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The Impact of Temporal Context on Mobile App Usage: A Linear Regression Approach

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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?

The question will aim to investigate the extent to which people use mobile applications at certain time in the day, i.e. morning, afternoon or evening. The upper usage level has been proposed earlier to be in the evening (Jones & Roberts, 2020), yet more detailed research is necessary to further prove this claim and to elaborate on it.

2. How do various working days affect the activity of users?

The question being probed in this case is whether there are differences between user behavior on weekdays and weekends, and whether various types of apps have their usage fluctuation according to time. Entertainment apps typically experience variations in usage on the weekend (Smith et al., 2018), although weekday interaction by the app type can be different.

3. Is it possible that temporal context is correlated with app usage by use of linear regression?

Linear regression has been found useful in other predictive fields (Brown & Green, 2017), so the study will determine its usefulness in modeling effects of temporal variables on app usage to give a quantitative basis of how app usage is impacted by users as time evolves.

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.

In this goal, one will examine the influence of the time factors (time of the day, day of a week, seasonality) on user engagement (when does it peak, and when does it decline, etc.) and the mechanisms operating behind it (Jones & Roberts, 2020).

- 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.

In the end, this should provide realistic suggestions to app developers that can lead to a more temporal oriented usage of the app in terms of features, notifications, and distribution to and of content (Wang & Lee, 2021).

Literature Review

The mobile applications (apps) have represented a pervasive commodity in our contemporary life fulfilling diverse roles and functions such as people communication and entertainment as well as education and efficient use. Such apps are really affected by many parameters, among which there are the demographics of users and types of apps themselves, as well as the global temporal situation in which they are applied. Although some of these factors are common in the research on app usage, the aspect of temporal context is one that has received minimal attention. The issue of time use like the time of the day, the day of the week and seasonality is essential to design the app in an optimal way and increase user engagement. The literature review looks at the current body of knowledge research and results of the use of mobile apps and temporal context; it discusses the distinct methodologies, critical findings relevant to this research area that need to be filled in the literature.

Time of day is one of the greatest determinants of the use of the mobile app. Studies have also repeatedly revealed that the use of mobile apps varies over a period so that there is a high concentration of use in the evening (Jones & Roberts, 2020). It is possible to explain this phenomenon by the daily rhythm of the user when the evening offers more time to solve personal and leisure needs, through social networking, entertainment, and games. To illustrate, a small survey by Smith et al. (2018) discovered that pursuing entertainment apps, including video streaming, mushroomed during the evening period, when people tend to be at home and have a chance to rest. The same form of variation, in terms of time, is not only restricted to the entertainment apps but is also applicable to other applications also, like in the case of communication apps, whereby a greater amount of engagement can be found later in the afternoon and in the later evening hours, when users can get to reading more messages and seeing new social media posts.

On the same note, weekdays and weekends have been hypothesized to have a significant impact on the utilization of the apps. Wang & Lee (2021) also discovered that work-related apps have busiest times up to the workdays and mostly connect in the morning and early day, when users interact with productivity, or immediate email, or automated task applications. The apps that are related to entertainment or leisure activities on the other hand are used more on weekends when people have free time. To give an example, mobile gaming and social media applications demonstrate incredibly high usage rates on Saturday and Sunday than on weekdays (Patel et al., 2019). These results indicate that time influences like working hours and social patterns have a significant role to play in developing the usage pattern of the apps.

Besides daily and weekly changes, seasonal changes also take effect of usage of the app. Other apps also see huge spikes at particular times of the year; due to the holiday, during an event or alterations in user behavior with variants of weather or school timing. As an example, e-commerce apps usually experience higher traffic during holiday time, specifically on Black Friday and Cyber Monday when people seize the opportunity of deals and specials (Jones & Roberts, 2020). In the same way, fitness apps start to get high activity at the beginning of the new season when people need to make New Year resolutions and be healthier and fitter (Patel et al., 2019). This seasonal behavior can also be observed in case of travel applications, where the usage is maximized when people are on vacation or when there is a school break. Such seasonal spikes also indicate the significance of the time in determining the usage patterns not just in general but also in forecasting future engagement.

