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

THE IMPACT OF TEMPORAL CONTEXT ON MOBILE APP USAGE: A LINEAR REGRESSION APPROACH

Hassan Mehmood Raja

Hassan Mehmood Raja
Khawaja Fareed University of Engineering and Information Technology, Raheem Yar Khan
Email: *rajahassan444@gmail.com*

Abstract
The recent increased popularity of the use of mobile apps has led to aggressive study of what makes user engagement and interaction. Temporal is one of the major areas that hasn Bow been well studied in terms of time of the day, day of the week or seasonal differences affecting the use of mobile applications. In this study, the hypothesis is to analyse how the context of time plays a part in predicting usage of mobile apps by using linear regression models. The main aim is to discover temporal variables, which can be considered an important aspect and to determine its connection with the frequency of use, the duration of the session, as well as the type of application. The authors utilize a dataset containing records on user activities in one of the most popular mobile apps over a six-months period to create a linear regression model. Findings suggest that hour of the day and weekday are other key factors impacting user engagement and that there are definite surges in the evening and weekends time. The results indicate that by profiling user experiences based on such temporal patterns developers of apps can optimize notifications and delivery of content to users. The study can be one addition to the rising number of studies on mobile app analytics and can also serve as a guide to investigators and other applications developers who may consider using temporal context to enhance user retention.

Keywords: The Usage of Mobile Apps, Time-Related Context, Linear Regression, User Interaction, Data Mining, Forecasts

Introduction

Digital age has influenced the interaction of people with technology greatly, and one of the greatest evolutions that can be witnessed is the spread of mobile applications (apps). Such applications have become a daily ritual and found their use in other spheres, such as social networking and communication, entertainment, work, education, and online shopping (Statista, 2023). Since the future of mobile continues to be shaped by the development of mobile technology, it is already observable that the use of mobile apps grows extremely rapidly, and the global number of downloads is expected to reach 230 billion in 2022 (Statista, 2023). Such growth supports the importance of the mobile apps present in current society and emphasizes the importance of finding the factors that align individuals to engage with it, how to use it, and the overall application of the application to strengthen its results and further engagement.

Mobile apps are of various and wide varieties such as productivity, social network, gaming and entertainment apps. Different categories have their own distinctive usage trends which are influenced by users' personal behavior, the environment and contextual issues. Temporal context, specifically, means how variables in time, like time of day, day of the week, etc. affect how users will interact with mobile applications. Although temporal context has relevance, little is known about the meaning of the temporal context when it comes to the use of mobile applications and existing literature tends to be sporadic when it comes to studying the effect.

There has been existing research that shows that the aspect of time plays an imperative role in terms of influencing user behavior towards interacting with mobile applications. To illustrate, the time of the day has already been proven to affect how the app is used, and the engagement patterns therein also differ between morning, afternoon, and evening (Smith et al., 2018). Moreover, it is identified that day of the week affects user behavior with the weekends (relative to weekdays) usually being more active (Jones & Roberts, 2020). Seasonal patterns also feature in the development of app use where certain apps are used more frequently during the holiday or special occasions (Wang & Lee, 2021). Nonetheless, as has been found in observational research, temporal effects on heath have been reported, but more serious consideration has yet to be done to the exact effects of these variables, especially in regards to predictive modelling.

Though much research has already taken place regarding the use of mobile apps, time context has still not been thoroughly reviewed, especially considering quantitative modeling that allows predicting user behaviour. Not many past studies have used statistical or machine learning models or valuable observational data to even estimate the relation between time-based features and user engagement (Patel et al., 2019). Linear regression is a proven statistical method with a good prospect of filling this vacuum. Linear regression would help developers to better understand the role of time in determining the way users are engaged and develop the methods of retaining them and obtaining the best user experience by modeling the relationship between temporal variables and app usage.

This study is intended to close this gap as it will adopt a linear regression methodology to investigate how the temporal context influences mobile app usage. The researcher will lay emphasis on the main time-related resources, i.e., the time of the day, day of the week, and seasonal patterns and correlate them with clues like the length of a session, multiple uses, and continued user rates. Creating a predictive model using these time-based factors will allow the study to provide actionable information to app developers on how they can optimize the user experience by tailoring any app based on the time usage, delivery of content, and notifications.

The major research questions that the study will follow are as follows:

1. In what way does the usage of mobile apps vary according to time of the day?
2. How do various working days affect the activity of users?
3. Is it possible that temporal context is correlated with app usage by use of linear regression?

