Data Analysis in Row Match

Prepared by Galip Sahin

Contents

1.Introduction

This report aims to analyze the performance and user behaviors of the "Row Match!" game, offering recommendations to improve the in-game experience. The objective is to conduct an in-depth analysis using various datasets and evaluate the current state of the game. The report calculates and analyzes key performance indicators (KPIs) to assess the game's performance. These indicators include Daily Active Users (DAU), Average Time Spent Per Level, Average Number of Moves Per Level, Level Completion Rate, Average Revenue Per Level, Most Difficult and Easiest Levels, Average Coin Expenditure, and User Retention Rate. The analysis involves the following steps:

1. Data Loading and Cleaning: Datasets were loaded from Big Query, and necessary data cleaning processes were performed.
2. Exploratory Data Analysis (EDA): The basic features and distributions of the data were examined.
3. Metric Calculation and Visualization: The identified metrics were calculated and visualized.
4. Evaluation of Results and Recommendations: Analysis results were evaluated, and recommendations for improvements were provided.

2. Literature and Market Research

In conducting this study, various articles in the literature were reviewed. Through these articles, the KPIs in the datasets were examined. The necessity of parameters in the datasets for users to continue playing the game and attracting new users was analyzed. The mobile gaming industry is a rapidly growing and increasingly popular sector today. In the book Apponomics, Saltz (2014) mentions a surge in applications causing significant bottlenecks in app discovery. He writes, "While popular apps rise to the top, others get lost in the pile." This situation creates the need for user acquisition by companies, but a single marketing strategy is insufficient to reach new users globally. Gaming habits, preferences, and the most common download channels are not the same worldwide. Each region has unique characteristics, and significant differences can exist even within a single region. Therefore, researching these differences is crucial for effectively marketing mobile games internationally. Data analysis provides mobile game developers with significant advantages in evaluating game performance, understanding user behaviors, and shaping future strategies. As Heide Lukosch and Scott Cunningham's article suggests, data analysis in mobile games can be highly beneficial, especially when used to explore complex concepts and real-world problems. Digital and mobile games offer the capability to collect, store, retrieve, and associate data from players. The importance of data analysis in mobile games is also emphasized in terms of user acquisition, retention, and revenue generation strategies. For instance, understanding in-game behaviors of users shows developers which features and content are more popular. This information can be used to attract more users to the game and ensure that existing users play for longer periods. As highlighted in Heide Lukosch and Scott Cunningham's study, games can collect and analyze data types associated with game scores by recording players' actions and decisions.

In addition to this, different companies conducting data analysis studies in the mobile gaming sector were examined, and their work was reviewed. Data analysis in mobile games is crucial for increasing the game's success. Large gaming companies like SEGA use data analysis tools to monitor player behaviors, identify in-game issues, and make necessary changes to enhance player experience. For example, SEGA saved 170 hours per game and automated 450 in-game insight reports using data analysis tools. Data analysis is a critical tool for game developers to improve player experience and increase game profitability. Metrics such as player engagement rates and user retention rates are important for the long-term success of the game. Data such as Daily Active Users (DAU) and level completion rates show which parts of the game are most engaging or challenging for players.

3.Examination of Datasets

3.1.Dataset Install

This dataset provides information on users who downloaded the game, categorized by country, platform, and network.

