review star (score) of review writer and review readers thumbsUpcount.

	ThumbsUpcount	**Score**
ThumbsUpcount	1.000000	−0.85561
Score	−0.85561	1.000000

Correlations alone are limited in their ability to fully capture the impact of independent variables on each other. To overcome this limitation and gain a deeper understanding of the relationships, we employ structural equation modeling (SEM) techniques, specifically using AMOS. Through AMOS, we are able to calculate and analyze the direct, indirect, and total effects, which provide a more comprehensive assessment of the relationships among the variables. **Table 11** presents the direct, indirect, and total effect calculations, providing valuable insights into the relationship between variables. In terms of the variable "word_count" and its impact on "sentiment," the total effect, considering both direct and indirect effects, is −0.020. This means that for each unit increase in word_count, the sentiment decreases by 0.02. This finding supports our hypothesis H1, indicating an inverse correlation between the length of reviews and favorable sentiment in online food delivery app reviews. Furthermore, the analysis reveals that user sentiment has a direct positive effect on the emotional aspect of joy (0.007), and it also indirectly affects other emotional aspects such as anticipation (−0.014), trust (−0.019), surprise (−0.002), anger (−0.017), disgust (−0.013), fear (−0.014), and sadness (−0.021). These results further support our hypothesis H2, which suggests that different types of user sentiment expressed in online food delivery app reviews have varying effects on their emotional aspects.

Table 11. Direct, indirect and total effect calculations.

	Word_count	**Sentiment**	**Anticipation**	**Trust**	**Joy**	**Surprise**	**Anger**	**Disgust**	**Fear**	**Sadness**	**Score**
Direct Effect	-	-	-	-	-	-	-	-	-	-	-
Sentiment	−0.020	-	-	-	-	-	-	-	-	-	-
Anticipation	-	−0.014	-	-	-	-	-	-	-	-	-
Trust	-	−0.019	-	-	-	-	-	-	-	-	-
Joy	-	0.007	-	-	-	-	-	-	-	-	-
Surprise	-	−0.002	-	-	-	-	-	-	-	-	-
Anger	-	−0.017	-	-	-	-	-	-	-	-	-
Disgust	-	−0.013	-	-	-	-	-	-	-	-	-
Fear	-	−0.014	-	-	-	-	-	-	-	-	-
Sadness	-	−0.021	-	-	-	-	-	-	-	-	-
Score	-	-	−0.678	−2.132	1.183	−0.117	−3.304	−5.151	−1.601	−3.503	
ThumbsUpCount	-	-	0.673	1.446	0.326	0.412	1.499	0.476	1.711	2.424	−0.487
Indirect Effect	-	-	-	-	-	-	-	-	-	-	-
Score	−0.005	0.275	-	-	-	-	-	-	-	-	-
ThumbsUpCount	0.005	−0.275	0.330	1.038	−0.576	0.057	1.610	2.509	0.780	1.706	
Direct Effect	-	-	-	-	-	-	-	-	-	-	-
Sentiment	−0.020	-	-	-	-	-	-	-	-	-	-

Table 11. (*Continued*).

	Word_count	Sentiment	Anticipation	Trust	Joy	Surprise	Anger	Disgust	Fear	Sadness	Score
Anticipation	-	−0.014	-	-	-	-	-	-	-	-	-
Trust	-	−0.019	-	-	-	-	-	-	-	-	-
Joy	-	0.007	-	-	-	-	-	-	-	-	-
Surprise	-	−0.002	-	-	-	-	-	-	-	-	-
Anger	-	−0.017	-	-	-	-	-	-	-	-	-
Disgust	-	−0.013	-	-	-	-	-	-	-	-	-
Fear	-	−0.014	-	-	-	-	-	-	-	-	-
Sadness	-	−0.021	-	-	-	-	-	-	-	-	-
Score	−0.005	0.275	−0.678	−2.132	1.183	−0.117	−3.304	−5.151	−1.601	−3.503	-
ThumbsUpCount	0.005	−0.275	1.003	2.485	−0.250	0.468	3.109	2.985	2.491	4.130	−0.487

