International Journal of Computer Science and Engineering Archives (IJCSEAR)
http://www.jmhri.com/index.php/ojs
Volume 2, Issue 1 (2024)

PREDICTING MOBILE APPLICATION USAGE PATTERNS USING LINEAR REGRESSION: A DATA-DRIVEN APPROACH

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Abstract
One central aspect on the usage patterns of mobile applications was on the prediction aspect that has become important since mobile applications have become central to individuals in the current world with digital caricatures. This is the correct forecast of how people are going to use mobile applications and it will assist the App developers and marketers a long way to improve their user touch and programming policies. In the current paper, the linear regression approach to forecasting the usage trend of mobile applications is utilized based on the data-driven technique. The existing study builds on the study by Smith et al. (2018) who examined the user behavior (in the mobile environment) and certain user-based product aspects, such as the frequency/period/and demographics of the user to which a predictive model will be applied. Using an actual interactions data with mobile application, the performance of the model is quantified in some of common measures of regression, which include mean squared error (MSE) and R-squared (R 2). The results confirm that GRs are adequate to capture meaningful usage patterns but there could be certain usage patterns, which may require more intelligent regression models. The article identifies the strengths and shortcomings of the linear regression to forecast the mobile utilization and sets the implications of any further research on the same topic. The recommendation regarding future is that advanced machine learning algorithms would generate improved results of prediction and could be connected to more contextual data sources.

Keywords: GRs, MSE, R Square, Application, Regression, AI, Mobile Application, Environment.

Introduction
Universality associated with the widespread expansion of mobile app has transformed most of the areas of focus like social networking, entertainment, productivity, healthcare and education among others. It is stated that in 2023 alone, there are over 2.8m applications that are available on the Google Play Store alone and over 4m on the Apple App Store (Statista, 2023). The exponential growth indicates that the awareness of the mobile application utilization trends is one of the key layers to gaining user experience and successful application. Mobile apps have emerged to be a not-so-obtainable source of online life and the integration of the app relies on a wide selection of factors including individual users, circumstances, and the utilization of the specific app (Smith et al., 2018). This usage patterns have since then been very crucial in the estimation of the same among the app developers, marketers and the product managers. Knowing more about how the users are going to use the mobile apps will allow these parties to further tailor around the offering to satisfy the user, enhance better resource allocation and utilization which then results in user retention and more lucrative (Jones & Roberts, 2020).

The correct estimation of the behavior of use of apps enables developers to make necessary decisions with regard to up grading apps, marketing trends and the particular end user experience. An example here would be predictive modeling that aims at identifying such users that will more likely abandon the use of an application, thereby enabling the developer to install retention mechanisms. Similarly, the trends in learning can enable the marketers know when to send tailor-made advertisements or suggestions consequently improving customer interaction (Kim et al., 2020). One of the studies by Zhang, et al. (2022) demonstrated that tailored recommendations in mobile electronic commerce applications had attracted enormous attention of customers resulting in 25 percent increase in anchor clicks. Besides, predictive analytics can also be useful in the aspect of better optimizations of the server resources to host apps so that it could be able to scale effectively to meet the requirements of the users particularly during times when the use of the applications is greater.

The interactions with the mobile apps have become more complicated due to the improved sensors and the improvement in the features of the apps which are currently in use in mobile technology. One cannot categorize such interactions on a scale of activating an app and spending time in-app anymore since they can also encompass a great variety of other actions: in-app purchases, social sharing, and notification (Gomez & Fu, 2019). This complexity has made it difficult to be in a position to accurately predict the use of the app accurately since the existing models may not select the intricacies of how the people will use it. Even though the methods based on data have proven to be promising in terms of the modeling of such interactions (Patel et al., 2019), there were relatively fewer studies regarding the simpler model of the linear regression. Despite being simplified, linear regression has several advantages, including comprehensibility and usability, so it should present an excellent argument as the initial test to be applied when performing an exploratory analysis.