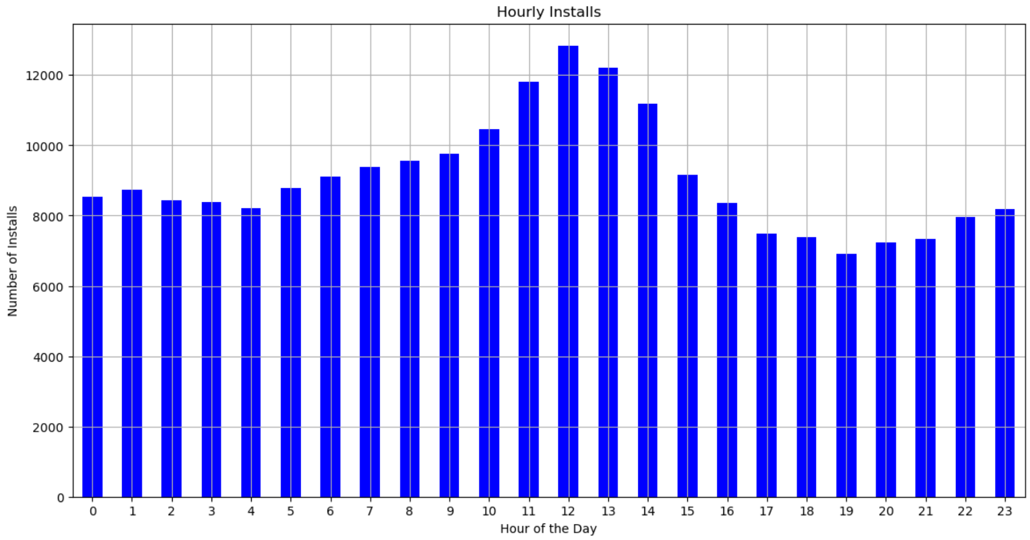
User Acquisition: By analyzing when, from which platforms, and from which countries more users are acquired, you can evaluate the effectiveness of marketing and advertising strategies.

Platform Performance: By comparing the number of downloads on different platforms such as iOS and Android, you can determine which platforms are more popular. This can help you develop platform-specific marketing strategies.

Effectiveness of Advertising Networks: By analyzing the performance of different advertising networks, you can identify which networks are more effective and attract more users. This information can be useful in optimizing the advertising budget and directing it towards the most effective networks.

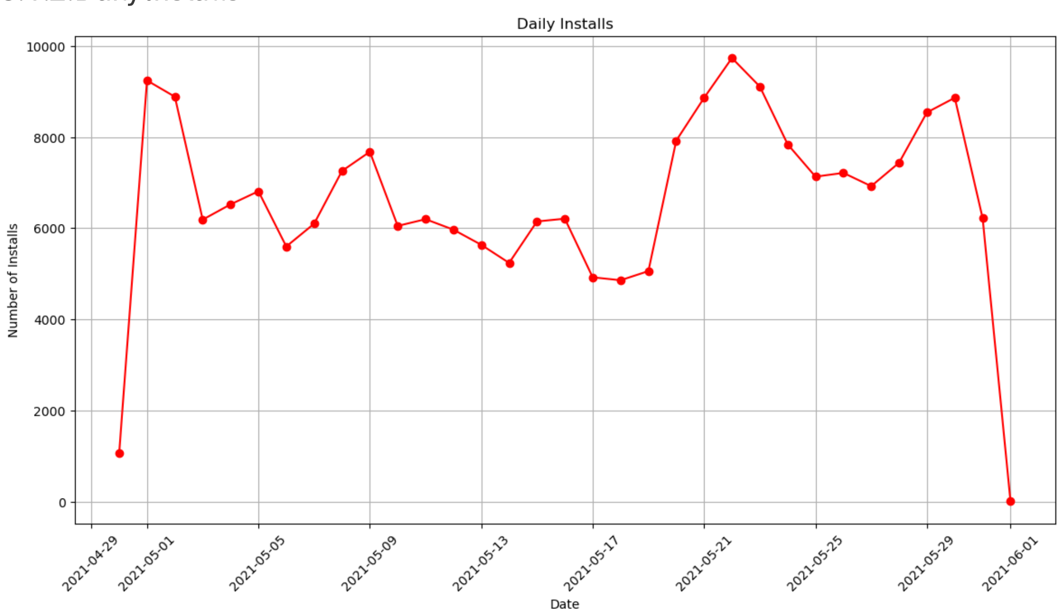
Geographical Distribution: By analyzing from which countries users are coming, you can determine in which regions the game is more popular and where marketing efforts need to be increased.