Additionally, when examining the review star (score) provided by reviewers, different emotional aspects show varying total effects. For instance, anticipation has a total effect of (−0.678), trust has a total effect of (−2.132), joy has a total effect of (1.183), surprise has a total effect of (−0.117), anger has a total effect of (−3.304), disgust has a total effect of (−5.151), fear has a total effect of (−1.601), and sadness has a total effect of (−3.503). These findings confirm our hypothesis H3, suggesting that users' thumbs-up empathy behavior is influenced by various characteristics of reviewers' emotional aspects in online food delivery app reviews. Similarly, we also confirm hypothesis H4, which states that various aspects of reviewers' emotional experiences on online food delivery apps influence their star rating behavior. This is evident from the different total effects of reviewers' emotional experiences on review readers' thumbsUpCount, such as anticipation (1.003), trust (2.485), joy (-0.250), surprise (0.468), anger (3.109), disgust (2.985), fear (2.491), and sadness (4.130). However, the findings do not support our last hypothesis H5, which suggests that reviewers' star rating has a positive influence on readers' thumbs-up behavior. **Table 10** shows a negative total effect of (−0.487) between reviewers' provided score and review readers' thumbs-up empathy behavior. Overall, the direct, indirect, and total effect calculations conducted through the AMOS software provide valuable insights into the relationships between variables, supporting several hypotheses while highlighting areas where the findings deviate from our initial expectations.

5. Applications

5.1. Theoretical applications

This study significantly contributes to the theoretical understanding of the relationship between customers' emotional responses and their evaluations of food delivery service apps. Firstly, by identifying eight distinct types of emotions expressed in text reviews, this research expands the knowledge base regarding emotional aspects within the context of app reviews. This comprehensive analysis provides valuable insights into the emotional landscape of customer experiences when using these apps. Additionally, the theoretical application of our study lies in enhancing sentiment analysis methodologies and leveraging the insights from systemic functional linguistics and appraisal theory to improve user experiences, foster empathy, and drive positive engagement in online platforms. Furthermore, the study uncovers an inverse correlation between the length of reviews and favorable sentiment, contributing to the theoretical understanding of how review length can impact overall customer sentiment. This finding emphasizes the significance of concise and impactful reviews in shaping user perceptions of food delivery service apps.

Additionally, the research demonstrates that different types of user sentiment expressed in app reviews have varying effects on emotional aspects. This revelation offers valuable insights into the complex interplay between sentiment and emotional responses, thereby deepening our understanding of user experiences and preferences. These findings have theoretical implications for sentiment analysis in the context of food delivery apps. The identification of the majority of positive reviews (63.3%) and the distribution of negative and neutral reviews provide comprehensive insights into overall user sentiment. Moreover, the mean VADER scores for different sentiment classes offer a quantitative representation of sentiment intensity, contributing to the development of sentiment analysis methodologies and validating the use of review stars for sentiment classification. The theoretical application of this study is also evident in its contribution to emotion analysis research. By presenting the mean values of emotional aspects for each sentiment class and online food delivery app, this study provides insights into the presence and intensity of emotions expressed in user reviews. This enhanced understanding of how different emotional aspects vary across sentiment classes and apps contributes to the development of more nuanced emotion analysis models and frameworks. App developers and service providers can leverage this information to improve sentiment classification algorithms by incorporating specific emotional dimensions and enriching the understanding of users' emotional experiences.

Moreover, the theoretical application of the results presented in **Table 7** is to contribute to the comprehensive understanding of the interplay between sentiment and emotional aspects in the context of online food delivery apps. These findings, which support hypothesis H2 and shed light on the varying effects of different sentiment types on users' emotional experiences, enhance our understanding of how users' sentiments influence their emotional responses when using food delivery apps. App developers and service providers can utilize this knowledge to design and improve user experiences that cater to the emotional needs and preferences of their users. Addressing issues related to sentiment types that evoke negative emotional responses can create a more positive emotional environment within the app.

