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Exploring the importance of mobile app attributes based on consumers' voices using structured and unstructured data

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Abstract

Purpose – This exploratory study examines and comprehends the relative importance of mobile app attributes from a consumer perspective. Both quantitative and qualitative analysis approaches explore users' behavior and attitudes toward the priorities of mobile app attributes and preferences, identifying correlations between attributes and aggregating individual attributes into groups.

Design/methodology/approach – Online convenience sampling and snowball sampling resulted in 417 valid responses. The numerical data are analyzed using the relative to an identified distribution (RIDIT) scoring system and gray relational analysis (GRA), and qualitative responses are investigated using text-mining techniques.

Findings – This study finds enhanced nuances of user preferences and provides data-driven insights that might help app developers and marketers create a distinct app that will add value to consumers. The latent semantic analysis indicates relationship structure among the attributes, and text-based cluster analysis determines the subsets of attributes that represent the unique functions of the mobile app.

Practical implications – This study reveals the essential components of mobile apps, paying particular attention to the consumer value component, which boosts user approval and encourages prolonged use. Overall, the results demonstrate that developers must concentrate on its functional, technical and esthetic features to make an app more exciting and practical for potential users.

Originality/value – Most scholarly research on apps has focused on their technological merits, aesthetics and usability from the user's perspective. A post-adoption multi-attribute app analysis using both structured and unstructured data is conducted in this study.

Keywords Mobile apps, Consumer behavior, RIDIT scoring, GRA, Text mining

Paper type Research paper

1. Introduction

Mobile devices have become integral to human life due to the growing popularity and access to the Internet, social media and mobile technology. Different user segments are using mobile devices for their business and personal use. As a result, continuous growth in smartphone usage and high Internet data consumption propel the current mobile application market.

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During the COVID-19 pandemic, mobile app users have increased drastically in figuring out various remote-based activities. Following the upward trend, companies and developers are creating a large number of mobile applications (mobile apps or apps) to add value to their users in various activities related to financial transactions, health and fitness, entertainment, online shopping, education and knowledge sharing, lifestyle, social media communications and gaming for increasing productivity.

The report presented by grandviewresearch.com (2020) revealed that the projected global mobile app market size in 2019 was USD 154.05bn. This report also predicted that the mobile app market will likely see a compound annual growth rate (CAGR) of 11.5% from 2020 to 2027. Another report from Statista.com (2021) has projected that the global app market revenue will reach USD 437.80bn in 2022 with a CAGR of 6.58%. It has indicated that paid app revenue is also growing and will reach USD 5.39bn in 2022, and the number of app downloads increased significantly to 229,922.5m in 2022. The Statista report (2021) has demonstrated that the top categories in the app market are entertainment, social networking, hyper-casual games, hardcore games, finance and business, sports, online shopping, lifestyle, travel and education. The mobile apps market forecast and analysis report presented by data.ai (2022) has exhibited that, unlike in developed countries, mobile apps' popularity relating to the number of downloads and revenue growth is increasing in emerging markets like China, India, Brazil, Russia, Mexico and Indonesia. It was also supported by Prnewswire.com (2022).

On average, thousands of new apps are launched monthly through the Google Store or Apple Store. As per globenewswire.com (September 21, 2022), the estimated market size of mobile application stores is expected to grow from US$165.9bn in 2022 to US$1027.21bn by 2032. The revenue generated by mobile application shops is projected to experience a CAGR of 20% from 2022 to 2032. It is also true that some apps are becoming so popular quickly. Sometimes, it is also visible that another new app is replacing a popular app (Pop, Hlédik, & Dabija, 2023). So, creating apps that cater to unique client desires and requirements may be a considerable challenge for app developers. These developers must guarantee that their apps are relevant and dependable and surpass the expectations of prospective consumers (Angeren, Vroom, McCann, Podoynitsyna, & Langerak, 2022; Khan *et al.*, 2023). According to the consumer theory, customers' revelation of a product's or service's functional benefit or hedonic value (Zhani, Mouri, & Ahmed, 2022) can increase their intention to use the product or service. The same holds for mobile applications (Zhani *et al.*, 2022). Previous research has shown that consumer feedback is the most effective means of comprehending the needs of present mobile app users during the post-adoption phase (Foroughi, Sitthisirinan, Iranmanesh, Nikbin, & Ghobakhloo, 2023; Sharma, Antony, Sehrawat, Cruz, & Daim, 2022a; Sharma, Pathak, & Siddiqui, 2022b). It facilitates additional value addition to attract a more extensive user base.

Mobile apps, as the new age technology-based services product, are gaining the attention of researchers because of the increasing competition in the apps market, changing patterns of consumer requirements and advancement of mobile technology and the fast technology adoption by mobile apps users (Al-Adwan & Sammour, 2021; Zolkepli, Mukhiar, & Tan, 2021). Some studies have investigated performance expectancy, effort expectancy, social influence and perceived convenience (Dhar & Bose, 2022; Guo, Peeta, Agrawal, & Benedyk, 2022). Few researchers have investigated the consumer app's likability-related playfulness, access flexibility and connectedness (Chopdar, Korfiatis, Sivakumar, & Lytras, 2018; Li, 2018). Those studies have been conducted in the developed nation context (He, Fang, Liu, & Li, 2019; Zolkepli *et al.*, 2021).

The majority of studies about consumer behavior concerning mobile applications have primarily examined user intention, satisfaction, retention and reuse behavior with an emphasis on the features, technological advantages, design and usability of these applications and the functional aspects of mobile applications (Chung, Park, Joung, &

Jhung, 2019; Fang, Zhao, Wen, & Wang, 2017; Prabhu & Soodan, 2020), app appeal (Prabhu & Soodan, 2020; Tian, Shi, & Cheng, 2021), technical glitch freeness or technical attributes (Balsalobre-Fernández, Agopyan, & Morin, 2017; Su *et al.*, 2020) and the app appearance or design (Brown *et al.*, 2020; Stocchi, Ludwichowska, Fuller, & Gregoric, 2021; Prabhu & Soodan, 2020; Wu, Ren, Pitafi, & Islam, 2020; Wenz, Jäckle, Burton, & Couper, 2022). However, most studies confine their research to a particular aspect of the app feature. There is a lack of empirical research in finding the multi-feature analysis of mobile apps at the post-adoption stage using both structured and unstructured data in the context of developing countries.