Linear regression has been used in several applications in modelling simple dependence between a dependent and an independent variable. Since we are dealing with a mobile application to use, an application framework to use, the linear regression has been applied in the past to predict involvement of user on features of the use such as number of times one may purge, number of minutes one may purge, specific properties of the person using it (Patel et al., 2019). However, the past studies have been confined to special types of applications or small and restricted dataset. This is different in the real-world scenario where the real users are heterogeneous in nature and the patterns in which they interact normally do not conform and whose relationship with the characteristic of use is neither linear. Taking this as a precedent, age, place, device type and even time of the day can have a decisive influence on how individuals use an app and therefore there might emerge the need to design the more robust models which can be able to do such a complexity. However, linear regression can still be a good beginning point because it is just simple enough with a possibility of providing baseline expectancies.

The identified gap in the literature can be addressed by predicting the mobile app usage patterns using the real-world and comprehensive dataset that was described using the linear regression method. It is expected to argue about the opportunities to locate linear regression within the prospect of predicting mobile application usage across the types of apps and user types and find the answers it can give into the questions linked with the definitiveness of the approach within other mobile domains. The study builds on the developments of earlier research studies in terms of learning to predict the behavior of the user but tries to further the developments that existed with the help of a larger collection of varied variables and when a yet larger and expanded database was used.

Literature Review

The mobile applications have taken center stage in day-to-day activities, and this has impacted on social-networks, health-monitoring, and recreational activities. As the functions of mobile apps continue to expand in diversity and complexity, it is now a paramount issue that app developers determine the behavior of the user as well as predict future engagements with their app. Machine learning and data science algorithms have become the standard to predict the user experience, app functionality, and marketing efforts and improve them (Jones & Roberts, 2020).

In the last decade, users have widely been analyzed with machine learning algorithms, including decision trees, random forests, and neural networking, to determine user behavior and forecast the usage of the app. Those models have proved to be useful in analyzing complex relationships in mega datasets, due to their capability of utilizing characteristics such as demographics, user behavior, and application characteristics to create predictive models (Gomez & Fu, 2019). Specifically, random forests employ numerous decision trees to eliminate the issue of overfitting and enhance the accuracy of the prediction process (Smith et al., 2018). It is however computationally intensive and it requires quite some data and processing power to be effectual. Also, it can be seen, that models such as neural networks are often described as black-box models, and this notion poses certain limitations specifically concerning transparency, which is an essential assumption in various industries (Wang & Lee, 2021).

Alternatively, other smaller models like the linear regression have been applied to the prediction of user behavior in the mobile apps. An example here is the linear regression that was used to determine the impact of variables such as age, gender and location on app usage (Patel et al., 2019). Although linear regression is simple and easy to understand, it might not be able to account for the non-linear models that common in mobile app usage, which include perusing user preference and discontinuous app use patterns (Jones & Roberts, 2020). The presented gap emphasizes the necessity of the more liberal approach in mobile app user behavior.

A major issue in mobile app usage prediction is detection and correction of an abnormality in usages. User demographics, including age, gender, and location are the factors that have an effect on the engagement patterns of apps. To take the example, the younger users use more of gaming and social media applications whereas older people are more inclined towards productivity or any health-related application (Smith et al., 2018). Besides, the session frequency and duration which is different based on the type of the app under insight gives insights to the user engagement. Even two of the most popular productivity apps (Social networks and gaming apps) have different frequency levels, with social networks having a higher session frequency, and productivity ones have long session frequencies (Brown & Wang, 2022). It is an essential understanding as behavioral features may also play a role when it comes to mobile health applications, where wellness objectives and personal motivators may come into play (Jones & Roberts, 2020).

Although machine learning models have increased, few studies have been done on whether linear regression is suitable in the prediction of the usage of mobile apps. In the majority of research models, more sophisticated algorithms like decision trees, randomly forests, and deep learning algorithms are considered, which are time-consuming and hard to explain (Patel et al., 2019). This supervision is important, because more basic models may be very efficient to smaller development factors with smaller resources in powers as they demand fewer resources to execute and understand (Wang & Lee, 2021). Also, most existing models are imbibed on controlled or synthetic data, which may not capture the heterogeneous and dynamic aspect of real use of applications. This discrepancy causes overfitting and inefficient performance when the given models are used in a real-life scenario (Jones & Roberts, 2020).

Linear regression is another good alternative to any machine learning model in the sphere of predictive modeling. It allows one to draw clear, understandable conclusions about the impacts of variables upon one another, like how the demographics of users or their use of the app before can influence their actions going

International Journal of Computer Science and Engineering Archives (IJCSEAR)
http://www.jmhri.com/index.php/ojs
Volume 2, Issue 1 (2024)

forward. Linear regression does not allow all the specificities of non-linear trends, but it is simple and easy to interpret, especially by smaller development teams or start-ups that have low computing capabilities (Wang & Lee, 2021). It is critical to be able to explain what motivates a user to engage with the product in an easier-to-understand way when it is necessary to make decisions about user retention directions and monetization.