The research will consider the answers to these questions by creating a linear regression model that would include time-related characteristics such as the time of the day, day of the week, and seasonal changes. Since there are many mobile app users, their data will serve as training data in the given model, and session duration and frequency of use will be dependent variables of engagement. The idea is to find the temporal trend which will have a bearing on the behavior of users and which will give the developer knowledge to maximize the user involvement and retention.

The aims of the study are the following:

- Aim at examining the influence of the temporal context on the formation of use patterns of mobile apps.
- To consider the possibility of creating linear regression model to predict user engagement according to time-related factors.

Using linear regression to measure the association of temporal context with app usage, the paper would thus contribute to proposing a predictive model to how users behave and engage with an app as time goes by (Brown & Green, 2017).

- To give practical information to app developers who would like to exploit the temporal patterns in user retention and engagement.

Literature Review

Applications (apps) that run on a mobile phone are now very important in contemporary life and they serve various purposes that include communication, entertainment, education, and productivity. Such applications are affected by such factors as users' demographics, type of apps, and the period in time but the latter has gained less coverage in the studies. The time of day, day of the week, and seasonality are considered temporal factors that are essential in user engagement and design of an app. The review of literature provides an overview of the existing studies on mobile app usage and the temporal orientation of the given field of study to show that further research on the topic is necessary.

Time of day can be one of the most important factors influencing the app usage and evidence shows that app engagement reaches its maximum level in the evening. This is the time when users are more likely to enjoy spare time to engage in such activities as social networking, entertainment, and gaming. To illustrate, a study conducted by Smith et al. (2018) revealed that there is a considerable increase in the use of entertainment apps in the evening. On the same note, the communication apps are also more active at the end of the day when the users follow up on messages and social media posts (Jones & Roberts, 2020).

The pattern of using apps also depends on weekdays and weekends. Work-related applications are more likely to drive individuals to use it during working days, especially in the morning and afternoon hours when individuals end up involving themselves with productivity apps or reading emails. On the contrary, most entertainment apps such as mobile gaming and social media are used more in weekends because individuals are not so busy during this period (Patel et al., 2019). This means each type of usage, work-related and leisure-related, will have different high use times which will be determined by the social and work schedule of the user.

Seasonal usage also defines how the products are used E-commerce applications, as an example, have increased traffic on such holidays as Black Friday and Cyber Monday when people buy goods on sale. The fitness applications are the most active during the beginning of the new year when people make their New Year resolutions to get in shape (Patel et al., 2019). On the same note, there are spikes in the use of travel apps during holidays or during school holidays. Such seasonal peaks are important in confirming the essence of time factors in forecasting and maximizing the app usage patterns.

Notwithstanding these observations, a lot of the available studies in the area of temporal context in mobile application use are based on descriptive analytics. Although such experiments contribute to determining trends, they are not the predictive models, which can be applied in order to maximize user engagement in real-time. The literature gap indicates that the development of the more specific models which will allow linking factors connected with time to the usage of the app and assist in helping the developers of the app to maximize the engagement and customize the features of the app and notifications according to the patterns will be needed.

One of the most common predictive models is linear regression, which has been successfully used in such areas as web traffic prediction, as time-based parameters, like time of day or day of the week, cause changes

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

in user behavior (Brown & Green, 2017). Nevertheless, it has not been effectively applied in the use of mobile apps. Provided in this review is a suggestion that linear regression may provide worthwhile information into how time-oriented variables affect the user engagement with mobile applications. Using user behavior as function of temporal variables, the developers are in a position to optimize notification and update of the applications and thus make it match with the timing when users are most active. Based on the predictive models, it was also possible to know the low engagement times and developers could make necessary action towards ensuring that there was still user activity.

Although linear regression is a simple, interpretable way in which the behavior of the users can be predicted, it is also possible to choose other types of models (decision trees and support vector machines are also possible). Some of the most challenging models have shown the ability to predict user behavior, but this was achieved at the cost of interpretability (Patel et al., 2019). The linear regression is a favorable solution among those working in the app development field due to its simplicity and its capacity to model the connection between time-based variables and user activity.

Although it is a very promising tool, the prediction of mobile app usage through temporal factors by means of the linear regression has not been examined in great detail. Previous researchers have emphasized on the relevance of time in utilizing apps and majorly employed descriptive statistics as opposed to predictive models. This study seeks to address this gap by to create a linear regression formula to determine the likelihood of app use based on tunefulness factors such as time of day, day of week and seasonal pattern. This model would allow the developers to align the patterns of user engagement with app features and notifications to have a better user experience and retention.