The existing studies in the domain of Internet and mobile technology-enabled services, information systems and mobile apps adoption have applied standard theories such as expectation confirmation theory (ECT) and expectation disconfirmation theory (EDT) (Bhattacherjee, 2001; Brown *et al.*, 2020; Chalomba, Duh, & Gujral, 2019; Ding, 2018; Fan & Suh, 2014; Hafez, 2022; Hsieh & Li, 2022; Lankton, McKnight, & Thatcher, 2014; Ray, Bala, & Dwivedi, 2021; Tam, Santos, & Oliveira, 2020; Zolkepli *et al.*, 2021). Those studies focused on particular characteristics and features of applications to understand consumer performance, satisfaction and switching behavior concerning mobile-enabled services, information systems and apps. However, there is a lack of empirical studies in identifying the multi-feature analysis of mobile apps at the post-adoption stage utilizing both structured and unstructured data in emerging nations. It is a significant gap in the field.

The current study has the following research objectives:

(1) To uncover the relevant variables (features or attributes) that add value to mobile app consumers and ensure use for a prolonged period.

(2) To rank the essential mobile app attributes in the order of priority based on the consumer's response data.

(3) To identify groups of keywords representing crucial app characteristics from the app user text comments and extract a relationship structure among the keywords using text analytics.

In this study, we have included all possible mobile app factors like technical advantages, functional usability, app appeal, technical glitch freeness, appearance or design, etc., that encourage consumers to use various mobile apps. We have conducted an online survey to review, investigate and analyze the various factors and attributes for an app selection and use. The closed-ended questions provide the rating of each attribute, whereas comments from the open-ended questions express the users' experience and capture the customers' voices. We performed the relative to an identified distribution (RIDIT) scoring method and gray relational analysis (GRA) to rank mobile app attributes from users' perspectives. We applied text-mining techniques to extract insights from users' text comments and validate the essential attributes of a mobile app from the comments. We generate suitable numerical summaries and graphical visualization to explore the content of text comments by app users. The research outcomes will act as a framework for policymakers and marketing professionals to take preventive and suitable measures to make the different mobile apps more impactful and best fit consumers' requirements for long-term success.

The rest of the article is organized as follows: Section 2 reviews the relevant literature that describes a mobile app's multiple attributes based on consumer expectation, perceived performance and confirmation theory. Section 3 outlines the proposed research methodology, including data collection and analysis approaches for analyzing structured and unstructured data. The results and analysis of collected data are presented in Section 4. Section 5 illustrates the analysis outcome. Finally, Section 6 concludes with the implications of the study.

2. Literature review

The theory of expectation confirmation (ECT) was introduced by Oliver (1977, 1980) to predict customer satisfaction in studies. The ECT is widely utilized for analyzing consumers' intention to repurchase. Another theory in social psychology is the EDT, which explores how individuals react when their expectations are not met during the post-adoption stage. EDT evaluates customer satisfaction, service, concerns regarding the product or service and overall experience after adoption (Oliver, 1977, 1980; Oliver & Swan, 1989). ECT and EDT may appear similar, but they are different. The ECT focuses on expectations and fulfillment. The EDT also takes into account perceived performance – the perception that consumers have of a product or service's performance. The information is reported by consumers' actual experiences with the product or service. The EDT is well-supported by both theoretical and empirical evidence. In marketing, particularly in consumer behavior literature, ECT examines customer satisfaction and post-purchase intentions.

The ECT and EDT have been extensively used by many authors to explain and comprehend customer behavior and satisfaction in the field of information systems, Internet services, adoption of mobile technology-enabled services and mobile apps (Bhattacherjee, 2001; Hsu and Lin, 2015; Hafez, 2022; Kim, Bae, & Jeon, 2019; Ray *et al.*, 2021; Tam *et al.*, 2020; Zolkepli *et al.*, 2021). These studies have primarily focused on the issues surrounding pre-adoption and the adoption stage.

According to ECT, people establish expectations about specific events, values, or persons based on past experiences. They prefer to seek information supporting their expectations while disregarding or dismissing evidence contradicting them. The theory also suggests that a consumer with optimistic expectations about a product is more likely to view its features and performance positively. Even if the product works well, people will find fault if they have unfavorable expectations. Limayem, Hirt and Cheung (2007) suggested that consumer habit directly influences information system continuation use by including it in ECT. According to existing literature, ECT may aid in app creation and operation by recognizing user expectations, monitoring app performance, optimizing app performance and boosting the user experience. Developers may enhance the user experience by learning about their customers' expectations and how they evaluate app performance (Hsu & Lin, 2015; Kim *et al.*, 2019). EDT examines how individuals respond when their expectations are unmet at the post-adoption stage. EDT measures customer happiness, service, product/service issues and overall experience post-adoption stage (Oliver, 1977, 1980; Oliver & Swan, 1989). This theory aids in understanding the factors that influence switching behavior. Consequently, EDT assists firms in understanding and satisfying consumer expectations, developing products and services, improving customer experience and preventing customers from switching. Inspired by customer satisfaction research, Bhattacherjee (2001) used the EDT to examine the ongoing usage of information technology. Several recent research have critically assessed EDT's role in information systems in determining the reasons for switching behavior and technological confidence (Ding, 2018; Fan & Suh, 2014; Lankton *et al.*, 2014).