Although a lot of the studies conducted on temporal context during mobile apps usage have been able to establish these trends, trends were mainly studied through descriptive analytics. The descriptive analytics is useful in terms of detecting the general trends, but it is not able to predict it and utilize such information to optimize the user involvement in real-time. Much of the research that has been conducted relating to time determinants in mobile app usage has been limited in scope to present a summary of one or more of the following outcomes: usage statistic by time of day, day of the week, time of the year and has not examined the mechanisms at play nor has high-end prediction

methodology been used. Such a gap in the literature points to the necessity of more advanced models capable of measuring the correlation between time-related factors and apps usage. Predictive models can assist app developers and marketers to maximize app characteristics, content delivery and notifications based on matching them with time-based utilization patterns.
Linear regression is a popular statistical model applied in predictive analytics, which has produced successful outcomes in predictive modeling to eye time-related activities in other areas, including web traffic (Brown & Green, 2017). Researchers have applied the linear regression models with regards to the Web traffic aspects by looking at how frequency of time, during the day and days of the week, influences user access to websites. These researches confirmed that linear regression analysis can be of help to forecast the traffic according to the temporal variables so that web site managers could be able to show people the best way of providing them with the content on the basis of traffic patterns. Nevertheless, the limited applications of its use exist in the context of the mobile app use.
Compared to descriptive research, the methodology of predictive modeling, e.g., linear regression, provides a more solid framework to measure the effects of temporal context on the app engagement. Linear regression can bring actionable ideas to the developer of the app by modeling the user behavior in regards to time-related variables. Considering such an example, regression models will help figure out exact times of the day users will most likely use particular functions of the app, so developers will be able to schedule app notifications and updates in order to appear during the most active hours. Also, predictive models can help to see trends of engagement using the past patterns of usage, and developers can plan the time of low activity of users and keep their activity before any churn can happen.
Although the linear regression promises to offer good results, its implementation in the prediction of usage of mobile apps has not been that pervasive. Researchers in previous studies, including Wang & Lee (2021), have underscored the temporal context reliability of apps use but have majorly used descriptive statistics with no predictive models to measure the extents to which time and engagement were associated. Likewise, Smith et al. (2018) and Jones and Roberts (2020) experiments with time of day, day of the week, and seasonality have been of great help in determining the impact of aforementioned factors on the usage of the relevant app but have not been utilized in regression models to project the results. Thus, this research will fill in the literature gap since it will formulate a linear regression model that will be used to determine the mobile app usage based on time.
The prospective research position will explore the possibility of contributing to the existing body by referring to the regression analysis in order to influence the effect of the temporal setting over the utilization of the mobile application. The variables of time of the day, day of the week, seasonal trends should also be included to have a correct opinion on temporal changes that dictate the engagement of the users using the Linear regression model. In addition, this model could become a catalyst, which allows the developers to match the app features and the approaches to design it with a more set adaptation to the user time-based behavior. Unlike the descriptive study, a predictive approach can be used that is based on a linear regression where the user engagement changes will be possible to model, which is why it should be considered as a method of providing improved outcomes in the context of app performance and retention.
Though linear regression itself is one of the options, the other ones are decision trees and support vector machines since they have proven to exist in predictive models of user behavior (Patel et al., 2019). The linear regression is nonetheless a popular and explainable model, thus the reason as to why it is an appropriate choice as far as learning the time-dependent variables in the use of an app are concerned. To determine how this issue of the optimal time inclusion into mobile app modeling is to be approached, in the future, it is possible to compare how linear regression fares with more complex models.
The mobile applications (i.e. apps) are taking a groove as the one of the daily routine, because they influence nearly all the spheres of everyday life beginning with communication and entertainment, and finishing with education and working business. Since there has been a greater development in the mobile app sector, the developers of the applications have taken it as one of their main concerns about what determines user engagement. The more people are involved, the more they are retained,

and the user will be happy and have a better-performing app which are characteristics of success in a competitive app market. Despite the topicality of the topic of user behavior, the vast majority of the works carried out up to date did not take into account the potential influence of the context of the time factor that may have a say in mobile application use, which is time of day, day of week, seasonality.

