Journal of Information Technology and Computing
https://jitc.sabapub.com
ISSN: 2709-5916

2023 Volume 4, Issue 2 : 39 – 52
DOI : 10.48185/jitc.v4i2.852

Online Customer Reviews and their Effect on the Download of Mobile Applications

Oyekunle Rafiat Ajibade[1,*], Yunus Danjuma[2], Balogun Naeem Atanda[1], Adedoyin Adeyinka[1]

[1]Department of Information Technology, University of Ilorin, Nigeria
[2]Department of Computer Science, Alhikmah University, Nigeria

Received: 02.10.2023 • Accepted: 06.12.2023 • Published: 30.12.2023 • Final Version: 30.12.2023

Abstract: This research investigated some characteristics of online reviews and their impact on the download of mobile applications. Data was collected from the Google Play store across five of the most popular app categories to provide answers to the research questions and test the hypotheses formulated for this study. A total of 12,169 reviews were provided on different apps under the top five categories, namely: education, business, music & audio, tools, and entertainment, during the study period. The results obtained from the OLS regression indicated that there is a statistically significant relationship between the length of reviews and the download of selected applications; the number of reviews provided for mobile applications and the number of downloads; the number of positive reviews and the number of downloads of the apps chosen; and lastly, the number of negative reviews and the number of downloads of the apps chosen. The overall results of the OLS-regression revealed that the adjusted R-squared value of the model is 0.712. This means that 71.2% of the variability of the dependent variable (app download) is explained by the variables considered in this study, an indication that the model is relevant for the study. Based on these findings, the study recommends that app developers incorporate features into their apps that will prompt users to provide reviews on online app marketplaces, as the number of reviews has a favourable impact on mobile app downloads.

Keywords: Mobile Apps, Downloads, Online Reviews, Google Play Store, Ratings

1. Introduction

Mobile applications (apps) have grown in popularity due to the increasing use of mobile devices such as smartphones, with over two million apps accessible on the Apple Store, Google Play, and Windows Phone Store (Liang et al., 2017). Users may locate, buy, and install mobile apps with only a few clicks using these application distribution systems. These platforms' expanding popularity, ease of sale and deployment, and huge communities of registered users make them mainly appealing to software developers (Pagano & Maalej, 2013). More than three-fifths of online customers check online reviews before purchasing a product, with ratings being 12 times more trustworthy than product descriptions offered by sellers (Georgiev, 2021). E-commerce has grown in popularity in recent years, and the number of customer evaluations for different products tends to expand tremendously. In the United Kingdom alone, about half of the populace (47%) has left an online review, resulting in a situation where a single product may receive hundreds of evaluations. This has several implications. From one point of view, customers are receiving more input from other buyers

* Corresponding Author: oyekunle.ra@unilorin.edu.ng

on the things that interest them and are thereby being better assisted in their purchasing decisions. Meanwhile, when the number of evaluations for a product grows, the ability to read all of them becomes increasingly limited. (Iacob et al., 2013) It's also harder to notice flaws in a product that other people have already pointed out, problems that keep coming up in all reviews of a product or group of products, and patterns across the reviews.

App stores for mobile devices are no exception. According to Khalid, Asif, and Shehzaib (2015), one of the most intriguing characteristics of the mobile app business is the attention paid to user feedback. Users can give public reviews of any app on any app distribution platform. Users can leave feedback through ratings and reviews for apps they've tried or downloaded. Users can share their thoughts and experiences regarding an app through this sort of feedback, which can either encourage or dissuade others from downloading it. Users typically share their thoughts on an app through star ratings and public free-text reviews. According to Harleen, Xiaofeng, and Swati (2014), in addition to being important to app users, public evaluations are also necessary for app developers to distinguish the significant qualities of mobile apps to meet the needs of consumers. Vasa et al. (2012) stated that reviews can be favourable or negative and can aid in the development of the mobile app market, consumer satisfaction, app quality assurance, and the identification of novel ideas. The app may get more downloads if the reviews are positive and it has a higher rating. And while unfavourable evaluations may result in lower download counts, they can assist developers in identifying and resolving bugs and other discrepancies. There is also a third type of review that is neither positive nor negative but can include new ideas, feature requests, and user requirements. Users can discuss and describe their needs in app reviews based on their real-world experience with the app. Low ratings and negative reviews can hurt the popularity of an app, which can hurt the developer's ability to make money.

The key emphasis of most studies, such as Cherelier & Mayzlin (2006) and Duan et al. (2008), has been contextual actions, like numerical ratings. Non-numerical factors such as, for example, credibility, usability, and social assistance have been relatively overlooked. Moreover, Pan and Zhang (2011) maintain that the extent of their helpfulness is still not well known despite the extensive use of online customer reviews and their excellent capability to attract customers. In light of those mentioned above, it is vital to determine the impact user reviews can have on mobile app downloads from various distribution platforms. Because a small fraction of apps accounts for a significant percentage of downloads, app downloads from online distribution platforms are not uniformly dispersed (Zhong & Michahelles, 2013; Petsas et al., 2013). Thus, why do certain apps available in the app store catch the attention of smartphone and tablet users while others fail to do so? This could be due to a variety of things, including user input. App shops, according to Khalid et al. (2015), include a review system that is made public, which allows users to share their thoughts on the applications they have used. The polarising response of 1 to 5 stars as well as user review comments can persuade download decisions. High ratings and positive comments can help an app's ranking in the app store, making it more visible and resulting in more downloads.