The prior studies mainly employed ECT and EDT theories in the area of online and offline consumer behavior; however, there has been limited examination of the behavior related to the consumption of mobile applications. Some recent studies have explored mobile app consumer value perceptions and sought to apply such theories to get an understanding of customer satisfaction and switching behavior (Ding, 2018; Fan & Suh, 2014; Hafez, 2022; Lankton *et al.*, 2014; Zolkepli *et al.*, 2021). However, these studies fail to consider the intricacies of mobile app attributes, features and compatibility in usage. These factors are crucial in providing value to mobile app customers and fostering long-term usage. This research investigates the different aspects of mobile apps and their related characteristics, utilizing the concepts of ECT and EDT theories. The objective is to identify the key variables contributing value to mobile app users and encourage them to use an app for an extended duration. This study utilized a ranking algorithm to prioritize the essential qualities of mobile apps using structured data. Using text analytics, this research aimed to identify clusters of keywords that represent the essential characteristics of an app. Additionally, it sought to establish a relationship structure among these keywords based on user comments about the mobile apps.

2.1 Functional attributes of app

A mobile app is application software designed to work on a mobile device such as a smartphone, tablet computer, or smartwatch. Apps take less memory space and provide limited individual functions such as online shopping, financial transactions, social media communication, entertainment and gaming. Visual design, navigation, transaction convenience and economic rewards can influence consumer mobile app adoption (Li, 2018). This is seen in the functional attributes and qualities of mobile apps, which are crucial in defining something that should be included in a mobile app system or product to enhance the user experience (Lew & Olsina, 2013). It has been observed that entertainment (emotional value) and freedom to explore (epistemic value) boost functional value, which assists in user engagement with the mobile app (Kim, Yoon, & Han, 2016). Different scholarly articles have demonstrated that app running quality (Fang *et al.*, 2017) is one of the essential elements of functional attributes of mobile apps. Depending on the app operating system, the process can be understood as the app program's running mechanism, which might consist of multiple execution threads that execute instructions simultaneously. For the better functioning of any mobile app, the process performs a significant role in supporting user experience (Chung *et al.*, 2019). By keeping the consumer viewpoints on battery drain issues, most mobile apps are concerned about the minimum battery consumption to strengthen the app functionality (Cerbas, Kelemen, Liang, Sik-Lanyi, & Van de Castle, 2021).

2.2 Consumer expectation of app

It has been observed that consumer mindset, expectations and requirements change related to app usability. ECT (Oliver, 1977) and EDT (Oliver, 1980) are useful for evaluating customer expectations to determine the level of consumer satisfaction with regard to information systems and mobile applications (Ding, 2018; Fan & Suh, 2014; Lankton *et al.*, 2014). To address the changing demands of users, various app solution providers concentrate on continual customer needs analysis and give app updates regularly to ensure seamless operation (Prabhu & Soodan, 2020). The researchers have stated that consumers believe that using an app to make life easier can be essential (Prabhu & Soodan, 2020); another critical dimension of apps is how they can solve consumer purposes (Fang *et al.*, 2017). Since modern smartphone users have so many options, customer expectations have risen, so meeting consumer expectations has become an essential standard for app selection (Fang *et al.*, 2017).

2.3 App appeal

The sum of utilitarian and hedonic attributes that create an affirmative consumer perception and attractiveness to adopt and use any app is known as app appeal. The researchers have illustrated app features and design (Prabhu & Soodan, 2020) are essential components that strengthen the app's appeal and motivate the users. From the utilitarian point of view, benefits are inherent in the app (Powell & Torous, 2020) and ease of use (Fang *et al.*, 2017) and performance (Fang *et al.*, 2017) can create the app attractiveness and appeal. Existing studies have shown that app aesthetics (Dai, Zheng, Peng, & Yu, 2021; Kumar, Jain, & Hsieh, 2021), user interface attractiveness (Tian *et al.*, 2021) and fun in use (Brown *et al.*, 2020) work as the hedonic elements to boost the app appeal.

2.4 Technical attributes of app

The researchers have indicated that the app success depends on the technical glitch freeness or quality of technical attributes (Huang & Ren, 2020; Prabhu & Soodan, 2020). Some of the technical qualities that strengthen the app popularity can be that the app does not crash (Su *et al.*, 2020) and it doesn't face force close (Balsalobre-Fernández *et al.*, 2017) or doesn't freeze (Prabhu & Soodan, 2020). Researchers have shown that functional abnormality can be seen as an impediment to the technical smoothness of the app (Huang & Ren, 2020).

2.5 Visual appearance of app

App appearance can be understood as the visual feel that attracts the user. Researchers have demonstrated that app appearance can be enhanced with app graphics (Prabhu & Soodan, 2020), font and style (Prabhu & Soodan, 2020), usability pixelation (Brown *et al.*, 2020; Prabhu & Soodan, 2020), texting facility (Wenz *et al.*, 2022) and screen size (Prabhu & Soodan, 2020). Researchers have argued that the app image can boost the overall appearance (Stocchi *et al.*, 2021; Wu *et al.*, 2020).

Based on the literature review, Table 1 summarizes the apps' primary dimensions and associated attributes that may create user value.