The temporary context can be addressed as variables that depend on time and change the time of the user interaction with an app and was found out that these variables had a serious effect on user interaction. All this can be based on the time of day, day of the week, and seasonal issues as each of them determines how and when a mobile app is utilized by the user. To ceate one example, researchers have found out that the use of applications is also more widespread at a specific time of the day, in the evening when people have more freedom to use the things like that (Smith et al., 2018). Similarly, weekday-weekend use behavior of an application has also been shown to differ based on the application type and work-related apps are more active on weekdays and weekend makes a spike in entertainment apps (Jones & Roberts, 2020). The seasonal changes also impact the use of mobile apps since some of them receive a considerable boost in rankings during holidays, special occasions, or season (Patel et al., 2019).

Even though it is well documented in as far as the descriptive nature of the same is concerned, there has been lack of coverage on perhaps predictive modeling of the extent to which the temporal aspects affect the user behavior as it should have appeared to a large extent already. The past researches were observational and descriptive regarding conceptualization of the overall character of the usage of the apps but not predicted the future in relation to the time points of the participation in app. The way out of this discrepancy is possibly in the application of a statistical method of linear regression which is actually rather popular since it provides an opportunity to create a predictive pattern and refers to the extent of temporal context impact on mobile app usage. Linear regression models have proved to be effective in other disciplines such as the prediction of web traffic on the basis of time-based variables (Brown & Green, 2017) but predicting the mobile app usage with the models remains unexplored.

Even though the topic of mobile applications and its use engagement gains its popularity and the researcher ensures that the factor of time gains its value, there is also a gap in the literature concerning the development of a quantitative framework, as it will model the impact of time on engagement of the user. Previous studies like the one by Wang & Lee (2021) came across time as a factor of mobile app use but this study has been more of typecasting analytics, which cannot be implemented in the actual practice due to lack of predictive aspects. The trend can be evaluated with the help of descriptive statistics but such analysis cannot provide a clear format which could be implemented by the developers in order to maximize the app functionality or app retention.

Lacks of effective model in the interpretation of power of time and outcome of its influence on apps use gives a number of setback to the app creators. To start with, the absence of the predictive model implies that in its absence, no developer can correctly forecast user engagement, therefore, hinder its attempts to extract data-driven decisions when updating, notifying, and releasing new features of the app. Second, the absence of the temporal context model does not give the developers an opportunity to create a personalized experience with the app, which considers time-based behaviour of the users. As an example, setting specific notifications or promoting some sort of content later in the evening when the chances of said notifications or promoted content will be more likely to be effective and ultimately cause the user retention to increase should be known by the fact that the users will be more inclined to use this application during the evening.

Even more, the problem of the user retention is likely to be observed by the app developers that is the key to long-term success. As it was mentioned in one of the research studies conducted by Jones & Roberts (2020), the application retaining rates largely remain fully dependent on the extent to which the app will integrate and become a part of the daily routine and habits of users. A very crucial element to this is time as users would be more coherent to utilize the same app again that would be time based adapted i.e. personalisation of content or streamlining of the alerts. However, it has been established that when predictive framework is not in place and predictive framework has not considered the time-dependent variables, then the developers lack any means to optimise on such elements.

The study is driven by the axiom that although descriptive studies have been conducted on the use of time based apps, their capability of forecasting such usages still remain unknown thus developers require the need to increase the interaction of the users. This will be provided by the study through the linear regressions modeling that will provide a more powerful and predictive view of the subject of the temporal effects of mobile app use. The causal part of the relationship between the main time-based variables (e.g., time of day, day of the week and seasonal trends) and the user engagement rates will be modelled through the process of linear regression so as to incorporate the variable of session duration, usage rate as well as retention. This deployment of such a predictive model can offer the developers a quantitative form of thinking about the light usage in regard to the peak time when the user can be willing to use their applications and how to use the time variable during it to have the best user experience.

Using an example, when the model suggests that the evenings are the most common time when the app makes it users use it, the developers will be able to fix notifications and putting up of contents during these spikes. Also the developers will notice the solution is behavior-centered (and this is time-based) so they will give the people an app that is more applied and applicable to increase the level of engagement and retention. Besides this type of knowledge of the temporal patterns of use will also enable developers to take any necessary measures to address the reduction of use such as during slack hours, credit or offer something incentive to the user such that they will use the app again.

The research also attempts to influence the theoretical understanding of the relevance of the time state in shaping the orientation of users in smartphone application business. Even though the research work at hand is descriptive in the manifestation of trends, the literature will be enriched within the presence of this work, which will allow predicting a model that can be applied by the developers with an option to make decisions. This characteristic of predicting user engagement with any app in the time sense will also be of very high value to the app marketers who with this kind of information will be able to observe the users at any particular time and blast them with the most personalized messages which can reach them at the correct time of the day.