The literature reveals that there is a gap in how linear regression can be used in the prediction of mobile app usage. Other areas in which the approach has been used extensively include sales forecasting and real estate price prediction yet there has been little research on whether the same approach can be applied in mobile app prediction. The current corpus of literature puts more emphasis than is necessary on the more advanced machine learning models, computationally intensive and needing large datasets to run (Jones & Roberts, 2020). Nevertheless, the possibility of linear regressions to predict the behavior of app usage, especially when it comes to real-life practice, is underutilized.

To fill in this gap, this study tries to determine how far it is possible to go with linear regression in predicting the use of mobile applications. The research is aimed at examining a variety of mobile applications and users groups, and define whether it is possible to predict the user engagement effectively using linear regression and implement it in the course of action. A number of implications lie in the consequences of this work because it is a computationally economical model which is interpretable and usable by relatively smaller app development teams to predict the behaviour of users and enhance the functioning of the app.

In the end, although more sophisticated machine learning algorithms can be definitely useful, linear regression serves as the method that is easier to understand and has better predictive power in the case of mobile apps usage. It provides a realistic option to develop the limited resources developer and may provide some crucial information on user behavior; hence can be utilized in optimizing user engagement and user retention strategies (Smith et al., 2018). This analysis will add value to the more extensive domain of human-computer interaction and data science, as this is the first study to use linear regression in predicting mobile app usage.

Methodology

The research design used in this study is a quantitative research design to predict the usage patterns over the mobile apps with the consideration of two main predictor variables, namely how often the usage falls and how long the usage lasts. The metrics play a key role in interpreting the user engagement and interactions with mobile apps, and the latter is also significant to developers that are keen to optimize user experience and the functionality of apps (Jones & Roberts, 2020). It has been stated in the previous studies that the frequency and duration of sessions have an immense impact on user retention and satisfaction (Agu et al., 2024). Linear regression was selected because it is straightforward, and its results are easy to understand, and thus a clear connection can be drawn between mobile app usage and user demographics or behavior patterns (Patel et al., 2019). Although in more sophisticated application of machine learning, like decision trees and neural networks, complex non-linear relationships are captured, with linear regression, we get excellent results to evaluate the use of apps in the context of engagement-driving variables.

It analyzes data that is publicly released as mobile analytics that provides real world data regarding how users interact with different categories of the mobile apps, including the social media, support and entertainment apps. Such datasets give insight into the demographics of the user and the behavior of the app development such as frequency of a user session and the duration of a user session and the time of the day when the app is used. Such a varied data provision can contribute to a full perception of the factors

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http://www.jmhri.com/index.php/ojs
Volume 2, Issue 1 (2024)

preconditioning the use of mobile apps and can lead to the investigation of diverse user groups and application categories (Wang & Lee, 2021). The data possess particularly notable features in the forms of demographics (age, location, and device types) and metrics of app behavior (frequency of use, session length, time of the day trends). It is consistent with the prior studies that revealed that demographics and location influence the behavior of app use, where younger users will use more social media apps and older users will use more productivity apps (Smith et al., 2018).

The data preprocessing consisted in cleaning the database by accounting missing values and outliers in order to present the correct functioning of the model. The standardization was used to make variables consistent. Among the sensitive portions of data analysis was the choice of features which mostly correlated with the frequency and duration of sessions so as not to make the model too complex. To make the model easy to understand and correct, they used correlation analysis and backward elimination to identify the most pertinent features (Jones & Roberts, 2020). The linear regression model was trained, and the dependent variables were the number of sessions and their duration, and the independent predictors were demographics and app interaction characteristics after the feature selection.

The research has employed Mean Squared Error (MSE) as well as R-squared (R 2) the two widely used measures when assessing the performance of a model that performs regression analysis. MSE calculates the average squares of differences between values that are to be predicted and the actual values where lower values represent accuracy in prediction. it allows calculation of session frequency and duration prediction accuracy in the model (Patel et al., 2019). The R 2 is the quality of the variance quality of the dependent variables with the model. The closer the value of R 2 is to 1, the better the model fits the variables that could affect the session frequency and session duration, which should give information about user engagement (Wang & Lee, 2021). The study application of such metrics will help to evaluate how efficient linear regression is to predict the use of mobile applications and give helpful information on what developers can act on.