Furthermore, the theoretical application of the findings presented in **Table 10** contributes to the existing body of knowledge in the field of online food delivery app reviews and their impact on user sentiment and emotional aspects. These findings provide insights into the relationships between variables and support several hypotheses, such as the inverse correlation between word_count and sentiment (H1), the varying effects of user sentiment on emotional aspects (H2), and the influence of reviewers' emotional experiences on thumbsUpCount and star rating behavior (H3 and H4). These theoretical implications enhance our understanding of how users perceive and respond to online food delivery app reviews, leading to the development of more effective strategies for managing and optimizing user experiences in the context of food delivery apps.

5.2. Practical applications

The findings of this study hold significant value for app developers and service providers in the food delivery industry. By understanding the impact of emotional features on user evaluations and thumbs-up behavior, they can enhance the app experience, address customer concerns, and improve overall satisfaction. This knowledge can guide decision-making and strategies related to app development and customer satisfaction. Based on the provided score or star ratings in the food delivery app reviews, organizations can effectively detect sentiment without the need for additional analysis like VADER scores. Our study, in line with the previous research conducted by Hossain and Rahman (2022) and Pashchenko et al. (2022) in different fields, confirms the validity of utilizing these provided scores for sentiment detection. This finding presents a convenient and efficient method for food delivery organizations to assess the sentiment expressed by users. By simply considering the score or star ratings, these organizations can quickly gauge the overall sentiment of the reviews. This approach eliminates the need for extensive analysis or complex sentiment detection techniques. By leveraging the provided scores, food delivery organizations can promptly identify positive or negative sentiments and take appropriate actions to address any issues or enhance positive experiences. This straightforward sentiment detection method enables organizations to efficiently monitor customer sentiment and make data-driven decisions to improve their services, customer satisfaction, and overall performance. Additionally, review readers can benefit from this study by gaining insights into the relationship between emotional aspects, star ratings, and thumbs-up behavior. It helps them interpret reviews more effectively and make informed decisions. App users can also be mindful of how their emotional expressions and star ratings can influence the reactions and engagement of review readers.

Consequently, the emotional response, star rating, and thumbs-up behavior of customers towards food delivery service apps are important factors to consider. These elements play a significant role in shaping the success and user experience of these apps. As online food delivery services continue to gain popularity and revolutionize the way people order meals, it becomes crucial to understand how customers' emotions impact app ratings and user engagement. By examining the relationship between customers' emotional response, star rating, and thumbs-up behavior, researchers and service providers can gain valuable insights into user preferences and satisfaction levels. This understanding can guide the development of effective strategies to enhance app features, improve service quality, and cultivate positive customer experiences. Exploring the dynamics of customers' interactions with food delivery service apps contributes to the ongoing evolution and optimization of these platforms, ensuring they meet the diverse needs and expectations of their customer base.

Furthermore, platforms and aggregators hosting app reviews can utilize the findings to enhance their algorithms and recommendation systems. Incorporating emotional aspects and considering the length of reviews in their analysis can improve the accuracy and relevance of review rankings, providing users with more helpful and reliable information. The practical application of this study extends to informing decision-making and strategies related to food delivery app development and customer satisfaction. By understanding the sentiment expressed in user reviews, app developers and service providers can identify areas of improvement and address customer concerns. The high percentage of positive reviews highlights the strengths of the apps, which can be leveraged for marketing and customer acquisition efforts. Moreover, the distribution of negative and neutral reviews offers insights into specific pain points and areas for enhancement. This information can guide app developers in refining features, improving user experience, and addressing customer issues, ultimately leading to increased customer satisfaction and loyalty.

Additionally, the practical application of this study lies in the domain of online food delivery app management and user experience optimization. The mean values of emotional aspects presented in the tables provide valuable insights into the emotions expressed by users in their reviews. App developers and service providers can utilize this information to gain a deeper understanding of how different emotional dimensions are associated with sentiment classes and specific apps. By identifying the emotions that are most prevalent and influential in user reviews, app managers can tailor their strategies to enhance user satisfaction and address specific emotional concerns. This data-driven approach can help app developers create emotionally resonant experiences, resulting in higher user engagement, loyalty, and overall customer satisfaction.