The effects of product ratings have been studied mostly for tangible objects. Sun (2012), for example, proposed a conceptual model in which a high average of consumer ratings suggests a superior product, whereas a significant variance in consumer ratings implies a "niche" product. The proposed model was tested using books purchased from Amazon's online shop. In contrast to the majority of traditional internet retailers, the newly formed mobile app markets have a unique offering in some ways. Khalid et al. (2015) argued that it is unclear what type of information is contained in app reviews and how an analysis of these evaluations can influence users of online distribution platforms' download decisions. Several studies have looked into how online reviews can be summarised (Hu, 2004; Jindal et al., 2010), how to extract usability and design information from online reviews (Iacob et al., 2013; Hedegaard, 2013), and how product sales have been impacted by online reviews (Bounie et al., 2008; Dellarocas, 2004; Chevalier, 2006); and customer behaviour (Bounie et al., 2008; Chevalier, 2006; Dellarocas, 2004; Jindal et al., 2010). Prior research has not addressed direct questions about the content or the influence of app reviews. This study has attempted to fill this gap by providing a superior understanding of how app review features are used, the contents of user reviews, and the impact of review characteristics such as length of review on mobile app downloads. The following hypotheses were formulated for the research:

H01: There is no significant relationship between the length of reviews and the number of downloads of the selected apps.

H02: There is no significant relationship between the number of reviews and the number of downloads of the selected apps.

H03: There is no significant relationship between the number of positive reviews and the number of downloads of the selected apps.

H04: There is no significant relationship between the number of negative reviews and the number of downloads of the selected apps.

The remaining part of this paper is organised as follows: the next section presents the conceptual and empirical literature review; this is followed by the methodology; then results and discussion; and finally, the conclusion, recommendations, and acknowledgment.

2. Literature Review

Online recommendations and user evaluations, according to Indgreen et al. (2013), have become an indispensable source of information for modern customers. It is hard for a customer to evaluate a product or service as well as the benefits and value it creates, especially in e-commerce. As a result, new buyers are more likely to rely on dependable autonomous information sources, such as users who have already used the product. Simply put, the customer trusts the opinions of other customers, professionals, or industry players who give helpful information about the product through various review and rating systems. Their experiences provide information from the user's or customer's perspective, reducing the risk and ambiguity that consumers feel. The phrase "electronic word-of-mouth" (E-WOM) refers to a variety of methods for delivering consumer feedback and ratings. E-WOM is spread through blogs, discussion forums, online opinion sites, online product reviews, online communities, and comments left by customers on web pages (Chan & Ngai, 2011; Cheung & Lee, 2012; Cheung & Thadani, 2012). It includes both verbal and numerical ways for customers to share their opinions and experiences (Zhu & Zhang, 2010; Chan & Ngai, 2011).

Mobile application development technology is advancing quickly in today's world. The quality and performance of mobile applications are the most essential variables in the mobile application market (Johnson, 2015). Users' experience plays a significant role in the success of a mobile app development project. As a result, user experience is now an essential feature of many working in the digital world (Johnson, 2015). When developing a mobile application, it is critical to take a user-centric approach because a poorly designed mobile app can result in an individual facing multiple undesirable characteristics such as numerous bugs and failures, complexity in function, and unexpected behaviour (Beniwal & Sharma, 2013). These problems tarnish the mobile app's reputation, undermine consumer loyalty and stifle the relationship between app developers and app users (Beniwal & Sharma, 2013). This is contrary to the position of Fling (2009), who claimed that a good user experience is a powerful instrument for gaining customer loyalty and increasing engagement. Besides, software that is well-designed can save a developer's time and money, as it lowers the cost of supporting various aspects of a mobile application development project, as well as other maintenance costs such as help desk and call centre assistance (Fling, 2009).

Johnson (2015) argues that an app that is properly designed is particularly effective at increasing traffic, dialogues, and transactions among various users. These factors have aided in the retention of more clients, as well as their positive feedback. By offering a good user experience, the mobile app developer can form relationships with users, which aids in the spread of positive word of mouth and increases sales of the app. This technique enhances consumer satisfaction and loyalty (Johnson, 2015). In this context, Gerber (2016) posits that multiple users are engaged and kept active by the crucial role push notifications play. It aids the developer in the transfer of information to various users about various events, locations, updates, scores, and new features. Notifications can also persuade users to open the app and use it based on their needs. When consumers download apps and forget about them, the developer can send various notifications to remind them of the app. Managing functions and the user experience can be made better by sending different notifications to get feedback (Gerber, 2016).

Cerejo (2012) found that the content available on apps impacts an individual's decision to download a mobile app. It also has an effect on an individual's perception, together with the popularity of mobile apps. Incidentally, information architecture has been identified as a critical component of mobile applications that establishes a systematic organisation of content and functionality that aids users in finding relevant information. It consists of numerous variables such as navigation, search, and data labelling, all of which play a significant role in the information search process on some mobile applications (Cerejo, 2012). For instance, the Mobile Design Pattern Gallery is a helpful tool for both primary and secondary navigation patterns primarily used for mobile devices. Most of these navigation patterns are vertical instead of horizontal, as accessible on desktop websites, and they play an essential role in attracting users to specific mobile applications (Charland & Leroux, 2011).