3.1.1.Hourly Installs



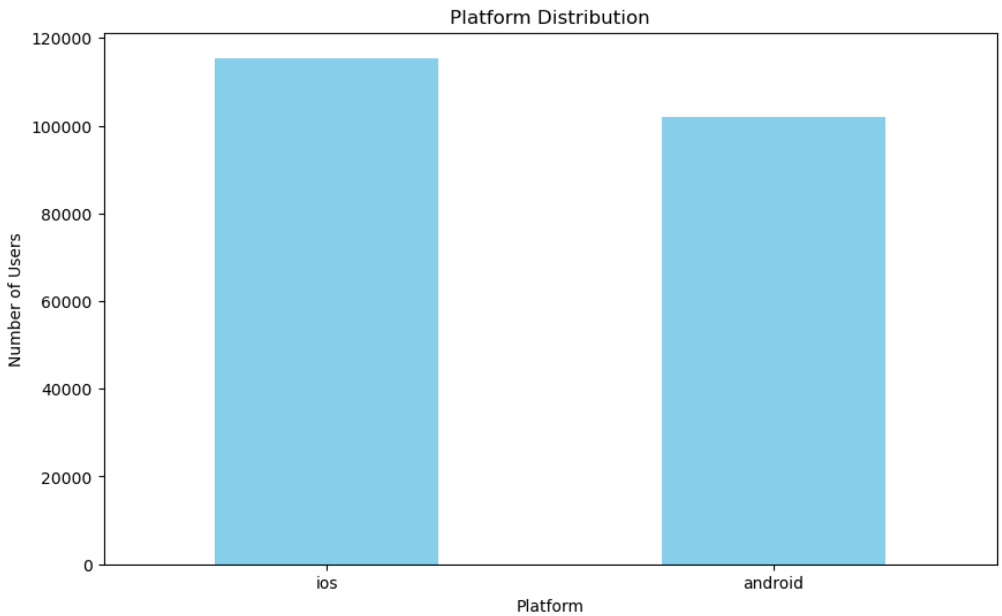
The "Hourly Installs" graph shows the number of downloads made at each hour of the day. Hours with significantly high download numbers indicate the time periods during which the game is most downloaded. It might be wise to intensify marketing and promotional activities during these hours. Understanding at which hours users are more active provides insight into the game's user base. For instance, high download rates during nighttime hours may indicate a global user base.

3.1.2.Daily Installs



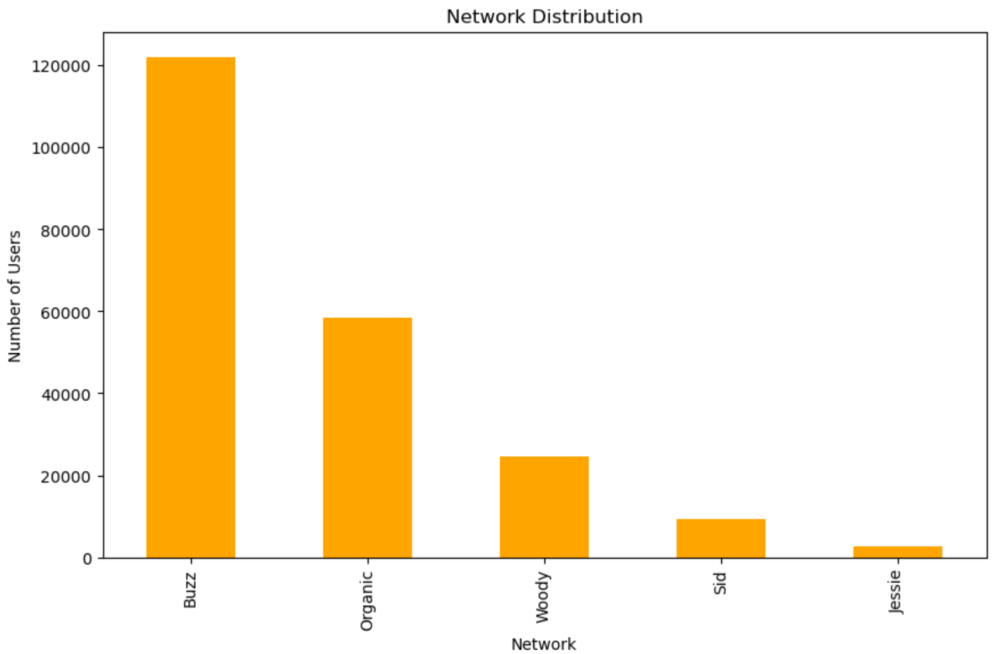
In the graph, each point represents the number of users who downloaded the game on a specific day. The red line shows the trend of daily download numbers over time. In the graph, increases or decreases in downloads can be observed during certain periods. These trends may be associated with marketing campaigns, game updates, or special events. Changes in download numbers can reflect users' interest in and behavior towards the game. Analyzing long-term download trends can indicate changes in the game's popularity. Sudden drops in downloads may point to potential issues or aspects of the game that users do not favor. This information can be used to make improvements in the game development process.