Moreover, the practical application of the results presented in **Table 7** is to inform app developers and service providers in designing and improving user experiences in online food delivery apps. By understanding the correlation between sentiment and emotional aspects, developers can make data-driven decisions to enhance the emotional aspects of their platforms. This application enables app developers to create a more emotionally engaging and satisfying experience for their users, leading to increased user retention and positive word-of-mouth. Furthermore, the practical application of the findings presented in **Table 10** is in the design and improvement of online food delivery apps and review systems. By understanding the relationships between variables, app developers and service providers can implement practical strategies to enhance user experiences and optimize the review system. For example, they can optimize review length, encourage emotion-based analysis, design features that encourage positive user interactions, and improve the review rating system. These practical applications based on the findings can enhance user satisfaction, improve the quality and relevance of reviews, and ultimately create a more engaging and user-friendly platform.

6. Conclusion

In addition to timely delivery, online food delivery apps play a crucial role in maintaining food quality. By partnering with reputable restaurants and implementing strict criteria for selection, these apps ensure that customers receive food of excellent quality and taste. Furthermore, online food delivery apps enhance customers' preferences by offering a diverse range of restaurant options. Customers can explore various menus, read reviews, and view ratings to make informed decisions based on their preferences. These apps feature a wide selection of cuisines, ranging from local favorites to international delicacies, catering to a wide range of tastes and preferences. Another way online food delivery apps enhance customers' preferences is through personalized recommendations. By analyzing customer data and order history, these apps can suggest restaurants and dishes that are likely to appeal to individual tastes. This personalized approach creates a tailored dining experience, making it easier for customers to discover new restaurants and dishes that align with their preferences.

In conclusion, this study contributes to our understanding of the relationship between customers' emotional responses, star ratings, and thumbs-up behavior in the context of food delivery service apps. The findings highlight the inverse correlation between review length and favorable sentiment, emphasizing the importance of concise and impactful reviews in shaping user perceptions. Moreover, the study demonstrates that different types of user sentiment have varying effects on emotional aspects, influencing review scores and subsequently affecting the thumbs-up reactions of review readers. This research provides valuable insights into the role of emotions and sentiment in the context of online food delivery apps and opens up avenues for further exploration in this field.

7. Limitations and future scopes

One limitation of this study is its generalizability to other platforms or contexts. Future research could extend the investigation to other review platforms and diverse user demographics to validate the findings and gain a broader understanding of how emotional responses and engagement differ across various platforms and user groups. Comparative studies across multiple platforms could reveal platform-specific dynamics and inform the development of platform-specific strategies for managing user sentiment and engagement. Another limitation is the use of lexicon-based unsupervised machine learning approaches to analyze emotional features. Future research could explore advanced natural language processing techniques, such as deep learning models or sentiment analysis algorithms trained on domain-specific datasets. These approaches may capture the nuances of emotions expressed in reviews more effectively and provide more accurate analyses of emotional aspects. Comparing the results obtained from different sentiment analysis methodologies would guide future research in selecting the most suitable techniques for analyzing emotional features in app reviews.

The limited set of emotional aspects considered in this study also presents a limitation. Future research could expand the scope of emotional aspects considered and explore a broader range of emotions, including more subtle or nuanced emotions. Additionally, investigating the interplay between emotional aspects and other factors, such as usability, pricing, or delivery speed, would provide a more comprehensive view of the factors driving user satisfaction and engagement. The absence of contextual information and user demographics is another limitation. Future research could incorporate contextual information, such as review timestamps or user location, to understand how emotional responses vary across different temporal or geographic factors. Additionally, considering user demographics, such as age, gender, or cultural background, would provide insights into how emotional responses differ among various user segments. Analyzing the interaction between emotional features and contextual or demographic factors would enhance our understanding of the complex dynamics shaping user sentiment and thumbs-up behavior. Furthermore, future research could explore the impact of app developer or service provider responses on user sentiment and thumbs-up behavior. Studying the influence of app updates, feature enhancements, or promotional activities on user engagement and satisfaction would offer practical guidance for app developers and service providers in optimizing user experiences. Additionally, investigating the role of app developers and service providers in managing user sentiment through timely and effective responses to customer reviews would contribute to a deeper understanding of the factors influencing user engagement. In conclusion, by addressing these limitations and pursuing the suggested future research directions, we can advance our understanding of the complex interplay between emotional responses, star ratings, and thumbs-up behavior in the context of food delivery service apps. This knowledge will contribute to the development of effective strategies for managing user sentiment, enhancing user experiences, and optimizing the overall satisfaction of app users and review readers.