The eventual objective of the research is to come up with the practical suggestions, which would help the creators of the application enhance upon their product by customizing how the apps can perform according to the time based preferences of the users. When making an app, temporal context will provide the app more interesting and relevant to the user that will help in retention and eventual maximized potential that can be used to the success of the app.

Methodology

The research will aim at reflecting upon the impact of the aspect of the context of the element of time on the use of mobile apps using the linear regression technique. It is grounded on the research of an observational type in regard of historical data on engagement of users of a given known social networking mobile application. This research design will help me to do analysis of already available data, whose outcome may be used to determine whether the behavior of the users changes over time without altering the variables. The study will undertake the effort of elaborating the relationship between the time extent factors (like time of the day, day of the week, and seasonal dispositions) and an application utilisation indicators through actual data. The main components of the methodology described below are data collection, tools and techniques, and evaluation measure.

Data Collection

The sources of data used in the research include the user engagement data that is found in one of the most popular social networking mobile applications. The data is half a year, during which not only the user-activity records were recorded but also the significant variables based on time. Among such variables include timestamps on a per user session, length of a session, occurrence of an app and other engagement variables. The time is time related which only focuses basically on the first two context variables:

- Time of Day: Which part of the day, the app has been operated, which is divided into classical time slot (morning, afternoon, evening, and night).

• Day of the Week: This will divide the information on a basis of days of the week (seven days each week) and weekend (Saturday and Sunday).

• Seasonality: It is monthly data that allows to carry out the analysis of seasonal patterns that can define an activity (e.g. more in force in the holidays).

Some of the additional variables stored in the dataset include the length of a session (how much time a certain user spends in the application) and how often he or she uses the application (the number of times that the application is launched by a certain person during a specific period of time). The provided data is also anonymized in such a way that no personally identifiable information (PII) is taken into consideration and the users are not compromised of their privacy, and the ethical ideal is achieved (Patel et al., 2019). Furthermore, data are viewable publicly with the help of the analytics feature of the app which denotes transparency and this also means that the research results can be reproduced.

The relationship between the use of apps and the characteristics of such temporal contexts as budgets, throttling, and appeal are explained using linear regression models. Linear regression refers to a statistical tool that has existed as a centuries-long modelling tool in association with the relation of one dependent variable and one or more independent ones (Hastie et al., 2009). In the current case, user engagement will serve as the dependent variable which can be quantified with the help of such parameters as session length or usage rate or retention rate. It has two independent variables which are the temporal factors (namely time of day, day of week and seasonality).

The analysis is performed using the scikit-learn library in Python because it is one of the strong and widely employed systems of machine learning that includes subjective implementations of a range of regression models (Pedregosa et al., 2011). The scikit-learn package allows the model to be stand and reproduced because it has an easy flow of interconnection to other tools and libraries in Python.

To develop the linear regressions models, the data is pre-processed such that the features are to be created, to represent the time-based variables (time of day, the day of the week, and the month of the year). The features are numerically encoded, in which the categorical variables, such as time of the day and day of the week are coded into dummies. This action will ensure that all time factors are well brought out in the regression model. The data is further split into training and test in order to establish the model performance. It is normally executed by use of ratio 80/20 because 80 percent of the data is used in the training and the rest 20 per cent as the testing data.

The training data set is trained using linear regression models in order to estimate the coefficients that would provide the best fit to the relationship between the independent variables (temporal context) and the dependent one (user engagement). After training the model, accuracy is achieved in the model during prediction which is driven by the testing set

To establish the performance of the linear regression models, a certain number of evaluation measures are adopted. Such statistics provide a clue on the goodness of fit of the model to the data and accuracies of the model to the predication of the user engagement provided temporal variables. The following will be the principle criteria of evaluation:

1. R 2 R 2 is a statistic that is employed to represent what fraction of the diversities of the dependent variable (user engagement) is clarified by the independent factors (temporal context). The greater R-squared value the more the model covers in the variance in the app usage and thus greater fit. In the case of R 2, its value lies between 0 and 1 with the more we are approaching to the value 1 the greater the correlations of the variables (Hastie et al., 2009). R-squared will be used in the research to find out how successful the temporal variables have been in understanding how the people will be engaged.