Besides linear regression, in the future, there could be the research on hybrid models that would unite the ease of linear regression and the ability of more complicated models like decision trees or neural networks. These hybrid models would offer a breakthrough between the accuracy and interpretability that would allow developers to make well-informed decisions about the design and functionality of the app on the basis of time-based functionality.

Improving experience within predictive models may be also performed with regard to the contextual data related to what kind of device, place, and apps were on pre-use. The inclusion of these factors would enable developers to develop much more personal and pertinent app experiences to consumers. Also the segmentation of the users by their engagement behavior may assist the developers in customizing their approach in various groups of users making them more satisfied and retained.

Methodology

This study looks at how the time aspect affects the use of mobile applications through the linear regression modelling. It uses the historical user engagement data on one of the more popular social networking apps more to the point of how the time of the day, day of week, and seasonality can manipulate the user behavior. The design is observational, wherein the usage model of the users over time is found based on available data without the use of the variables.

The data is within six months and contains most vital temporal variables: time of day time split into morning, afternoon, evening and night; day of a week with an emphasis on weekend; and seasonality with a split based on months to observe engagement habits during holidays or seasonal changes. There are further parameters, the length of the sessions and usage frequency of the application, and the information will be anonymous to ensure the privacy of the users, which will make it to have both transparency and reproducibility.

The relationship between user engagement that will be measured by the length of the session, usage rate and retention will be looked into with use of linear regression analysis of the independent variables namely, the factors of time. It will be analyzed by the help of a well-known Python library scikit-learn, which provides great facilities with machine learning, and with the help of it, the regression models will be created and tested. Data preprocessing is an activity which includes encoding the time-based variables to numerical values and division of the data into training (80 per cent) and test (20 per cent). The training set is used to train the model estimating optimal coefficients involved in the relationship between the climate and user engagement and the results of the model are analysed with a set of metrics.

The proportion of the variance in the data that can be attributed to the temporal factors is measured using R 2 (R-squared) which is 0.72, this means that 72 percent of the variation in user engagement can be determined by the time-based variables. Mean Squared Error (MSE) which verifies the mean of the square of errors between actual and predicted is 0.21 which depicts relative coverage of prediction. This is represented by Root Mean Squared Error (RMSE), an easier to interpret error figure of 0.46, which shows that on average the model is incorrect by 0.46 in showing how many users are engaged.

The model needs to be validated using K-fold cross-validation, where the data is divided into a number of small subsets to make sure that the model exhibits a good performance on all the data subsets. The given type of such approach can be useful in avoiding coping with overfitting and maintain the model stability.
The model discovered that day of the week and time of day are then pivotal to anticipate user engagement. The highest activity was during evening hours when the users had more free time and this is in keeping with the earlier studies. Also, a different pattern in terms of usage was presented across the weekend and the five working days in that weekday's usage patterns promoted more use of work-related apps, whereas the weekend usage patterns were more focused on entertainment and social media apps. Seasonality was not especially influential to the engagement success in users however, it could be the short span of data or that the app is one that users do not use during the season.

The linear regression model proved that time elements were critical determinants of how mobile applications would be used. The model performance with R 2 of 0.72, MSE of 0. 21, and RMSE of 0. 46 suggests that the factors about time could be utilized to make effective projections about the engagement of the users. This study demonstrates the possibility to use predictive models such as linear regression to streamline the functionality and contents delivery of the app by correlative behavior with time. It may also be possible to add new variables to the model to increase the accuracy of predictions in the future. Examples of the new variables in the model might include app features or demographics of the users.

Discussion

The outcomes of the study are quite solid since they indicate the significance of time-related context the effects of which on forming usage patterns of mobile apps are critical. The linear regression model that was built as the segment of the present research proved that the time-based features such as time of day, the day of week, the time of the year affect the usage indicators significantly and they are composed of the length of the session, frequency of use, and retention, etc. This discussion is consistent with the growing body of evidence pointing to the role to be played by temporal factors in specifying the times and ways of interaction with mobile apps by the users (Patel et al., 2019; Jones & Roberts, 2020). To be more precise, the given research found out that the time when people use the app most is evenings and weekends, and, therefore,

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

introduced the idea that people have more time to use the apps when they are doing nothing, e.g., after work or during the weekends.

Experience of time and mobile applications Time perception Time is the measure of a fixed duration between events, estimated and measured by an awareness of time moving forward and time passing in the past.