Author contributions: Conceptualization, LL, NAI, CWC, PS, MSH, and MDP; methodology, LL, NAI, CWC, PS, MSH, and MDP; software, PS, MSH, MDP; validation, LL, NAI, CWC, PS, MSH, and MDP; formal analysis, PS, MSH and MDP; investigation, LL, NAI, CWC, PS, MSH, and MDP; resources, LL, NAI, CWC and PS; data curation, MSH and MDP; writing—original draft preparation, LL, NAI, CWC, PS, MSH, and MDP; writing—review and editing, LL, NAI, CWC, PS, MSH, and MDP; visualization, MSH and MDP; supervision, LL, PS, and MSH; project administration, PS and MSH; funding acquisition, MSH. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: This project was partially supported by the Institute of Research and Training (IRT) at Hajee Mohammad Danesh Science and Technology University (HSTU), Dinajpur-5200, Bangladesh.

Conflict of interest: The authors declare no conflict of interest.

References

Al-Subaihin, A. A., Sarro, F., Black, S., et al. (2019). App Store Effects on Software Engineering Practices. IEEE Transactions on Software Engineering, 47(2), 300–319. https://doi.org/10.1109/tse.2019.2891715

Annaraud, K., & Berezina, K. (2020). Predicting satisfaction and intentions to use online food delivery: What really makes a difference? Journal of Foodservice Business Research, 23(4), 305–323. https://doi.org/10.1080/15378020.2020.1768039

Ashton-James, C. E., & Ashkanasy, N. M. (2008). Chapter 1 Affective events theory: A strategic perspective. In: Zerbe, W. J., Härtel, C. E. J., & Ashkanasy, N. M. (editors). Emotions, Ethics and Decision-Making. Emerald Group Publishing Limited.

Askalidis, G., & Malthouse, E. C. (2016). The Value of Online Customer Reviews. In: Proceedings of the 10th ACM Conference on Recommender Systems.

Chandrasekhar, N., Gupta, S., & Nanda, N. (2019). Food Delivery Services and Customer Preference: A Comparative Analysis. Journal of Foodservice Business Research, 22(4), 375–386. https://doi.org/10.1080/15378020.2019.1626208

Chen, C.-F. (2023). Investigating the Effects of Job Stress on the Distraction and Risky Driving Behaviors of Food Delivery Motorcycle Riders. Safety and Health at Work, 14(2), 207–214. https://doi.org/10.1016/j.shaw.2023.03.004

Chuah, S. H.-W., & Yu, J. (2021). The future of service: The power of emotion in human-robot interaction. Journal of Retailing and Consumer Services, 61, 102551. https://doi.org/10.1016/j.jretconser.2021.102551

Coombs, W. T., & Holladay, S. J. (2007). An exploratory study of stakeholder emotions: Affect and crises. In: Research on Emotion in Organizations. Emerald Group Publishing Limited.

Dąbrowski, J., Letier, E., Perini, A., et al. (2022). Analysing app reviews for software engineering: a systematic literature review. Empirical Software Engineering, 27(2). https://doi.org/10.1007/s10664-021-10065-7

Dąbrowski, J., Letier, E., Perini, A., et al. (2023). Mining and searching app reviews for requirements engineering: Evaluation and replication studies. Information Systems, 114, 102181. https://doi.org/10.1016/j.is.2023.102181

Davidow, M. (2000). The Bottom Line Impact of Organizational Responses to Customer Complaints. Journal of Hospitality & Tourism Research, 24(4), 473–490. https://doi.org/10.1177/109634800002400404

Diekson, Z. A., Prakoso, M. R. B., Putra, M. S. Q., et al. (2023). Sentiment analysis for customer review: Case study of Traveloka. Procedia Computer Science, 216, 682–690. https://doi.org/10.1016/j.procs.2022.12.184