According to Albert and Tullis (2013), the design of an app is the most essential element of the mobile application development process, and it must be based on a specific consumer's interest and necessity. The visual appearance and interactive experience of a mobile application are related to the branding, graphic design, and layout of the mobile application. The design of a mobile app is a combination of these sub-aspects. As a result, it is crucial to maintain visual consistency with numerous other touch-points and experiences by employing distinct colours, typeface, and personality, all of which contribute to the consumers' overall experience (Albert & Tullis, 2013). It helps mobile developers manage communication with target consumers via non-verbal messages. Harris et al. (2015) claim that the most prominent concerns among smartphone users are interaction, privacy, and security of information. These factors have a significant impact on users' selections when it comes to selecting the most acceptable mobile applications to satisfy various criteria. In this context, if a mobile app gives users the ability to manage their private information that they can share in the app by asking before collecting their location data, it boosts consumers' trust in the app (Harris et al., 2015).

Consumer participation in online communities is frequently motivated by factors other than money (Chen & Huang, 2013). According to Peres et al. (2011), online WOM spreads due to social, emotional, and functional effects. The impulse to share the buying experience, whether happy or negative, is an example of an emotional drive. The factors referred to as "social" are the aspects that represent one's social position, while the "functional drive" refers to the necessity to deliver information to clients. Intriguingly, Peres et al. (2011) found that in the online context, social and functional reasons are the most important, while in the offline setting, emotional motivation is the most significant. In a comprehensive literature analysis, Hennig-Thureau et al. (2004) identified eleven consumer motives for participating in eWOM. Based on a poll of 2083 active online customers, the top eight reasons are: helping other customers; expressing bad feelings; self-improvement; assisting companies; assisting platforms; economic motivations; social benefits; and seeking assistance. Hennig-Thureau et al. (2004) found that the main reasons people use online customer ratings (OCRs) are to help other customers, improve themselves, help society, save money, and communicate with others.

Gruen et al. (2006) employed the motive, opportunity, and ability (MOA) theory to investigate eWOM antecedents, arguing that opportunity and ability are required skills in an online context. Nonetheless, their findings show that consumers' willingness and ability to engage in eWOM have a considerable impact, whereas opportunity does not. This could be because the bare minimum of opportunity is inexpensive; therefore, any rise in the level of opportunity does not affect consumer engagement in electronic word of mouth (Gruen et al., 2006). In contrast, the study by Shih et al. (2013) revealed that consumers' ability and opportunity have a substantial impact on eWOM. However, motivation had little effect on the intention of consumers to participate in eWOM communication. But ability had a bigger effect on eWOM participation than opportunity, which suggests that opportunity is less important in the online world.

Picoto et al. (2019) have identified elements that influence app rankings in the Apple App Store and suggested a model to predict ratings for various apps. The authors used a total sample of 500 Apple's top-grossing apps to analyse the topmost 50 and lowest 50 apps. Multivariate logistic regression was employed to determine the impact of factors like package size, the app release date, and category popularity on the success of an app. The results indicated that category popularity, package size, diversity (i.e., number of languages supported), and app release date are the factors that boost the probability that an app will be ranked among the top 50. Finkelstein et al. (2017) analysed the relationship between ratings, popularity, and pricing in the BlackBerry app store by extracting app descriptions, ratings, popularity, and price information using data mining and then using natural language processing (NLP) to elicit each app's claimed features from its description. Their findings revealed that consumer ratings and popularity are highly correlated. Numminen and Sällberg (2017) investigated how average rating scores, dispersion of ratings, and volume of ratings affect the download of free apps on Google Play and the Apple App Store. The regression analyses revealed that the volume of ratings has a significant positive effect; the average rating score has a positive but relatively insignificant impact; and the dispersion of ratings records a significant positive impact but is contingent on app type.

Khalid et al. (2016) investigated the association between app ratings and static analysis warnings for 10,000 free-to-download Android applications. The study’s findings suggest that app developers can identify the bugs responsible for the problems that users complain about before the release of an app using static analysis tools. According to Tian et al. (2015), the size of an app, advertising graphics, and the goal of an app are the most significant influencing components of high-rated applications. They examined 28 factors along eight dimensions to determine how high-rated apps differ from low-rated apps. The study further applied a random-forest classifier to detect high-rated apps. Hyrynsalmi et al. (2014) investigated the connection between the paid app download category and Google Play average ratings. They reasoned that user ratings are less critical in free-to-install programmes since it is quicker to try the software than to go through the review comments. The study discovered a modest negative link between the number of app downloads and the average rating of the programs, which was statistically significant. Goods with only a few reviews were included among the 52,679 applications, which may have affected the outcome. Also, because their dataset showed a situation that didn't change, it is impossible to tell if the rating had any effect on how popular an app got.

3. Methodology

The signalling theory serves as the theoretical foundation for this research. Signalling theory, according to Dunham (2011), prescribes:

1. What are the conditions under which one party, the sender, sends information to another party, the receiver?
2. What is required of the recipient for the information to be considered dependable?