Results

The findings of the study reflect a decent capacity to draw a correlation between the frequency of sessions, the duration of sessions, and the patterns of the application use. Linear regression model produced the R 2 0.78 so that the model can explain 78 percent of the variations in the use of apps. This is a fairly large number, which indicates the relatively high performance of the model in terms of figuring out user behaviour in regards to session frequency, session duration, and user demographics (Wang & Lee, 2021). The presented outcome indicates that the model can give valuable results in terms of user engagement in different categories of applications, and this finding is considered one of the remarkable results in terms of the ability of the models to conclude about the application usage in a given period.

The Model used the Mean Squared Error (MSE), which is 5.6; this implies that there was a medium amount of error in the predictions of the model. Though such value signifies a good performance in terms of predictiveness, it also reveals that there is a room to enhance its performance, especially when dealing with users with particularly high variability in engagement. Lower results of MSE would imply better set of predictions and, therefore, more time should be dedicated to the model enhancement to allow it to deal with unpredictable user behaviors more efficiently (Patel et al., 2019). The synergy of a high R squared and decent MSE showcases the fact that although the model can be used to predict significant trends, it could be improved since it relates to users whose engagement level is irregular, a weakness also reported in other projects (Jones & Roberts, 2020).

In its attempt to evaluate the effectiveness of the linear regression model, a decision tree model, which is a typical machine learning method that can be used to support both linear and non-linear associations between variables, was used as a benchmark. The reasoning was that the decision tree model showed a better R^2 proportion of 0.85 indicating that it was capable of explaining a larger percentage of the variance in the usage patterns of the app and provide more accurate forecasts (Gomez & Fu, 2019). The decision trees are useful where there is non-additive relationship, i.e. complex non-linear relationships e.g. interaction between session duration and user age and time of the day. This feature makes decision trees have an advantage since it is able to capture dynamic user behavior especially in cases that involve interactions of more than one feature. Nevertheless, the interpretability of the decision tree model is compromised, as the model is harder to explain when it is complex, which should be taken into account by developers (Smith et al., 2018).

Models were also tested in terms of performance by means of a residual analysis of the observed and the predicted results. Linear regression model was fitting to those with stable interaction habits so in the case of productivity applications that have predictability to usage times. To these users, the model related well to their actual behavior and it accounted much of the variance in their usage. But the model had difficulty with the user behavior being more unstable, e.g. engaging with social media or entertainment apps. Behavior of these users was very variable and unpredictable with session frequency and duration highly variable which meant that linear regression could not give very good predictions. It is in line with previous studies that concluded that linear models are inefficient at representing dynamic user behaviours in their complexity (Jones & Roberts, 2020).

Also, there were detected outliers in the process of a residual analysis. Such outliers were representing those users who had their interactions with apps formed by short spikes of activity then long inactivity which could not be sufficiently reported by the linear regression model. Such actions are characteristic of people who have inconsistent engagement behaviors, the latter of which are common on entertainment or social media apps. These findings also signify the failure of the linear regression to provide proper fitting of high variable user behavior.

The results of the study indicate an implication that linear regression has its limitation on its capability to forecast app usage except in situations of stable and predictable levels of usage. In case of more erratic behavior, the predictions with the decision tree model or other more sophisticated models can be expected to be more accurate. The implications of the study include the fact that the linear regression is a valuable baseline model that has to be complemented by utilizing more complex models such as decision trees or neural networks when the user behavior is highly variable. Linear regression can still be helpful in smaller data sets or in more predictable scenarios, but requires larger and more evolved models in order to deal with the completeness of real-world mobile app usage. As developers and data scientists choose the right model to use in their real-world application, they are also to be conscious of the trade-off between model interpretability and predictive power.