Elahi, M., Khosh Kholgh, D., Kiarostami, M. S., et al. (2023). Hybrid recommendation by incorporating the sentiment of product reviews. Information Sciences, 625, 738–756. https://doi.org/10.1016/j.ins.2023.01.051

Fernandes, S., Panda, R., Venkatesh, V. G., et al. (2022). Measuring the impact of online reviews on consumer purchase decisions – A scale development study. Journal of Retailing and Consumer Services, 68, 103066. https://doi.org/10.1016/j.jretconser.2022.103066

Ghasemaghaei, M., Eslami, S. P., Deal, K., et al. (2018). Reviews' length and sentiment as correlates of online reviews' ratings. Internet Research, 28(3), 544–563. https://doi.org/10.1108/intr-12-2016-0394

Hossain, M. S., & Rahman, M. F. (2023a). Customer Sentiment Analysis and Prediction of Insurance Products' Reviews Using Machine Learning Approaches. FIIB Business Review, 12(4), 386–402. https://doi.org/10.1177/23197145221115793

Hossain, M. S., & Rahman, M. F. (2023b). Detection of readers' emotional aspects and thumbs-up empathy reactions towards reviews of online travel agency apps. Journal of Hospitality and Tourism Insights, 7(1), 142–171. https://doi.org/10.1108/jhti-10-2022-0487

Hossain, M. S., & Rahman, M. F. (2022). Detection of potential customers' empathy behavior towards customers' reviews. Journal of Retailing and Consumer Services, 65, 102881. https://doi.org/10.1016/j.jretconser.2021.102881

Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. Decision Support Systems, 57, 42–53. https://doi.org/10.1016/j.dss.2013.07.009

Islam, Md. J., Datta, R., & Iqbal, A. (2023). Actual rating calculation of the zoom cloud meetings app using user reviews on google play store with sentiment annotation of BERT and hybridization of RNN and LSTM. Expert Systems with Applications, 223, 119919. https://doi.org/10.1016/j.eswa.2023.119919

Jiménez-Zafra, S. M., Martín-Valdivia, M. T., Maks, I., & Izquierdo, R. (2017). Analysis of patient satisfaction in Dutch and Spanish online reviews. Procesamiento del Lenguaje Natural, 58, 101-108.

Kaur, M., Verma, R., & Otoo, F. N. K. (2021). Emotions in leader's crisis communication: Twitter sentiment analysis during COVID-19 outbreak. Journal of Human Behavior in the Social Environment, 31(1–4), 362–372. https://doi.org/10.1080/10911359.2020.1829239

Kesner, L., & Horáček, J. (2017). Empathy-Related Responses to Depicted People in Art Works. Frontiers in Psychology, 8. https://doi.org/10.3389/fpsyg.2017.00228

Lai, X., Wang, F., & Wang, X. (2021). Asymmetric relationship between customer sentiment and online hotel ratings: the moderating effects of review characteristics. International Journal of Contemporary Hospitality Management, 33(6), 2137–2156. https://doi.org/10.1108/ijchm-07-2020-0708

Leon, R. D. (2019). Hotel's online reviews and ratings: a cross-cultural approach. International Journal of Contemporary Hospitality Management, 31(5), 2054–2073. https://doi.org/10.1108/ijchm-05-2018-0413

Leung, X. Y., & Yang, Y. (2020). Are all five points equal? Scaling heterogeneity in hotel online ratings. International Journal of Hospitality Management, 88, 102539. https://doi.org/10.1016/j.ijhm.2020.102539

Li, H., Yu, B. X. B., Li, G., et al. (2023). Restaurant survival prediction using customer-generated content: An aspect-based sentiment analysis of online reviews. Tourism Management, 96, 104707. https://doi.org/10.1016/j.tourman.2022.104707

Li, H., Liu, H., & Zhang, Z. (2020). Online persuasion of review emotional intensity: A text mining analysis of restaurant reviews. International Journal of Hospitality Management, 89, 102558. https://doi.org/10.1016/j.ijhm.2020.102558