The high level of R-squared 0.72 of the linear regression model indicates that the linear regression model explains a significant proportion of variance in the user engagement which is because of the presence of the temporal variables. This underlines the fact that time constitutes a significant aspect defining the user behaviors and engagements. Such findings can be compared to the research results that have been presented in the literature before and stated the highest usage at specified times of the day (Smith et al., 2018). The prime time here was seen in the evening, and it connects to the fact that when consumers do not have work-related stuff to be completed, or other daily obligations distract them, they are more absorbed in using cell phone applications (Jones & Roberts, 2020).

Interestingly, a second high-usage period that was during weekends was also surfaced in the model. The given observation has become apparent, as the existing literature shows that the weekend is related to a high activity level contrasted with a working day in terms of using entertainment applications or social media (i.e., social medias applications) (Wang & Lee, 2021). The trend implies the typical pattern of utilisation of mobile applications since customers utilise the tools on their free time, whether as the means of getting a social life social interaction, being entertained or doing what they are personally enthusiastic about. As an example, video streaming apps and mobile games are some of the applications which have high usage as shown by more time spent on them on the weekend due to the willingness of consumers to utilize an additional amount of time on this specific application.

Also, though time of day and day of week may have been the most central factors influencing the model, their season patterns do not seem to contribute significantly to the user engagement according to some of the reports. Such insignificance can be explained by the fact that the duration of the data set is six months, which is unlikely to reveal a significant seasonal shift that could enable one to diagnose some visible shifts. There can also be additional research which will be longer in duration to identify precise impact of some holidays or seasonal processes on the utilization of the apps. As an example, discounts, promotions, or those that are tied to time of the year-related apps may be particularly energetic at those times of the year when it relates to most popular shopping days- i.e. during the Black Friday or Christmas time (Patel et al., 2019). To an extent, one of the original findings of the given study is the creation of the sharp evening peak and the weekend surge of the activity. Intensity of peaks recorded in the evening and weekend peak periods in the current research perhaps was more acute than the results of previous studies who registered peak utilization at a specific period of time. This observation implies that the engagement of the users is not likely to be random and not time-related as it has been seen so far and the lessons that can be relayed to the developers of the mobile app use this information to maximize the user experience. When using these peak times to synchronize their notification in the app, send content, and update features, developers would be able to assist in ensuring that users become more willing to use the content at times that would be most more convenient to them.

Go in fact the entertainment and social networking applications that will guide them to start the updates of promotion as well as notification during evenings as well as the relational days in case any such user is likely to use any application. This type of time optimization could even lead to an infinitely improved user retention rate and potential reduction in churn which is vital to the app developers in the industry which is increasingly competitive.

Even though linear regression model has a lot to teach, it is necessary to note that it is limited in some ways. One of the key assumptions of the model is the assumption that interaction of the variables of time and the use of the app is also assumed to be linear. Any such assumption may be oversimplistic with regard to the issue of user behavior. The thing is the user engagement behavior may be not always linear in relation to time factors when speaking with time aspects. To cite an example, this is just one factor that may influence the engagement of the users because the linear regression model does not consider many other things that might interfere in the process such as app content, user preferences, phone model, social influence etc.

Moreover, the relations that the model will not pick up can be some non-linear ones. A preferable example would be user activity where decreasing returns and/or spikes at particular time of the day can be observed that cannot be reflected on a linear performative. In this sort of cases, such a more detailed model may be necessary to present more realistic description of user behavior.

Correction of these restrictions could be further researched using in further studies, non-linear models or additional high-end techniques, i.e., deep learning or decision trees, in order to be able to trace more minor patterns of the engagement of the users. On an illustrative example, the non-linear dependence between the time-related variables and the number of app uses that should provide a more in-depth understanding of the time impact on the engagement may be presented by the neural networks. Even random forests, or gradient boosting machines would help in specifying higher orders of interaction that have been unspecified by linear regression between factors of time and user interaction.

Nevertheless, the results of this study have significant consequences to the developers of the mobile apps in regard to the limitations. Investigation into the pattern of how the user engagement evolves with time provides developers with a chance to either speed up or slow down on the app feature by prioritizing it differencing to time related preferences of the users. In one case, a more personalized app that shows customized notifications or content according to the time of the day can be very useful as the customer or user is getting the information at the most opportune time that they can utilize that information. Moreover, it can be utilized in such a way that upon the knowledge of the fact that more engagement will occur on the weekends, a developer can use this time when to introduce a feature or promotion.

It also allows to prophesize high usage times and so, it provides the developers with a resource of reducing workload during the time when the server is not too busy with users by providing the system maintenance or system update during the time which is not so busy with users. It would have an advantage of ensuring the upkeep of the best performance of the apps and not slowing user experience during the situations of impact.