3. Methodology

3.1 Data collection and sampling

Based on the literature review, this study has identified the key dimensions and corresponding attributes that can directly or indirectly influence and motivate users to download and utilize analyzed the quantitative data from closed-ended responses. Transforming unstructured data into a structured analytical concept can be difficult, requiring accurate and dependable results. Therefore, effective and efficient techniques for analyzing text data are employed to understand users' experiences various apps for their benefit. In order to ensure specific analytical findings, this article utilized a combination of qualitative and quantitative data analysis methods (Iacobucci, Petrescu, Krishen, & Bendixen, 2019). The present study utilized a survey instrument to gather data from adult users of mobile apps, excluding those who use gaming or entertainment apps. The researchers employed two sampling methods: online snowball sampling (Naderifar, Goli, & Ghaljaie, 2017) and convenience sampling (Frey, 2022). This has been proven helpful in other studies examining consumer behavior related to apps and has produced accurate and credible results (Kim *et al.*, 2019; Kumar *et al.*, 2021; Zolkepli *et al.*, 2021). We have developed a survey questionnaire that includes closed-ended and open-ended questions to collect structured and unstructured data. The closed-ended questions were formulated based on empirical measures identified in the existing literature. The response rating for closed-ended questions was collected using a five-point Likert scale, ranging from strongly disagree to strongly agree. The open-ended questions aim to capture users' experience of the mobile app features based on the text comments provided by the respondents. These textual comments assist in comprehending the customer's perspective and integrating a comprehensive outlook (Krishen and Petrescu, 2017) on the preferences and dislikes of app features and users' expectations regarding apps. Open-ended questions broaden the range of valuable information that can be collected and allow participants to express their opinions freely. The questionnaire was given in English, and since the consumer panel members had previously taken part in English-speaking market research studies, their language proficiency was not considered a hindrance. A total of 417 valid responses were collected. Next, the RIDIT scoring method and GRA analyzed the quantitative data from closed-ended responses. Transforming unstructured data into a structured analytical concept can be difficult, requiring accurate and dependable results. Therefore, effective and efficient techniques for analyzing text data are employed to understand users' experiences better.

Dimension	Attribute	Scale	Source
App functional attributes	Running quality	App running quality is important to me	Fang *et al.* (2017). (Adopted and modified)
	Process	App process time matters to me	Chung *et al.* (2019). (Adopted and modified)
	Battery drain	Battery drain is an issue for using the App	Cerbas *et al.* (2021). (Adopted and modified)
	Auto-update	Auto App update helps in smooth functioning	Prabhu and Soodan (2020). (Adopted and modified)
	Making life easy	The App I use should make things simpler	Prabhu and Soodan (2020). (Adopted and modified)
	Purpose solved	When I use an App, it ought to perform the thing it was meant to do	Fang *et al.* (2017), Alturki and Gay (2019). (Adopted and modified)
	Expectations fulfillment	Expectations fulfillment related to the App matters to me	Fang *et al.* (2017). (Adopted and modified)
App appeal	Features	The features of an App make me really like to install it	Prabhu and Soodan (2020), Alturki & Gay (2019). (Adopted and modified)
	Design	The design of the App motivates me	Prabhu and Soodan (2020), Alturki and Gay (2019). (Adopted and modified)
	Benefits	The practical benefits of the App are what made me choose it	Powell and Torous (2020), Alturki and Gay (2019). (Adopted and modified)
	Performance	App performance quality is very important to me	Fang *et al.* (2017). (Adopted and modified)
	Aesthetics	App aesthetics or beautifulness or look matters to me	Dai *et al.* (2021), Kumar *et al.* (2021). (Adopted and modified)
	Ease of use	I expect an App to be easy to use	Fang *et al.* (2017). (Adopted and modified)
	Fun in use	I would like an App to be fun to use	Brown *et al.* (2020). (Adopted and modified)
	UI attractiveness	While using an App, I value entertainment part	Tian *et al.* (2021). (Adopted and modified)
Technical attributes	App does not crash	Sometimes I worry that the App will not crash	Su *et al.* (2020). (Adopted and modified)
	Force close	Sometimes I worry that App does Force close	Balsalobre-Fernández *et al.* (2017). (Adopted and modified)
	Freeze	Sometimes, I think that perhaps the App might freeze	Prabhu and Soodan (2020). (Adopted and modified)
	Function not abnormally	Yet another issue is that the App does not function normally	Huang and Ren (2020). (Adopted and modified)
App appearance	Apps graphics	Graphics in Apps are important to me	Prabhu and Soodan (2020). (Adopted and modified)
	Fontan style	App font and style are relevant to me	Prabhu and Soodan (2020). (Adopted and modified)
	App image	The App image entices me to install it	Stocchi *et al.* (2021), Wu *et al.* (2020). (Adopted and modified)
	Usability pixelation	Pixelation is an issue for any App's usability	Brown *et al.* (2020), Prabhu and Soodan (2020). (Adopted and modified)
	Screen size	App screen size matters to me	Prabhu and Soodan (2020). (Adopted and modified)
	Texting facility	The texting facility is a valuable component of any App	Wenz *et al.* (2022). (Adopted and modified)

Source(s): Table by authors

Table 1.
App dimensions and their associated attributes

3.2 Data analysis approach

After gathering the data, the structured and unstructured responses were separated. We have applied the RIDIT scoring method and GRA to evaluate and rank the attributes in order of preference in the app acceptance and use context. In survey data, the response rating of attributes is often highly skewed distribution. The RIDIT method doesn't require any prior assumptions about population distribution because this is distribution-free (Bross, 1958; Fleiss, Chilton, & Wallenstein, 1979). It efficiently calculates the RIDIT score of each attribute or item for ranking survey attributes using Likert scale data (Wu, 2007; Kumar & Bhattacharya, 2016). GRA is another approach for ranking survey attributes. It computes the gray relation grade for each attribute to determine its relative importance (Wu, 2007; Kumar & Bhattacharya, 2016). RIDIT and GRA analysis are effective techniques for analyzing distribution-free data to examine variables captured in the Likert scale (Wu, 2007; Kumar & Bhattacharya, 2016; Sharma *et al.*, 2022a, b). RIDIT analysis is a technique that aims to operate with the inherent order of categories rather than quantifying them (Uwawunkonye & Anaene, 2013). The GRA methodology is a component of the gray system theory and is useful for analyzing data series with a discrete nature. The literature presents evidence of the successful implementation of GRA in different decision-making problems (Deng, 1989; Lin, Lu, & Lewis, 2007).

Consequently, this system has gained recognition as an effective solution for complex problems that entail intricate interrelationships among multi-attribute base rankings. The present study employed RIDIT and GRA analysis for an assessment process for evaluating the significance and relevance of attributes of mobile apps and ranked them in the order of priorities, using consumer feedback. Subsequently, we employed text-mining techniques to extract valuable insights from user-generated textual feedback and assess the inherent qualities of a mobile application, as indicated by the comments. We employ numeric summaries and visually appealing graphical representations to analyze the textual comments generated by application users. Finally, the RIDIT and GRA analysis findings and the text-mining results have been summarized to understand better the importance of mobile app attributes based on consumers' feedback.