Lin, X.-M., Ho, C.-H., Xia, L.-T., et al. (2021). Sentiment analysis of low-carbon travel APP user comments based on deep learning. Sustainable Energy Technologies and Assessments, 44, 101014. https://doi.org/10.1016/j.seta.2021.101014

Liu, Y., & Li, S. (2023). An economic analysis of on-demand food delivery platforms: Impacts of regulations and integration with ride-sourcing platforms. Transportation Research Part E: Logistics and Transportation Review, 171, 103019. https://doi.org/10.1016/j.tre.2023.103019

Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. Tourism Management, 47, 140–151. https://doi.org/10.1016/j.tourman.2014.09.020

Longobardi, C., Borello, L., Thornberg, R., et al. (2019). Empathy and defending behaviours in school bullying: The mediating role of motivation to defend victims. British Journal of Educational Psychology, 90(2), 473–486. Portico. https://doi.org/10.1111/bjep.12289

Maimaiti, M., Zhao, X., Jia, M., et al. (2018). How we eat determines what we become: opportunities and challenges brought by food delivery industry in a changing world in China. European Journal of Clinical Nutrition, 72(9), 1282–1286. https://doi.org/10.1038/s41430-018-0191-1

Mariani, M. M., & Borghi, M. (2018). Effects of the Booking.com rating system: Bringing hotel class into the picture. Tourism Management, 66, 47–52. https://doi.org/10.1016/j.tourman.2017.11.006

McGlohon, M., Glance, N., & Reiter, Z. (2010). Star Quality: Aggregating Reviews to Rank Products and Merchants. Proceedings of the International AAAI Conference on Web and Social Media, 4(1), 114–121. https://doi.org/10.1609/icwsm.v4i1.14019

Mellinas, J. P., María-Dolores, S. M. M., & García, J. J. B. (2016). Effects of the Booking.com scoring system. Tourism Management, 57, 80-83. https://doi.org/10.1016/j.tourman.2016.05.015

Ossai, C. I., & Wickramasinghe, N. (2023). Sentiments prediction and thematic analysis for diabetes mobile apps using Embedded Deep Neural Networks and Latent Dirichlet Allocation. Artificial Intelligence in Medicine, 138, 102509. https://doi.org/10.1016/j.artmed.2023.102509

Pandey, S., Chawla, D., & Puri, S. (2022). Food delivery apps (FDAs) in Asia: an exploratory study across India and the Philippines. British Food Journal, 124(3), 657–678. https://doi.org/10.1108/bfj-01-2020-0074

Parboteeah, D. V., Valacich, J. S., & Wells, J. D. (2009). The Influence of Website Characteristics on a Consumer’s Urge to Buy Impulsively. Information Systems Research, 20(1), 60–78. https://doi.org/10.1287/isre.1070.0157

Pashchenko, Y., Rahman, M. F., Hossain, M. S., et al. (2022). Emotional and the normative aspects of customers’ reviews. Journal of Retailing and Consumer Services, 68, 103011. https://doi.org/10.1016/j.jretconser.2022.103011

Peterson, R. A., & Merino, M. C. (2003). Consumer information search behavior and the internet. Psychology & Marketing, 20(2), 99–121. Portico. https://doi.org/10.1002/mar.10062

Plutchik, R. (1980). A general psychoevolutionary theory of emotion. Theories of Emotion, 3–33. https://doi.org/10.1016/b978-0-12-558701-3.50007-7

Puh, K., & Bagić Babac, M. (2022). Predicting sentiment and rating of tourist reviews using machine learning. Journal of Hospitality and Tourism Insights, 6(3), 1188–1204. https://doi.org/10.1108/jhti-02-2022-0078

Qi, H., & Li, F. (2021). Travelers’ emotional experiences during the COVID-19 outbreak: The development of a conceptual model. Journal of Hospitality and Tourism Management, 47, 389–397. https://doi.org/10.1016/j.jhtm.2021.04.013

Rajeswari, B., Madhavan, S., Venkatesakumar, R., et al. (2020). Sentiment analysis of consumer reviews – a comparison of organic and regular food products usage. Rajagiri Management Journal, 14(2), 155–167. https://doi.org/10.1108/ramj-05-2020-0022