Because mobile apps are experiential goods (Soon et al., 2013), one cannot determine their real quality before they are used (Kirmani & Rao, 2000). When deciding whether or not to download an app, potential customers rely on internet ratings and reviews as indicators of its quality. Consumers are the senders of online ratings; the rating is the signal delivered, and potential consumers are the receivers. The expectation of reciprocity is an advantage of rating (Munzel & Kunz, 2014). By rating and evaluating a product, the consumer anticipates other potential customers rating and reviewing similar products in the future, which may interest the first rate consumer. As a result, online ratings and reviews serve as a bond between consumers and potential consumers, ensuring that the online rating mechanism remains relevant.

The overall goal of this research is to examine the impact of online reviews on mobile app downloads. The study examined review features such as the frequency of feedback supplied, the number of reviews users provided, the number of reviews provided per user, and the number of reviews provided by users per day. The study also examined the content of user reviews, including aspects such as the length of feedback provided by users, the volume of ratings, and other content features specified by coding parameters developed for this study. A survey on the online mobile app store was carried out to select a data source, and the reasons for choosing the Google Play Store are the following: The groupings used for categorising apps are like those used by different app stores; the number of apps in each category and the number of reviews per app match favourably with those in other app stores, implying that there is a possibility of further generalisations across app stores.

According to AppBrain (2021), the five top popular categories with the most significant number of apps are education, business, music & audio, tools, and entertainment. This threshold was the basis on which the relevant statistical tests were carried out. For each randomly selected app, a modern visual web data extraction software for crawling and scraping, Octoparse, was used at a specified date to collect data relating to feedback frequency, number of reviews, the number of reviews per day, length of review, as well as the contents of the review. Additional information collected is the aggregate number of ratings assigned to an app. For each review, the posting period was automatically collected, the rating given by the user, and the title, as well as the text of the actual review. The four independent variables included in the model adopted for this study are the length of review, number of reviews, positive reviews, and negative reviews. Thus, the ordinary least square (OLS) regression equation used in this study is as shown in equation 1:

$$\mathit{Downloads} = b1 + b2 + b3 + b4 \qquad (1)$$

Where,

Downloads = amount of times an application was downloaded,

b1 = Length of review,

b2 = Number of reviews,

b3 = Number of positive reviews, and

b4 = Number of negative reviews

4. Results and Discussion

The data collected contained 12,169 reviews made by 9,334 different reviewers, which is an average of 1.30 reviews for each reviewer. A breakdown of the feedback provided per app category is presented in Figure 1.

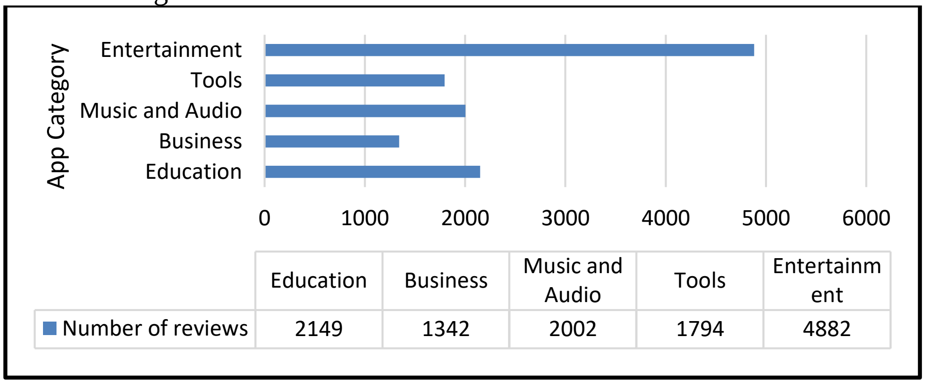

Figure 1. Number of Reviews per App Category

In line with the findings of Pagano and Maalej (2013), a direct explanation of this result is that popular categories with large user communities, like the entertainment category, enjoy more excellent feedback, while others, referred to as the niche categories, enjoy much less. This could be a result of the fact that apps in categories such as business and education typically offer information-rendering services, while those in the entertainment category present relatively complex feature sets and, as a result, generate or stimulate more feedback. It can therefore be said that apps in the entertainment category encourage the participation of users who have the tendency to spend more time on the app, thereby developing a relationship with it. This kind of relationship usually makes it more likely for users to give feedback while using and interacting with the mobile app.

Data collected as presented in Figure 2 indicates that across all app categories considered in this study, 3,128 (25.7%) of the reviews were anonymous. In contrast, the rest were done with named usernames, even though it is doubtful if these names truly identify the users. Generally, the reviews per user appear to follow a power-law distribution, as 11,746 (96.6%) of the reviewers have written only one review. In comparison, 423 (3.4%) account for more than five reviews. This shows that only a small number of users are always writing reviews and giving feedback.