The RIDIT scoring method utilizes a reference group from a known population to determine the score value for each category of preference levels for an item or attribute. The computed score for each category represents the percentile rank of an item within the reference population. The value is calculated by taking half the total number of items in the subject category, adding the number of attributes in all lower categories and then dividing the result by the population size. First, the RIDIT scores for each category have been determined. The RIDIT score for an item is calculated by summing the RIDIT scores of all its categories. The RIDIT scores of the items (or attributes) are computed to determine their ranks. Finally, a nonparametric Kruskal–Wallis test is applied to determine the difference in attribute score values from the mean RIDIT score.

In GRA, we first generate m number of reference data series where m is the number of items (or attributes). Next, normalized the data series based on the L-point Likert scale and measured the absolute deviation from the original data series as an absolute difference series. We find the global minimum and maximum values from the absolute difference series. Next, transform each data point in each absolute difference series into a gray relational coefficient and compute each attribute's gray relational grade value. A higher value of the gray relational grade of an attribute indicates that the respondents, as a whole, have a high degree of favor for that particular attribute. Finally, sort the gray relational grade in descending order to determine the priority level of the attributes to facilitate managerial interpretation.

In the context of text-mining techniques, our initial step involved extracting insights from users' text comments and identifying the key attributes of a mobile app based on these comments. We generate appropriate numerical summaries and graphical visualizations to explore the content of text comments made by app users. Initially, a total of 550 text comments were collected, which were based on the online responses to open-ended questions. After removing comments that contained fewer than 20 characters, a total of 417 comments were extracted. We have completed four important steps in our process: importing and loading raw text data, parsing and filtering the text to clean it, transforming the text and reducing dimensions to convert the unstructured text into a structured format. We then applied text-mining techniques to identify key attributes, analyze the relationship structure among these attributes and group them based on mobile app characteristics. In text mining, a bag-of-words refers to a document that consists solely of semantically relevant words. A unigram refers to a single word along with its frequency count. When two consecutive words are combined as a single feature, it is referred to as a bigram (Silge & Robinson, 2016; Hobson, Howard, & Hapke, 2019). We utilized R software and its packages to conduct text data analysis. Specifically, we employed bigrams as a meaningful unit of text to capture the sequence of words and gain insights into the respondents' perceptions. A frequency analysis and word cloud diagram can reveal how much a specific word has influenced all the comments. Based on paired associations, the structural relationship between words creates a semantic network structure that aids in comprehending the perceived communication links among the words. A cluster analysis is performed on words using weighted term frequency and inverse document frequency (TF-IDF) to identify groups of words that represent the characteristics of a product or service (Isson, 2018; Kwartler, 2017).

4. Result and analysis

The profile of the respondents is given in Table 2. The response rating follows a five-point Likert scale (from strongly disagree to strongly agree) of closed-ended questions. The Likert scale assumes a continuous measurement scale in consumer and social science research. This assumption criticizes applying the parametric methods as a data analysis approach. The data collected using the Likert scale is usually an ordinal or interval scale. Thus, we applied nonparametric methods such as RIDIT scoring and GRA to study the app attributes' preference ratings and determine their ranks. The split-half reliability method (McKelvie, 1989; Pronk, Molenaar, Wiers, & Murre, 2022) was employed to evaluate the data's reliability. It was done by measuring the correlation between the initial and subsequent halves of the measurement. In order to ensure the consistency of the data, a correlation analysis was performed on the even and odd items of the measurement. An additional step was taken to ensure the reliability of the data. The split-half coefficient, also called the half-and-half correlation coefficient, yielded a value of 0.9752. Additionally, the Spearman-Brown adjusted reliability coefficient for the replies was determined to be 0.9874. The results indicate that the Split-half coefficient (odd vs even) yielded a correlation value of 0.9972, while the Spearman-Brown adjusted reliability coefficient for the collected data was determined to be 0.9986. It suggests that the data demonstrates a significant level of validity (Pronk *et al.*, 2022). The observed skewness and kurtosis values of the attributes lie between −1.93 to −0.3 and −0.097 to 6.66, respectively. It indicates that app attribute ratings have a skewed distribution. First, we performed the RIDIT scoring method to determine the attributes' overall ranks. Subsequently, we applied the same method to determine the rank of each attribute within a dimension (or individual group), as shown in Table 3. We carry out the Kruskal-Wallis test to know the significant difference between the attribute score values from the mean RIDIT score value. The test statistics value and p-value (W = 963.117 and p = 0.000) demonstrate a significant difference (Wu, 2007; Bhattacharya & Kumar, 2017). Then, we employed the GRA method to rank the same app attributes. It is observed from Table 3 that the RIDIT and GRA provide app attributes ranks with a minor difference.

	Frequency	Percentage
Gender		
Male	242	56
Female	175	44
Total	417	100
Occupation		
Students	329	79
Service	64	15
Family business	9	2
Unemployed	15	4
Total	417	100
Age		
16–25	129	31
26–35	118	28
36–45	89	21
46–55	52	12
Above 55	29	8
Total	417	100
Association with smartphone		
0–5 years	208	50
6–11 years	131	31
11–16 years	56	13
more than 16 years	22	6
Total	417	100
Free or subscribed App user		
Using free mobile Apps	218	52
Using free and subscription based App	199	48
Total	417	100
Nature of App use		
Mobile Apps mainly using for utility and entertainment	167	40
Mobile Apps mainly using for entertainment and games	192	46
Mobile Apps mainly used for utility	58	14
Total	417	100

Source(s): Table by authors

Table 2.
Profile of respondents

We segregated the priorities of the features related to app adoption and use, as shown in Table 4, into three categories: highly important, important and moderately important, based on the ranks obtained from Table 3.