Discussion

The results of the present study offer positive insight to interpretation into the application of the linear regressions in finding out mobile application use-patterns. Though a linear regression is such a simple and understandable model, it has demonstrated its worth in assessment and explanation of the interlinkages between definite user attributes (including demographics and the frequency of using the app) and the level of involvement in the app. The $R^2 = 0.78$ and MSE = 5.6 shows that linear regression may have been applied to predict the trends of usage of an app at selected customers with a huge success especially where the rate of usage of an app is relatively constant or structured. This fact validates the findings of other studies that were conducted using linear regression in predicting user behavior (Wang & Lee, 2021; Smith et al., 2018).

However, linear regression cannot represent the depth of highly variable user behavior as it was demonstrated during the discussion of residuals of the model. When the users describe their non-regular involvement, either inconsistent use of an application or fluctuating propagation session, the prognostication exactness of the model diminishes. This observation follows the existing knowledge in the literature in the case of the invalidity of the linear regression in such cases that need difficult and non-linear interaction (Patel et al., 2019). The more advanced methods of machine learning, such as decision trees and neural networks could then be better performing in such a situation. Such techniques are supposed to measure the non-parametric patterns and correlation between the variables that can provide a closer representation of the user behavior in the real-world. In their turn, neural networks are well able to unveil more elusive and obscure trends in the information code, and, with decision trees, one may intuitively mimic hierarchical associations and respond to interaction between separate predictors effectively (Gomez & Fu, 2019).

Despite these limitations, linear regression at other levels may not be that good but it has been one of the most outstanding and convenient in that mobile app developers have to deal with information that is easy to understand and simple to follow up in action. Intuitiveness of linear regression cannot be paid when the developers need to quickly get to know the relationships between the user demographics, behaviour and patterns in the applications and sessions. In contrast to other more complex machine learning algorithms that might have been called a black box solution, a linear regression is transparent in character already since it provides explicit coefficients proving the degree of the effect of each variable on the user engagement (Jones & Roberts, 2020). To give an example, the developers can just learn what demographical parameters can affect a session frequency and duration to the greatest extent so that they can take those improvements to their application in the form of content, or functionality.

Practical Implications

This study has a number of implications in the practical sense in terms of mobile app developers and marketers. Among the most significant findings, it is possible to rate the idea that linear regression can serve as the effective base to predict the app usage, particularly in situations when the user behavior is relatively well-stabilized and foreseeable. To illustrate, productivity applications or poorly defined audience applications can be better informed by linear regression applications because the former have more predictable behaviours of their users. By using such apps, developers can use linear regression to predict users' actions and come up with specific actions that would increase the user retention. As an example, in case users younger in age are shown to use a social networking app more often in comparison with their older users, developers can create features or run advertising campaigns that specifically take into consideration the reception of younger customers.

In addition, with a fairly small value of MSE, the model can be used as an optimizing application in real life to give a reasonably suitable forecast of outcomes and thus its potential use in optimizing an application in real life, especially where the backgrounds of ease of computations and optimization constraints are significant concerns. In smaller development groups or startups, linear regression can appear as an effective and cost-friendly option to study the user engagement with no significant demands in terms of computing resources or complicated algorithms (Wang and Lee, 2021). Through integrating the linear regression in their apps development processes, these teams will be able to get important information regarding their users and take data-backed decisions to enhance app performance.

Nonetheless, as the research discovered, linear regression is, in reality, inappropriate when it gets to the modeling of highly changeable user behaviors. Such a restriction implies that those developers who have to work with the applications that have a great amount of variability in user penetration, i.e., gaming applications or time-sensitive content apps (e.g., news or event-based applications) will not obtain a potentially-high level of results with the linear regression alone. In the case of such kind of apps, more sophisticated approaches such as decision tree, random forest or neural network might be required to characterize more dynamic components of user behavior.

Not linear relationships and interaction among several features may be addressed using decision trees, as an example. Also, they are relatively easy to explain in the same way as linear regression, yet can incorporate more complex behaviors, since they can be used to divide up the user base into smaller groups according to the observed patterns on the data (Patel et al., 2019). Conversely, the neural networks can be used to model apps with very unpredictable usage patterns or those which have many, many relationships between variables, because a neural network is a learning machine which can capture very complex relationships between variables. As much as neural networks can provide higher accuracy, these models are traded off through being data intensive, expensive to compute, and having expertise needed to develop the model.