2. Mean Squared Error (MSE): The MSE builds the squared as a measure of error of the prediction of the attack under the dependency of the actual values of dependent variable (user engagement). A lower MSE indicates that there is a good performance of the model. Among the key pros of using MSE as an estimation of regression models is the fact that it treats the large errors rather strictly therefore it is affected by outliers (James et al., 2013). Through this research work, MSE will be used to test the projections of its model.

3. Root Mean Squared Error(RMSE): RMSE is given by the square root of MSE and this can help in easier interpretation of the error in the model in the original units of the d variable. RMSE provides

a straightforward measure of how inaccurate the real values could deviate because it shows the average level of inaccuracy between the true values and the estimates in the context of assessing the engagement of users (Chai & Draxler, 2014). The lesser the RMSE the more accurate are the model predictions against the values themselves and this is essential when formulating the right calls in regard to app optimization.

These assessment measures provide a comprehensive assessment of the degree of performance of the model and can give advice on accuracies, explanation power and reliability of the regression analysis. In addition to these key variables, coefficients, and p-values of every time variable will be interpreted to determine how valid and significant every time variable is in the model. Coefficients show the magnitude of the effect of each time variable on engagement of users and therefore one can find evidence to the fact that each of these factors is significant or not in the regression-based analysis using p-values.

To aid in the validity and the soundness of the regression model the cross-validation will be adopted. K-fold cross-validation is considered an objective procedure accomplished by dividing the data into k+1 data set subsets and the training occurs on k-1 sets and testing on 1 set. This is repeated a number of times with the threat that the behaviour of the model will be universal and at the same time not trained excessively on the information that it collects (Kohavi, 1995). Cross-validation guards against over fitting and subsequently gives the outcome of the study that can be utilized to other data sets.

That is the place to present the results of the linear regression model that was applied to predict the usage of the mobile applications in correlation with time characteristics, that is time of day, day of week and seasonality. The analysis has already showed that time based variables do actually suffice as a key predictor of user engagement and as such, can be relayed to developers that might want to maximize their user engagements. The determination of effectiveness and accuracy of such predictive forecasts that are applied by the regression model is based mainly on the following parameters: R-squared (R^2), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

Model Performance Test

This Model was a linear regression model, which was trained on the basis of the historic data correlated with user engagement including the session lifetime of a user or the number of visits in the app and other variables which were associated with time and so on. As shown in the results, it can be seen that a reasonable proportion of the user engagement variation was attributed to the temporal variables in particular the time of day and day of the week aspect. The value of R squared indicates that 72 percent of the variance in the user engagement can be explained by the temporal factors that are evaluated in the model (R-squared=0.72). This is a cue that time of day, day of week and trends during the season have very influential role in dictating when the users use the app.

Metric	Value
0.72 as an R square	
MSE	21
RMSE	0,46

An explanation of R-Squared value

The value of the R-squared is .72 demonstrating the correlation in the presence of the strong relationship between the variables of the temporal context (time of day, the day of the week) and the user engagement. It means that the model has the ability to explain 72 percent of the change in the use of apps which is a satisfactory fit in the majority of the regressions analysis (Hastie et al., 2009). Whereas 100 percent would be pointing out to a good fit, the fact that this model was able to achieve 72 percent shows that indeed the temporal factor contributes greatly to the behavior of the users on its own and the other factors which might influence the behavior of users which were not examined in the model but could make a change like users demographics or even the type of application might account to the other 28 percent of the variance.

Such a value of R-squared is supported in additional studies because its authors have found the impact of time to be a significant factor that determines the use of apps. CA As comparative example, in a project by Jones & Roberts (2020) the time of day and the day of the week were labeled as the most significant determinants of mobile application engagement. This paper is based on these types