3.1.2.Platform Distribution



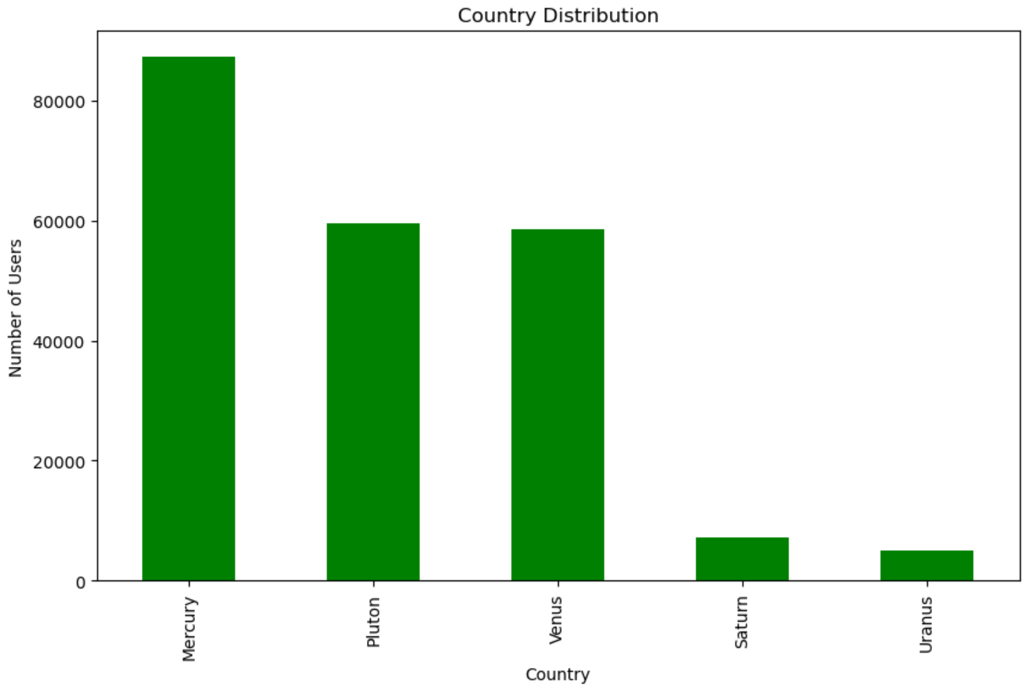
This graph shows which platforms (iOS, Android, etc.) the game is downloaded from the most. Understanding which platforms users prefer helps in making platform-specific optimizations during the game development process.