Table 4 shows that the most crucial features are smooth functioning, purpose-solving ability, running quality, overall benefits, performance, ease of use, avoidance of app crashes, force close, app graphics and usability pixelation. These crucial features add value and maximize the satisfaction of the app users. Similarly, the attributes like process, battery drain, expectations fulfillment, features, design, not facing freeze, screen size and texting facility appeared as important attributes for app adoption and use. Finally, app updates, entertainment, fun in use, aesthetics, normal functioning, font and style and image have been identified as moderately important attributes.

After analyzing the structured data, this study followed text-mining techniques to analyze unstructured responses. Applying text-mining techniques, we find keywords that imply an app's crucial attributes and relationship structure among the attributes and group the

Dimensions	Attributes	RIDIT ranks Rank within the dimension	Overall ranking	GRA ranks
App functional attributes	Running quality	3	9	9
	Process	5	20	20
	Battery drain	6	21	21
	App update	7	23	22
	Making life easy	1	5	5
	Purpose solved	2	6	6
	Expectations fulfillment	4	17	17
App appeal	Features	4	4	4
	Design	5	12	11
	Benefits	3	3	3
	Performance	1	1	1
	Aesthetics	7	18	18
	Ease of use	2	2	2
	Fun in use	8	19	19
	Entertainment	6	16	16
Technical glitch freeness/ Technical attributes	App does not crash	1	13	13
	Force close	2	22	23
	Freeze	3	24	24
	Function not abnormally	4	25	25
App appearance	Apps graphics	1	7	7
	Font and style	6	15	15
	App image	5	14	14
	Usability pixelation	2	8	8
	Screen size	3	10	10
	Texting facility	4	11	12

Source(s): Table by authors

Table 3.
Attributes ranks based on RIDIT and GRA

Dimensions	Highly important	Important	Moderately important
App functional attributes	Making life easy/smooth functioning, purpose solved, running quality	Process, battery drain, expectations fulfillment	App update
App appeal	Benefits, performance, ease of use	Features, design	Entertainment, fun in use, aesthetics
Technical glitch freeness/Technical attributes	App does not crash, force close	Freeze	Function not abnormally
App appearance	Apps graphics, usability pixelation	Screen size, texting facility	Font and style, app image

Source(s): Table by authors

Table 4.
Prioritized groups of features of each dimension

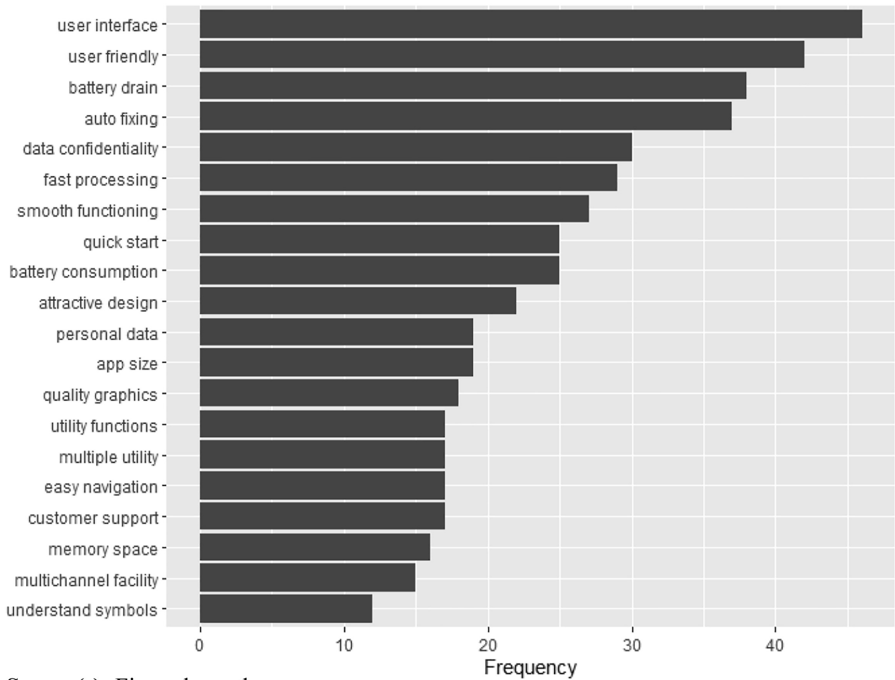
attributes into multiple clusters representing multiple app characteristics based on the voice of the app users. Table 5 summarizes the frequency distribution of bigram.

We executed two pictorial views using the frequency distribution. Figure 1 is a bar chart in which the length of the bars representing the frequencies of the bigrams visually explains the most frequent terms. It shows the distribution of the most frequently used words. A word

Bigram	Frequency
User interface	46
User friendly	42
Battery drain	38
Auto fixing	37
Data confidentiality	30
Fast processing	29
Smooth functioning	27
Battery consumption	25
Quick start	25
Attractive design	22
App size	19
Personal data	19
Quality graphics	18
Customer support	17
Easy navigation	17
Multiple utility	17
Utility functions	17
Memory space	16
Multichannel facility	15
Understand symbols	12

Source(s): Table by authors

Table 5. Frequency distribution of bigram



Source(s): Figure by authors

Figure 1. Bar chart of top 20 bigram

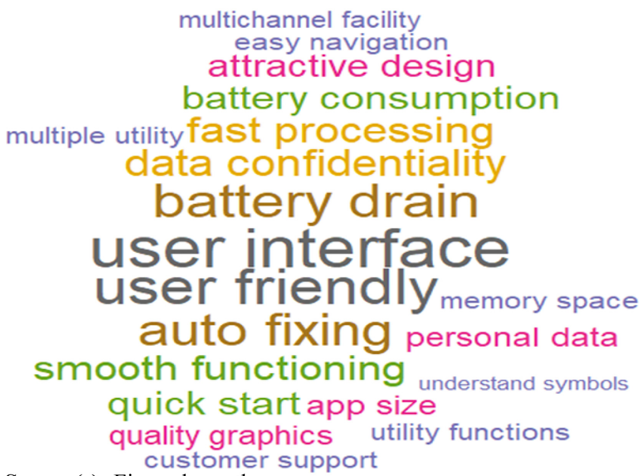
cloud of bigram is shown in Figure 2, another visualization of word frequency and helps understand the most frequent words in the users' comments. The more frequent keywords are shown in a larger font.