There are various ways in which the study can be developed in the future. First, the non-linear modeling can present improved performance when predicting model accuracy to achieve complex relationships between time and user behavior. Second, other user-related parameters, such as demographic, device-type/and or app features, might be considered in order to have a rather comprehensive picture of determinants of app engagement. Lastly, a bigger multivariate data over many years or even taking into consideration various types of application such as game apps, productivity apps and health apps would have helped perform a more specific study on the effects of time factors on the various types of mobile application.

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

Conclusion

This study indicates that the temporal factors (time of the day, day of the week and seasonality) consistently possess substantial influence on how mobile apps are used. The results indicate that most users could be found during evenings and at weekends, which has been established in previous studies (Smith et al., 2018; Jones & Roberts, 2020). Knowing how users will be using apps will assist developers to know how to optimize functions and contents of the app in order to improve user retention and usage. As an example, the evening hours should be used to send notifications and updates because the most active time also occurs in the evening.

What the implication is to the app developers is of great concern. Knowledge of when the app is most utilized enables developers to create better notifications, offers, and modification of the applications. Apps that users use at work may be specified on weekdays and other apps that are less professional will focus on the weekends. Such awareness in time assists developers to devise superior user retention techniques since he/she realizes the time when users will most probably interact. Since user engagement is a prominent indicator of the retention (Patel et al., 2019), designing app activities on the basis of user-time patterns helps to make the relationship with the users stronger, leading to higher retention rates.

In spite of its worth, there are limitations in the study. The regression model employed presupposes that the tie between temporal factors and user engagement is linear and that it is not the case in practice. No other alternatives like content, preferences of the users or the environment were considered. The connection of the time and the app usage could also be studied with the help of non-linear models, including neural networks or random forests.

Moreover, the research was limited to time of day, day of the week, and seasonality, but other time-related phenomena, such as holidays or other special events, might significantly influence the app usage too. As an illustration, e-commerce apps exhibit peak-use in times of holiday sales and special occasions such as product launching can generate high spike rates in use. The next evolution of this research should include factors such as these more refined measurements of time, so that a more nuanced picture of user behavior can be gathered.

It would also be useful to include various demographic and geographic aspects of the study (e.g., age, gender, locality) to gain further richness in the model as well as characteristics of the app (e.g., app type, functionality). Demographics plays a critical role in determining how different consumer groups interact with the apps because some groups of consumers may use social media or gaming apps, whereas others use news or productivity apps (Jones & Roberts, 2020). Indeed, these variables may enhance the precision of the regression model and provide more information regarding the relationship between time and other aspects in determining user engagement.

Even more advanced (but also time-consuming) methods like time series forecasting or deep-learning algorithms (e.g. Recurrent Neural Networks, Long Short-Term Memory networks) can offer a more solid profile of the user behavior which mobile technology and predictive modeling are developing in this direction (Goodfellow et al., 2016). These approaches are able to analyze the sequence of user interactions. Moreover, statistical techniques like gradient boosting machines and random forests could be used to further increase the predictive power because they combine several models to handle difficult interactions between the variables (Breiman, 2001). Such innovations may further be able to make the prediction of app usage patterns more accurate, giving a very important insight into the professionals in the field of app- related development and marketing.

References

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5-32.

Brown, L., & Green, A. (2017). Predicting web traffic using linear regression models. *Journal of Web Analytics, 15*(2), 122-135.

Chai, T., & Draxler, R. R. (2014). Root Mean Squared Error (RMSE) or Mean Absolute Error (MAE)? – Arguments Against Avoiding RMSE in the Literature. *Geoscientific Model Development, 7*(3), 1247–1250. https://doi.org/10.5194/gmd-7-1247-2014

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining,Inference, and Prediction* (2nd ed.). Springer.

Jones, T., & Roberts, R. (2020). The influence of time on mobile app usage: A case study. *International Journal of Mobile Computing, 25*(4), 298-314.

Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *International Joint Conference on Artificial Intelligence (IJCAI), 1137-1143*.

Patel, S., Lee, K., & Smith, J. (2019). Mobile app usage and time-related factors: A comprehensive review. *Mobile Technology Journal, 8*(3), 200-212.

Smith, A., Brown, B., & Green, C. (2018). Temporal patterns in mobile app usage: An exploratory study. *Journal of Digital Interaction, 12*(1), 45-58.

Statista. (2023). Mobile apps: Industry statistics and global trends. Retrieved from https://www.statista.-com/statistics/297691/global-mobile-app-revenue-forecast/

Wang, P., & Lee, D. (2021). Understanding time-based variations in mobile app usage. *Journal of Mobile Analytics, 10*(2), 157-170.