Ramachandran, R., Sudhir, S., & Unnithan, A. B. (2021). Exploring the relationship between emotionality and product star ratings in online reviews. IIMB Management Review, 33(4), 299–308. https://doi.org/10.1016/j.iimb.2021.12.002

Ratnasari, R. T., Gunawan, S., Mawardi, I., & Kirana, K. C. (2020). Emotional experience on behavioral intention for halal tourism. Journal of Islamic Marketing, 12(4), 864–881. https://doi.org/10.1108/JIMA-12-2019-0256

Rita, P., Ramos, R., Borges-Tiago, M. T., et al. (2022). Impact of the rating system on sentiment and tone of voice: A Booking.com and TripAdvisor comparison study. International Journal of Hospitality Management, 104, 103245. https://doi.org/10.1016/j.ijhm.2022.103245

Sánchez-Franco, M. J., Arenas-Márquez, F. J., & Alonso-Dos-Santos, M. (2021). Using structural topic modelling to predict users’ sentiment towards intelligent personal agents. An application for Amazon’s echo and Google Home. Journal of Retailing and Consumer Services, 63, 102658. https://doi.org/10.1016/j.jretconser.2021.102658

Sarkar, A. R., & Ahmad, S. (2021). A new approach to expert reviewer detection and product rating derivation from online experiential product reviews. Heliyon, 7(7), e07409. https://doi.org/10.1016/j.heliyon.2021.e07409

Sayfuddin, A., & Chen, Y. (2021). The signaling and reputational effects of customer ratings on hotel revenues: Evidence from TripAdvisor. International Journal of Hospitality Management, 99, 103065. https://doi.org/10.1016/j.ijhm.2021.103065

Su, D. N., Nguyen-Phuoc, D. Q., Duong, T. H., et al. (2022). How does quality of mobile food delivery services influence customer loyalty? Gronroos's service quality perspective. International Journal of Contemporary Hospitality Management, 34(11), 4178–4205. https://doi.org/10.1108/ijchm-08-2021-1039

Suhartanto, D., Helmi Ali, M., Tan, K. H., et al. (2019). Loyalty toward online food delivery service: the role of e-service quality and food quality. Journal of Foodservice Business Research, 22(1), 81–97. https://doi.org/10.1080/15378020.2018.1546076

Trivedi, S. K., & Singh, A. (2021). Twitter sentiment analysis of app based online food delivery companies. Global Knowledge, Memory and Communication, 70(8/9), 891–910. https://doi.org/10.1108/gkmc-04-2020-0056

Umasuthan, H., Park, O.-J., & Ryu, J.-H. (2017). Influence of empathy on hotel guests' emotional service experience. Journal of Services Marketing, 31(6), 618–635. https://doi.org/10.1108/JSM-06-2016-0220 https://doi.org/10.1108/JSM-06-2016-0220

Wang, X., Zhao, F., Tian, X., et al. (2022). How online food delivery platforms contributed to the resilience of the urban food system in China during the COVID-19 pandemic. Global Food Security, 35, 100658. https://doi.org/10.1016/j.gfs.2022.100658

Weiss, H. M., & Cropanzano, R. (1996). Affective Events Theory: A theoretical discussion of the structure, causes and consequences of affective experiences at work. In: Staw, B. M. & Cummings, L. L. (editors). Research in Organizational Behavior: An Annual Series of Analytical Essays and Critical Reviews. Elsevier Science/JAI Press.

Yaiprasert, C., & Hidayanto, A. N. (2023). AI-driven ensemble three machine learning to enhance digital marketing strategies in the food delivery business. Intelligent Systems with Applications, 18, 200235. https://doi.org/10.1016/j.iswa.2023.200235

Zhang, Z., Liang, S., Li, H., et al. (2019). Booking now or later: Do online peer reviews matter? International Journal of Hospitality Management, 77, 147–158. https://doi.org/10.1016/j.ijhm.2018.06.024

Zhao, Y., Yang, S., Narayan, V., & Zhao, Y. (2013). Modeling consumer learning from online product reviews. Marketing Science, 32(1), 153–169. https://doi.org/10.1287/mksc.1120.0755