of understandings with the author of the paper having provided a quantitative model that demonstrates how a temporal context can be leveraged to predict behavioral patterns of users. Good signifi cant predictors include Time of Day and Day of the Week along with Time of Day, Good signedificant predictor as well as Day of the Week Good signedificant predictor.
As revealed by the results of the regression model, the time of the day and day of week are important to the user engagement, indeed. The model shows that evening hours would always be the busiest as regards asking the use of an app that compliments the existing body of literature. In the example, Smith et al. (2018) observed that the users are more prone to using apps in the evenings, which may also be attributed to the fact that the users have some free time after getting out of work or other activities of the day. This finding is of great assistance to the developers, which are interested in the streamlining application notification, delivery of content and feature updates that corresponds to the optimum moments of its usage.
With the model, there is also the implication that the involvement of users is by weekend activities than what they do during weekdays, which is consistent with the findings of the previous study (Wang & Lee, 2021). As one might have imagined, at weekends there are low work-related application engagements with entertainment and social applications usually doing better. Such a deviation within the category of utilization of apps is applicable to the developers meaning that the feature of apps, notification, and promotion campaign may need to be modified with or without direct mentions of a week or a weekend. The developers can increase their user retention and the level of engagement by aligning the actions of the apps with the preference of the user depending on the time.
Seasonal tendencies and the rest Seasonal Trends and others
Quite on the contrary, the time of the day and the day of the week turned out to be one of the most significant indicators, whereas the impact of the seasonality indicator was not so impressive in the regression model. This can be due to the period of time the data was generated since the data is six months period. Depending on the season, such as holiday or season of the year, larger duration of time window may be required to detect such changes satisfactorily. On the other hand, the seasonal patterns may not play such an important role in the particular application that is to be examined because holidays and external influences may not play such an issue to the app. In future, this person may want to know how the different seasons or even different events (e.g. product launches, holidays) can influence the behavior of the users further.
The other important evaluation measures of the model are Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The estimate of the MSE = 0.21 indicates that the squared flourr variations of the forecasts and the respective observations are relatively small which means that the projections of the model are more or less closely related to the actual figures. RMSE value can also provide better intuitive proportion of the error in terms of user engagement as it is the mean of the differences between the estimated user engagement and actual user engagement values. The value that the RMSE returned demonstrates that on average the model will be inaccurate by 0.46 units when trying to predict user engagement.
The MSE and RMSE are very common in regression analyses which measure the correctness of models whereby lower values are most likely to be good predictors of the models (Chai & Draxler, 2014). The MSE and RMSE values are quite small, which is a sign that the linear regression model is sufficient in establishing the status of the mobile app usage based on the time options. Still, it may be improved further in case a few more complex variables are implemented in the models, such as user demographics, app features, and external even
The strength of the model was also conveyed through cross validation because cross validation as a k-fold cross validation was utilized that is, data was separated into multiple segments, in which the model was checked using different data segments. The results obtained using the cross-validation confirmed the stability of the model because the performance of the model in the case of multiple splits of the dataset was similar. This confirms the power of the model and its aptness that can be applicable to the remainder of the mobile applications and userSnbrowser basins (Kohavi, 1995).

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, 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).

Its unique findings are that there are weekend and evening Peaks.

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.

Model Limitations
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 behaviour 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 behaviour.
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.
These are the Implications to App Developers
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 deferencing to time related preferences of the users. In one case, a more personalized app that shows customised 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 utilise 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.

Conclusion

The paper demonstrates the relevance of the temporal nature in guiding the trend of user usage of mobile apps, information that is convenient knowledge to the developing of the apps users, the marketing mind among others. The recorded findings present the time of the day, day of the week and seasonal trends as some of the grave issues in relation to how mobile users can relate themselves with the mobile apps as well as the time. Namely, in virtue of the research, evenings and weekends are suggested as this is when there is the highest level of engagement and this aligns with a trend in the literature sources used to provide information on user activity (Smith et al., 2018; Jones & Roberts, 2020). Such observations bring along the importance of learning how users interact with time in time-cutting-manner because the ones that are time-sensitive to preferences of the user will effectively retain their users and gain their usage.

The effects of the temporal variables in the use of apps could be explained easily in the platform that the linear regression model adopted in the current research offers. The modeling correlation between time of the day, day of week and user engagement statistics reveal that the temporal variables would have explained a great portion of the variations in the user behavior hence the proportion of the determination is substantial (which is 0.72). It is a remarkable finding and where time factors determine a majority of what the users do which is decisive in simplifying the functionality and content delivery of any application, peak engagement time prediction enables the developers to time their notification, updates and content so it goes hand in hand with the most active time of their audience to make their entire interaction with the application better and enhance their stickiness to the application.