The frequency analysis and word cloud diagram observed that the top five words are "user interface", "user friendly", "battery drain", "auto fixing" and "data confidentiality". In addition, we investigate the association among words. The association measures how often any two words appear together relative to how often they appear separately among all the comments. The phi coefficient is used to quantify the pairwise association between the words statistically. A correlation network diagram visually depicts the relationship among words based on pairwise association. Figure 3 provides a semantic network structure of bigrams based on the correlation value between words connected by a line. It shows bigrams with a higher width connected line have a higher correlation than bigrams with a lower width.

It is observed from the semantic network diagram that "multiple utility", "multichannel facility" and "utility functions" are highly correlated relationship patterns and have a greater degree of perceiving communication links. Similarly, "quality graphics", "memory space" and "user interface", "understand symbols" have a medium correlated relationship structure. "attractive design", "fast processing", "App size", "personal data", "data confidentiality" and "battery consumption", "quick start" observed with an average degree of correlation.

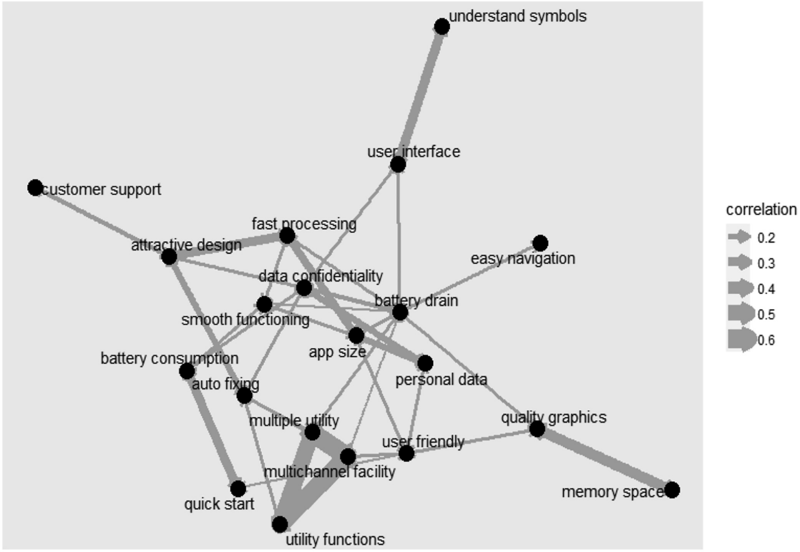
Finally, we perform a text clustering technique that organizes individual words into groups or clusters of similar words. Each cluster represents a particular characteristic of a mobile App. We have applied a hierarchical clustering method using Ward's minimum variance criteria and cosine similarity as a distance measure between pairs of words to determine clusters. Cosine similarity is beneficial for text data to measure the similarity between words. Figure 4 cluster dendrogram of bigram is an output of hierarchical cluster analysis.

The *y*-axis of the dendrogram is height and represents the calculated distance between clusters. The clusters that merged near the bottom of the chart are most similar and co-occur in the documents. It is observed from the dendrogram that four distinct clusters are observed where similar keywords are present in each cluster. The first cluster consists of "utility functions", "multiple utility" and "multichannel facility". It represents app functional attributes or the performance of an app. The keywords "user interface", "understand



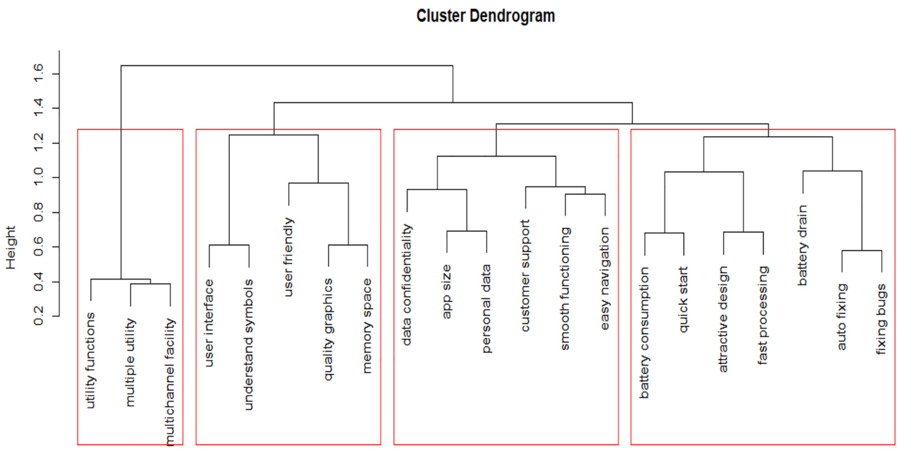
Source(s): Figure by authors

Figure 2.
Word cloud of bigram



Source(s): Figure by authors

Figure 3. Semantic network diagram of bigram



Source(s): Figure by authors

Figure 4. Cluster dendrogram of bigram

symbols", "user friendly", "quality graphics", "memory space" are merged into the second cluster. It is representative of app appearance or app outlook. Similarly, the third cluster can be called technical attributes or technical glitch freeness because the keywords appeared like data confidentiality, app size, personal data, customer support, smooth functioning and easy navigation. The fourth cluster comprised of battery consumption, quick start, attractive design, fast processing, battery drain, auto fixing and fixing bugs may be understood as app appeal. These clusters identified from the text mining captured the app users' perspectives on app hedonism and performance from the unstructured data.