Future research directions A theoretical framework for investigating the learning process In this research project, we use the following theoretical framework to identify the learning process. In light of the results of the current study, the future directions of the research must be the study of hybrid models where the advantages of the linear regression are united with more complicated methods. As an example, it was suggested that hybrid models may involve the use of the linear regression to discover the strongest predictors of app usage and then run a more powerful algorithm, including decision-tree models or neural networks, with the aim of enhancing the predictions using the non-linear relationships (Gomez & Fu, 2019). Such combination of models may end up creating a balance of interpretability and accuracy, giving co-developers a kind of tool that is comprehensible and efficient.

The other area that should be researched in future entails bringing in more features to enhance predictive capabilities of the models. Although the work concentrated on demographics and simple indicators of the usage of applications (frequencies and durations), adding more specific data, like previous behavior, interactions with the content or external inputs (such as the device type, or the internet connection) would help improve the accuracy of the model. The contextual data analysis can improve and allow developers to make their own predictions in regards to the changing contexts of the user (e.g. location or time of day can influence the usage of apps) (Jones & Roberts, 2020).

Lastly, longitudinal research might be useful in sharing useful information about the changes in user engagement. Only a snapshot of a user behavior is observed in a single cross-sectional analysis as is done in this study, whereas longitudinal research may monitor the alterations in the engagement patterns as users are more acquainted with an app or the usage is affected by some external factors (Patel et al., 2019). These studies might be beneficial in terms of identifying long term trends and might also assist the developers with making stronger future user behavior forecasting models.

International Journal of Computer Science and Engineering Archives (IJCSEAR)
http://www.jmhri.com/index.php/ojs
Volume 2, Issue 1 (2024)

Conclusion

The performance of most mobile apps that range between social media, entertainment, productivity, and health speak to the importance of valuing the insight derived from predicting user engagement. The purpose of the study was to determine how effective linear regression was at predicting the patterns of the usage of apps in terms of the frequency of sessions and the duration of sessions. The findings indicate that linear regression has the potential to be a useful model to carry out the probability forecast of user activity in apps where there exist consistent, predictable usages.

The linear regression model established within the framework of this paper has obtained the R 2 value of 0.78, which clarifies 78 % of the variance in the use of apps. It implies that linear regression can be utilized to clearly find out about significant tendencies in user engagement, particularly, when behaviors are comparatively steady. The Value of Mean Squared Error (MSE) at 5.6 shows that the model has a moderate error rate in its predictions, but can be useful in keeping a common trend of usage particularly on users whose engagement levels are non-volatile. The model, nonetheless, is less effective in cases where the user behavior is highly volatile or unpredictable compared to other cases like gaming or entertainment apps whose engagement is usually organized in a more complex manner (Jones & Roberts, 2020; Wang & Lee, 2021).

Simplicity and interpretability turn out to be one of the key advantages of linear regression that was identified in this paper. The outputs of a linear regression model are also interpretable and understandable, and as such, it is especially useful to developers and marketers compared to the more complex models such as decision tree or neural networks. It gives clear understanding of the effects age and locations have on the use of the apps. As an illustration, social media apps may be used more frequently by younger users as well as those residing in urban areas. Such awareness can then be applied in simplifying the functions of an app and the marketing strategies.

Still, linear regress is not very good when input behaviors are very erratic and non-linear. The model cannot be as successful of a forecaster of engagement in users whose patterns are less predictable due to being impacted by external environments or are irregular, which has also been documented in other studies (Patel et al., 2019). In more dynamic apps that involve a more fluid user behavior or behavior guided by other trends, more advanced models such as decision trees or neural networks would be required.

The research even postulates that the linear regression may be the base of more multifaceted models. Linear regression can be an excellent first step to developing models to predict the cause of user engagement and finally, developers can turn to more complex models to take care of non-linear behaviors. Also, incorporating the contextual data, e.g. the device type, time of the day, or location, may enhance the accuracy of the forecast because these variables considerably contribute to the user behavior (Jones & Roberts, 2020).

Hybrid models can be considered as a possible direction of research linking the interpretability superiority of a linear regression and the predictability superiority of more complex algorithms. The models they are equipped with have costs that generate a tradeoff between clarity and performance. Also, in order to optimize predictions, segmenting users in terms of engagement behaviors may enable developers to classify strategies in recognition of specific user characteristics. More insight on user behavior over chronological time periods would also yield valuable data that can be used to derive how the levels of engagement shift and developers can predict long term trends in app usage (Wang & Lee, 2021).

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