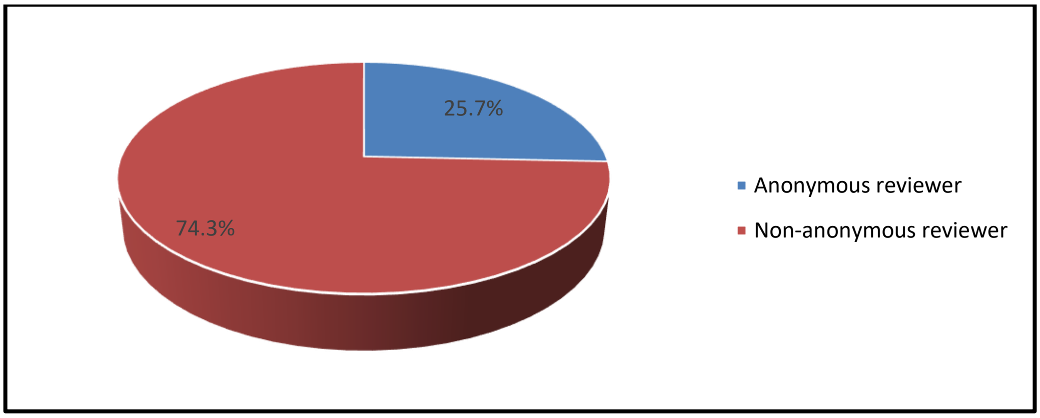

Figure 2. Anonymous and Non-anonymous Reviewers

This study also collected data on the feedback behaviour of users over time. The findings presented in Figure 3 show that across all app categories, a total of 5110 reviews were supplied within the first 50 days the app was released. Also, about 3846 reviews were provided between 51-100 days after the release of an app, while a total of 3213 reviews were provided after about 100 days and above. According to Pagano and Maalej (2013), most feedback is provided by users in the first few days after the release of an app, leading to a long tail over time. This suggests that new releases trigger feedback from users.

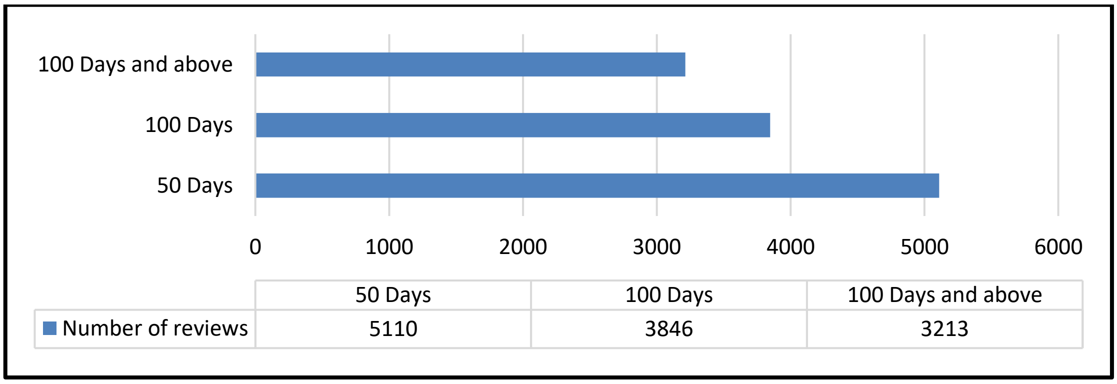

Figure 3. Number of days after the First Release the Reviews were supplied

Measured against the following parameters as adopted by Pagano and Maalej (2013): a tweet message (140 characters), SMS (160 characters), and one-third of a printed page (675 characters), data collected indicated that 5,120 (42.0%) of the feedback was less than 140 characters, while 7,329 (60.2%) was less than 160 characters. Also, a total of 11,114 (91.3%) of the total feedback provided was less than 675 characters. Therefore, it can be concluded that app feedback typically consists of short messages, more similar to a tweet than to other communication artefacts such as email. From the perspective of the application vendor, a possible understanding of this result is that a great number of the messages – although not all – are irrelevant, inspiring a systematic means to sieve useless feedback. From the user's perspective, this result shows that users do not take their time while giving feedback. Besides, it is a well-known fact that mobile users also use multimedia together with text to communicate complex content (Schneider et al., 2010).

Due to the vastness of data relating to the content of user reviews, ten reviews were randomly selected from each of the five selected app categories. An independent researcher coded the random samples of user reviews to find topics contained within them. The assignment of multiple topics was allowed as most feedback included more than a single topic. As presented in Table 1, the most popular word is "praise", taken to be any form of appreciation or praise for the app. This word is predominant in over 61.2 % of the samples analyzed. Also, a total of 31.4% of the feedback indicated helpfulness, which indicates that the app downloaded has been helpful to the user. Data collected further revealed that 16.9% of feedback was used to express shortcomings related to the use of the app, which is taken to be an indication that users were not happy with the application. Also, a total of 22.0% of the feedback provided contained the topic "other app." In this case, users made references or comparisons to other apps. The "content request" was provided by 17.3% of the users, as shown in cases where users have asked for particular content or features to be built-into the application. The topic "dispraise" appeared in the feedback provided by 22.8% of the users. This indicates that the user has criticised certain features or aspects of the mobile app. Meanwhile, Chen et al. (2022) noted in their study that online merchants should be attentive to negative comments by resolving them as soon as possible through careful analysis. In addition, 3.4% of the feedback fell under "noise," which means that reviews provided contained information without any form of meaning, while 33.9% of the feedback analysed focused on the topic "question." Here, users enquired about the use of the respective application downloaded. Bug reports accounted for 16.2% of the feedback provided, which means that users reported a bug in the app or a crash, as the case may be. Finally, 11.7% of the feedback received was classified as "recommendation," implying that users offered suggestions on how developers could improve the app to better meet their needs.