We compare the outputs from structured data using RIDIT and GRA analysis with text-mining analysis of unstructured text data. We can see some commonalities in terms of functional, technical and app appeal dimensions in connection with the users' priorities. However, text-mining analysis has provided better consumer insight and sentiments. Referring to Figure 3, the semantic network structure based on the correlations among the different app attributes provides insight into understanding what attributes are expected by app users. This analysis also helps comprehend the app characteristics and associated features (or attributes) that will increase user acceptance.

5. Discussion and implications

It has been observed that smartphone users tend to utilize service apps more frequently compared to desktop users. This phenomenon indicates a significant increase in mobile applications within the industry. Mobile apps have already significantly impacted the business and new media industry. Mobile apps are steadily emerging as one of the most sought-after tools for effectively reaching diverse client groups and catering to their specific needs. These apps aim to provide exceptional value to users by offering a range of distinctive features. Amidst the escalating competition in the app industry, evolving consumer expectations, advancements in interactive technology and users' swift adoption of technology, mobile apps have become the focal point of academic reports. This study examined the factors influencing consumers to use a mobile application for an extended duration. Furthermore, we utilized both structured and unstructured data to prioritize and categorize the essential attributes of mobile applications based on their significance and appeal.

In this research, we employed the RIDIT and GRA algorithms to ascertain the relative order of importance of mobile app features that generate value for app users. In addition, we utilized text-mining techniques to delve into unstructured text comments and gain insights into the customers' perspectives. The text-mining techniques showcased the fundamental characteristics of the apps, which are closely associated with their specific attributes. The findings of our study offer valuable insights for developing consumer products that are engaging and highly valuable. This, in turn, can lead to increased adoption and long-term success, aligning with consumer expectations of value. The qualitative and quantitative data analysis conducted in this research offers insights into the experiences of users and their future expectations. These findings suggest that the user community may continue using the app for an extended period. This indicator can potentially encourage the user community to continue using the app for an extended duration. The research findings also indicate that customers have expectations regarding app features that can attract more users, particularly in terms of charging methods. The research findings have established a classification system for customers' diverse expectations by combining open-ended and closed-ended feedback from the customer. The main objective of this study is to examine the consumer perspective after adopting any app. The focus will be on understanding theories such as ECT (Oliver, 1977) and EDT (Oliver, 1980) by delving into the finer aspects of consumer preferences. The aim is to improve the consumer experience by adhering to the principles of app user satisfaction. One of the main objectives of this study is to determine the consumer perspective after adopting any app. This research aims to evaluate and standardize mobile apps in order to optimize their performance. It achieves this by analyzing the most popular features among customers, as indicated by their feedback. This study also contributes to the evaluation and standardization of mobile application performance in order to improve it. The switching behavior will be limited as a result, and the user will continue to use the mobile application that was previously installed.

According to the quantitative analysis, the essential attributes are smooth functioning, purpose-solving ability, operating quality, overall benefits, performance, ease of use, avoidance of app crashes, force closure, app visuals and usability pixelation. These critical features add value and increase app user pleasure. Similarly, workflow, battery drain, expectation fulfillment, features, design, not freezing, screen size and messaging facility were identified as essential app uptake and use criteria. Important qualities such as app update, entertainment, joy in use, aesthetics, normal operation, font and style and app picture are equitably crucial in generating user value. The latent semantic analysis helped establish a relationship structure among the keywords. The cluster analysis organized the keywords into groups reflecting multiple app characteristics based on the app users' voices. Each cluster stands for a unique function of a mobile app. The text-mining techniques captured app users' perceptions of hedonism and performance. We discovered similarities in functional, technical and app appeal aspects concerning the users' priorities when comparing the outputs of RIDIT and GRA analysis outputs utilizing structured data analysis and text mining of unstructured data. Text-mining analysis produced deeper customer insight for understanding user behavior and attitudes toward the mobile app attributes. Both types of analysis also aid in understanding the app's qualities and associated features (or aspects) that will boost user experience.

6. Conclusions and future research scope

Mobile apps are a highly prominent service product that continues to evolve in response to consumer demands and technological advancements. Mobile app developers worldwide strive to create more comprehensive apps that meet consumer requirements and provide a better user experience, strongly emphasizing delivering value to consumers. In this article, we have utilized standard theories such as ECT and EDT to gain insight into the dimensions of mobile apps and their associated attributes that have the potential to enhance user experience. Quantitative analysis techniques, namely the RIDIT and GRA scoring systems, were used to ascertain each characteristic's overall rank and individual rank within a given dimension. This study unveiled the behavioral patterns and attitudes about prioritizing features and preferences in mobile applications. Text-mining methods were used to analyze unstructured text answers to get insights into the consumer's voice. The results of the text data analysis revealed the app's fundamental characteristics or qualities, identified associations between these qualities and established the hierarchical organization of these qualities.

Additionally, the study identified the specific subsets of features that encapsulate the distinct functionalities of the mobile app. Similarities in functional, technological and app appeal features may be identified when comparing the results of quantitative analysis using structured data analysis with text-mining analysis of unstructured data. This study identified the essential characteristics contributing to the perceived value of mobile applications among users, hence fostering prolonged use. The findings indicate that developers should prioritize enhancing mobile applications' functional, technical and esthetic aspects to enhance their attractiveness and utility for potential users. This study contributes to a comprehensive and refined comprehension of user requirements and preferences, using this knowledge to facilitate the design and development of the mobile application.

The present study exhibits certain limitations that warrant the need for additional research. The research findings are derived from 417 valid samples, predominantly consisting of Indian app users. The statistical and text-mining outputs yield more reliable and consistent results by increasing the sample size. Furthermore, our study encompassed a diverse range of app users rather than solely concentrating on a specific utility sector. Consequently, this research has the potential to be extended to a specific demographic of application users and replicated using large-scale datasets. The future study can utilize the various dimensions identified in this study. A formative model can be developed to assess the impact of app quality on user app choice, retention behavior and overall user satisfaction. This can be achieved by incorporating various mediation variables within user segments, such as intention to use or preservice.

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