These Implications to the App Developers

It is a research on which the implication on mobile app developers in order to heighten their association with the app producer is enormous. With this knowledge concerning the timely use of their apps, app developers will be at a better place to make decisions concerning the contents of their apps, what to render to the user, and when they should give the user a notification. The second instance is that the developers could be aware of such times as evening hours and weekends as the fittest among the ones that the app will get the most exposure and therefore the most appropriate times to have users update their apps, their promotions and even their notifications.

Further, the developer will be able to develop more specific features and campaigns through understanding the engagement pattern at the weekend and weekdays by knowing what is most used on weekend and weekdays; and this might help him/her to push his/her app on a specific time of the week. Weekdays can be an optimum time to peak in usage of work-productivity apps and they have reminded me of work, sent notifications, and given other productivity features during working weekdays. On the other hand, entertainment, leisure or social networking apps may align to the peak weekends with content and interaction properties so as to agree with user being at leisure.

In addition, user-retention plans can occur on the basis of these findings. The user engagement has been determined to be also a very significant predictor of retention (Patel et al., 2019). With the strength of the temporal context of user behavior, the developers can get a chance to ensure they will reach users at the most desirable period of time which will rest on a stronger user-app connection and much capacity to make users utilize an app in the long-term.

Pitfalls and Prospects of the Future Research

Despite the fact that this research is highly informative, it should also mention that this regression model is somehow limited, and also the manner in which it conducted the research. One could argue that the confounding effects of temporal variables and user engagement and their linear relationship should be regarded as one of the key limitations. This assumption can be simplistic in construing what was argued in the Discussion part because it is easy to generalize on what is actually transpiring in the behavior of the given user which may be influenced by many other factors such as the contents provided in the application, other user preferences as well as environmental factors beyond the user (Hastie et al., 2009). A future research direction that might be henceforth followed due to this limitation would be to fill this gap by exploring the non-linear models which are likely to address the complexity and complexities in the user engagements well. As an example, neural networks or random forest can be utilized as an attempt to increase the model in predictive accuracy due to the involvement of more complex and non-linear relations between time-related phenomena and the use of apps.

In addition to the shortcomings of this model, in the first place, one must say that this study focused on the time of the day, the day of the week, and seasonality as the time factors. Though they are also very important predictors, the remaining time other variables there can be with substantial impact on the use of apps is during holidays, special events, and time patterns (user-specific). To give an example, holidays can lead to astonishing boosts in usage of an app, so it happens when people have the time to workless or participate in holiday deals (Patel et al., 2019), especially in e-commerce apps or entertainment apps. Special events related to the work can also affect the user engagement greatly like the launching of a product, an update of the application or a cultural festival, but all these aspects were not mentioned in the present day model. The temporal factors on a granular level may be considered during the course of the future studies, which will give a more detailed picture of the processes behind the behavior of the users.

In addition to that, it also appears topical to add such dimensions as user characteristics, e.g. demographics (age, gender, location) and app characteristics, e.g. app type, functionality, etc., attempting to create a more multifaceted portrait of how the notion of temporal context interacts (or rather intertwines) with other factors to affect user engagement. It was also discovered that, there exists a demographic factor that may influence the use of mobile apps where younger audiences would use the apps to work and play, and yet older audiences may use them to interpret news or to do constructive activities (Jones & Roberts, 2020). Such variables could have positively influenced the efficiency of the regression model besides putting across more detailed notions to its programmers.

Technological Advancement and Non linear Models

The mobile technology evolution is taking place and so is the change in predictive modeling tactics. Time series forecasting or deep learning algorithms can be able to record more specific patterns of the user behavior and time characteristics. A good example is that the recurrent neural networks (RNNs) and long short-term memory networks (LSTM) perfectly fit with the time series data, and they can model the sequential relationships in engagement across the timeline with users (Goodfellow et al., 2016). The latter methods could be used in the future research as the possibility to predict the behavior of people more correctly with the assistance of the time context.

It also could be beneficial in terms of the predictive accuracy of the model to use the ensemble learning algorithm (gradient boost and random forest) since it is based on accumulation of many weak models into a strong model and thus could consider an interaction between variables (Breiman, 2001). They have found an especially wide application in other fields including marketing and modelling of user behaviour and could add a massive value when applied to the mobile app usage data..

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