Table 1. Topics in Users Feedback

Topic	Description	Frequency
Praise	Expression of appreciation	61.2%
Helpfulness	App has been useful to the user	31.4%
Shortcoming	User is not happy with the application	16.9%
Other apps	The user has made references or comparisons to other apps	22.0%
Content request	The user has asked for a particular content to be built-in	17.3%
Dispraise	The user has criticized certain aspects or features of the app	22.8%
Noise	The review contains information without meaning	3.4%
Question	Making inquiry into the use of an app	33.9%
Bug report	The user has reported a bug or a crash	16.2%
Recommendation	Making recommendation on how to improve the app	11.7%

Based on the hypotheses formulated and advanced in this study, the method used in determining the impact of user review characteristics on the download of mobile applications is ordinary least square regression. The length of review, number of reviews, positive reviews, and negative reviews are the four variables used in this study. Tests carried out on STATA 15 to ensure that the data collected fits the basic assumption of the classical linear regression model include normality, multicollinearity, and heteroscedasticity tests. The results are presented below.

4.1. Normality Test

This test checks for the normal distribution of the error term. The null hypothesis is that the error term is normally distributed, while the alternative hypothesis states that the null hypothesis is not valid. If the p-value is statistically significant at 0.05, there is no normality. Table 2 presents the summary of the Jarque Bera test. The estimated value of the Jarque-Bera statistic is 0.509229, and the corresponding probability value is 0.534128, which is greater than 0.05, indicating that the null hypothesis of a normal distribution is not rejected. Hence, the error term is normally distributed.

Table 2. Summary of Jarque-Bera Normality Test

Jarque-Berra	1.254238
Probability	0.534128

4.2. A Test for Serial Correlation

The H0 states that there is no serial correlation, whereas the alternative states that the null is not true. Table 3 presents the results for the Breusch-Godfrey test of serial correlation. Based on these results, the p-value of the F-statistics and the p-value of Chi-Square are greater than 0.05. This indicates that the H0 of no serial correlation is accepted. Hence, the variables explicitly captured in the estimated regression model are not serially correlated.

Table 3. Summary of Breusch Godfrey LM Test

F-Statistics	0.244406	Prob. F-Statistics	0.3486
Ob*R-squared	2.439247	Prob. Chi-Square	0.1147

4.3. Heteroscedasticity Test

The supposition of homoscedasticity is vital to linear regression models. It describes a condition in which the error term is similar across all values of the independent variables. The null hypothesis states that there is no heteroscedasticity, whereas the alternative states that the null is not valid. Table 4 presents the results of the Breusch-Pagan-Godfrey test for heteroscedasticity. The p-values corresponding to both the F-statistic and the Chi-Square statistic are more than 0.05. This indicates that the H0 of no heteroscedasticity is accepted. Therefore, there is no heteroscedasticity in the model.

Table 4. The Breusch-Pagan-Godfrey Test for Heteroscedasticity

F-Statistics	2.185267	Prob. F- Statistic	0.0744
Ob*R-squared	22.13640	Prob. Chi-Square	0.1388

4.4. Regression Analysis

The overall results of the OLS regression for the equation used to test the four hypotheses based on the total sample used in this study are shown in Table 5. The adjusted R-squared value of the model is 0.712, which means that 71.2% of the variability of the dependent variable (app download) is explained by the variables considered in this study, while the other 28.8% of the variance in the dependent variable is explained by other variables not considered in this study. In addition, the value obtained for the F-statistic is 12.162, implying that it is significant and indicating that this model is relevant for the study.

Table 5. Regression Analysis

Variables	Unstandardized co-efficient		Standardized co-efficient		
	B	Std. Error	Beta	T	Sig.
L_OR	.124	.018	.823	6.830	.000
N_OR	.116	.019	.792	2.161	.003
N_PR	.162	.041	.776	1.103	.002
N_NR	-.022	0.74	-.039	-.301	.000

R-Squared	**0.771**
Adjusted R-Squared	**0.712**
F-Statistics	**12.612**
Prob (F-Statistics)	**0.000**

The results obtained from the OLS regression in Table 5 further indicated that the length of reviews of mobile apps is statistically significant; thus, there is a relationship between the length of reviews and the download of selected applications with a *p-value* of 0.000 ($p<0.05$). Hence, the H0 was rejected. With regards to the relationship between the number of reviews and the number of downloads of the selected apps, a *p*-value of 0.003 ($p<0.05$) was obtained, indicating a statistically significant relationship. Therefore, the null hypothesis was rejected. Also, the third and fourth null hypotheses were rejected with a *p-value* of 0.002 ($p<0.05$) and 0.000 ($p<0.05$) respectively. This shows that the number of positive and negative reviews has a positive and negative effect on the download of mobile applications, respectively.

5. Conclusion and Recommendations

For 21st-century software firms, customer feedback and participation are a necessity. App distribution platforms and stores are more and more being used by users to review and score apps.

This study has revealed that the length of reviews, number of reviews, number of positive reviews, and number of negative reviews affect the rate at which the selected apps are downloaded. Although some of this feedback may not be sincere, the fact that most of the reviews are not posted anonymously gives some credibility to the content of user reviews; other kinds of input consist of helpful comments, issue reports, user experience, and feature requests. This can assist developers in comprehending user demands and extending the service in a "democratic" manner to crowd-sourced requests. Current platforms, conversely, are yet to allow developers to systematically aggregate, filter, and categorise user feedback to extract what they require in prioritising development efforts.

Based on the outcomes of this study, it is recommended that app developers implement appropriate mechanisms to encourage users to offer detailed and meaningful feedback, which can be reassuring to potential app users and lead to a rise in the number of mobile app downloads. Software vendors should look at ways to reduce the time it takes to submit feedback, such as encouraging users to share their experiences ahead of time and offering textual descriptions, as the number of reviews has a beneficial impact on mobile app downloads. App developers should incorporate features into their apps that prompt users to provide reviews on online app marketplaces. Bidirectional communication options such as replying to or referring postings are currently unavailable in app stores. This stops app developers from contacting specific users to seek clarification or to let them know that their issue has been resolved. Because most users provide comments soon after a new release, one strategy to improve communication is to link new features and changes to user feedback that impacted or led to them. Users would be more engaged, and the rationale for the change would be better understood.

Acknowledgment

This research didn't get a specific grant from a government, business, or not-for-profit organization.

Conflicts of Interest

We declare that there is no conflicts of interest attached with this manuscript.

References

[1] Albert, W. & Tullis, T. (2013). Measuring the user experience: collecting, analyzing, and presenting usability metrics. Elsevier Inc.

[2] AppBrain (2021, October 15). *Most popular Google Play categories*. https://www.appbrain.com/stats/android-market-app-categories

[3] Beniwal, K. & Sharma, A. (2013). Explosive growth of Mobile Technology and its Potential Impact on Youth & Education. *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, 2(4), 12-15. http://www.ijaiem.org/Volume2Issue4/IJAIEM-2013-04-02-001.pdf.

[4] Bounie, D., Bourreau, M., Gensollen, M. & Waelbroeck, P. (February, 2008) Do Online Customer Reviews Matter? Evidence from the Video Game Industry. (Working Paper No.ESS-08-02). http://dx.doi.org/10.2139/ssrn.1091449

[5] Cerejo, L. (2012, July 12). *The Element of Mobile User experience*. Nmagazine. https://www.smashingmagazine.com/2012/07/elements-mobile-user-experience/

[6] Chan, Y.Y. & Ngai, E. (2011). Conceptualizing electronic word of mouth activity: An input-process-output perspective, Marketing Intelligence and Planning, 29(5), 488-516. https://doi.org/10.1108/02634501111153692

[7] Charland, A. & Leroux, B. (2011). Mobile application development: web vs. native. *Communications of the ACM*. 54(5), 49-53. https://doi.org/10.1145/1966989.1968203

[8] Chen, T., Samaranayake, P., Cen, X., Qi, M. and Lan, Y. C. (2022). The Impact of Online Reviews on Consumers' Purchasing Decisions: Evidence from an Eye-Tracking Study. Front Psychology, 13, 865702. http://doi.org/10.3389/fpsyg.2022.865702

[9] Chen, H. & Huang, C. (2013). An investigation into online reviewers' behavior. *European Journal of Marketing, 47*(10), 10-10. https://doi.org/10.1108/EJM-11-2011-0625

[10] Cheung, C. M. & Lee, M. K. (2012). What drives consumers to spread electronic word-of-mouth on online consumer opinion platform? Decision Support Systems, 53(1), 218-225. https://doi.org/10.1016/j.dss.2012.01.015

[11] Cheung, C. M. & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461-470. https://doi.org/10.1016/j.dss.2012.06.008

[12] Chevalier, J.A. & Mayzlin, D (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research,* 43(3), 345-354. https://doi.org/10.1509/jmkr.43.3.345

[13] Dellarocas, C. (2004). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. Management Science, 49(10), 1407-1424. https://doi.org/10.1287/mnsc.49.10.1407.17308

[14] Duan, W., Gu, B. & Whinston, A. (2008). Do Online Reviews Matter? – An Empirical Investigation of Panel Data. Decision Support Systems. 45, 1007-1016. https://doi.org/10.1016/j.dss.2008.04.001

[15] Dunham, B. (2011). The Role for Signalling Theory and Receiver Psychology in Marketing. In: Gad S. (ed.), Evolutionary Psychology in the Business Sciences, (pp 225-256). Springer.

[16] Finkelstein, A., Harman, M., Jia, Y., Martin, W., Sarro, F. & Zhang Y (2017). Investigating the relationship between price, rating, and popularity in the Blackberry World App Store. Information and Software Technology, 87, 119–139. https://doi.org/10.1016/j.infsof.2017.03.002

[17] Fling, B. (2009). Mobile Design and Development: Practical concepts and techniques for creating mobile sites and web apps. O'Reilly.

[18] Georgiev, D. (October, 2021). Latest Online Reviews Statistics in 2020 – The Impact on Business. https://review42.com/resources/online-reviews-statistics/

[19] Gruen, T., Osmonbekov, T. & Czaplewski, A. (2006). eWOM: The impact of Customer-to-Customer Online Know-how Exchange on Customer Value and Loyalty. *Journal of Business Research*. 59, 449-456. https://doi.org/10.1016/j.jbusres.2005.10.004

[20] Harleen K.F., Xiaofeng W. & Chande, S.V. (2014). An Investigation on the Characteristics of Mobile Applications: A Survey Study. International Journal of Information Technology and Computer, 6(10), 21-27. http://doi.org/10.5815/ijitcs.2014.11.03

[21] Harris, M. A., Chin, A. G. & Brookshire, R. (2015). Mobile app installation: the role of precautions and desensitization. Journal of International Technology and Information Management, 24(4), 47–62.

[22] Hedegaard, S. & Simonsen, J.G. (2013). Extracting usability and user experience information from online user reviews. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '13) (pp 2089-2098). ACM.

[23] Hyrynsalmi, S., Suominen, A., Mäkilä, V. & Knuutila, T. (2014). The Emerging Application Ecosystems: An Introductory Analysis of Android Ecosystem. International Journal of e-Business Research, 10(2), 61-81. http://doi.org/10.4018/ijebr.2014040104

[24] Iacob, C. & R. Harrison (2013). Retrieving and analyzing mobile apps feature requests from online reviews. 0th Working Conference on Mining Software Repositories (MSR) 2013. IEEE. (pp. 41-44). http://doi.org/10.1109/MSR.2013.6624001

[25] Jindal, N., Liu, B. & Lim, E. (2010). Finding unusual review patterns using unexpected rules. In *Proceedings of the 19th ACM Conference on Information and Knowledge Management 2010 (pp.* 1549-1552). ACM. http://doi.org/10.1145/1871437.1871669

[26] Johnson, K. (April, 2015). *The Importance of User Experience for Mobile Apps*. http://www.business2community.com/mobile-apps/importance-userexperience-mobile-apps-01321326#7Dsjbu9rXoxDmhRz.97

[27] Khalid, H., Nagappan, M. & Hassan, A.E. (2016). Examining the Relationship between FindBugs Warnings and App Ratings. IEEE Softw 33, 34–39. http://doi.org/10.1109/MS.2015.29

[28] Khalid, M., Asif, M., & Shehzaib, U. (2015). Towards Improving the Quality of Mobile App Reviews. I.J. Information Technology and Computer Science, *10, 35-41*. http://doi.org/10.5815/ijitcs.2015.10.05

[29] Liang, T., Chen, L., Ying, X., Yu, P.S., Wu, J. & Zheng, Z. (2017). Mobile Application Rating Prediction via Feature-Oriented Matrix Factorization, In 2017 IEEE International Conference on Web Services (ICWS). (pp. 261–268). http://doi.org/10.1109/ICWS.2017.41

[30] Pagano, D. & Maalej, W. (2013). User feedback in the App store: An empirical study. In 21st International Conference on Requirements Engineering, 2013 (pp. 125-134). IEEE. http://doi.org/10.1109/RE.2013.6636712

[31] Pan, Y. & Zhang, J. Q. (2011). Born unequal: a study of the helpfulness of user-generated product reviews, *Journal of Retailing,* 87(4), 598-612. https://doi.org/10.1016/j.jretai.2011.05.002

[32] Peres, R. Shachar, R. & Lovett, M. (2011). On Brands and Word-of-Mouth. *Journal of Marketing Research*, 50(4), 427-444. https://doi.org/10.1509/jmr.11.0458

[33] Petsas, T., Papadogiannakis, A., Polychronakis, M., Markatos, E. P. & Karagiannis, T. (2013). Rise of the planet of the apps: A systematic study of the mobile app ecosystem. In *Proceedings of the 2013 Conference on Internet Measurement* (pp. 277–290). ACM. http://doi.org/10.1145/2504730.2504749

[34] Picoto, W. N., Duarte, R. & Pinto, I. (2019). Uncovering top-ranking factors for mobile apps through a multimethod approach. Journal of Business Research, 101, 668–674. http://doi.org/10.1016/j.jbusres.2019.01.038

[35] Numminen, E. & Sällberg, H. (2017). The impact of online ratings on downloads of free mobile apps. Proceedings of the *11th European Conference on Information Systems Management*. (pp. 225 – 232). Genoa.

[36] Schneider, K., Meyer, S., Peters, M., Schliephacke, F., Mörschbach, J. & Aguirre, L. (2010). Feedback in Context: Supporting the Evolution of IT-Ecosystems. In M. Ali Babar, M. Vierimaa, M. Oivo (eds), *Product-Focused Software Process Improvement. PROFES 2010*. Lecture Notes in Computer Science, Vol 6156. Springer. http://doi.org/10.1007/978-3-642-13792-1_16

[37] Sun, M. (2012). How does the variance of product ratings matter? Management Science, 58(4), 696-707. http://doi.org/10.1287/mnsc.1110.1458

[38] Tian, Y, Nagappan, M, Lo, D. & Hassan, A.E. (2015). What are the characteristics of high-rated apps? A case study on free Android Applications, In 2015 IEEE International Conference on Software Maintenance and Evolution (ICSME), (pp 301–310). http://doi.org/10.1109/ICSM.2015.7332476

[39] Vasa, R., Hoon, L., Mouzakis, K. & Noguchi, A. (2012). A preliminary analysis of mobile app user reviews. In *Proceedings of the 24th Australian Computer-Human Interaction Conference*, ser. OzCHI '12. ACM. http://doi.org/10.1145/2414536.2414577

[40] Zhong, N, & Michahelles, F. (2013). Google Play is Not a Long Tail Market: An Empirical Analysis of App Adoption on the Google Play App Market. In Proceedings of the 28th Annual ACM Symposium on Applied Computing, SAC '13. (pp. 499–504). ACM. http://doi.org/10.1145/2480362.2480460

[41] Zhu, F. & Zhang, X.M. (2010). The impact of online consumer reviews on sales: The moderating role of product and consumer characteristics, Journal of Marketing, 74(2), 133-148. https://doi.org/10.1509/jm.74.2.133