3.1.3.Network Distribution



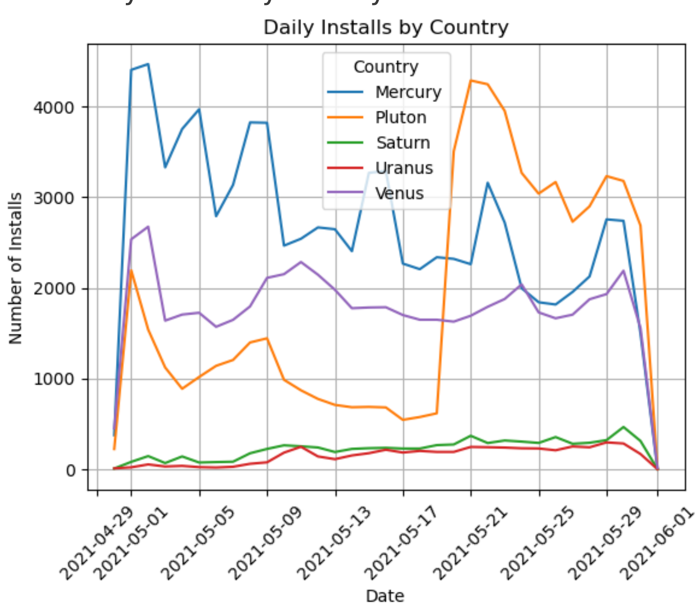
This graph shows which advertising networks or marketing channels users are downloading the game from. The tallest bars indicate the most effective advertising networks or marketing channels. This information can help make strategic decisions about where to allocate the advertising budget. By comparing the performance of different networks, it is possible to identify the most efficient user acquisition channels. Strategies for less effective networks can be reviewed or changed.

3.1.4. Country Distribution



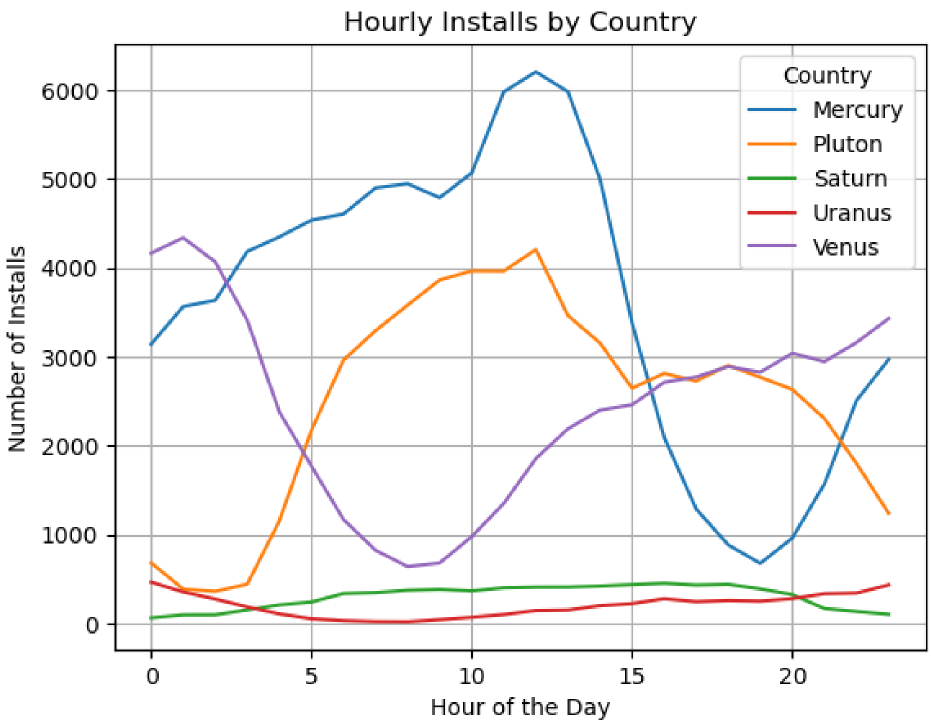
This graph shows the countries from which the game is downloaded the most. Understanding user behavior in different countries is important for localization and cultural relevance. For example, content or events popular in certain countries may differ from others. Countries with low download numbers can be considered potential growth areas. Marketing efforts can be increased or local features can be added in these regions.

3.1.5. Daily Installs By Country



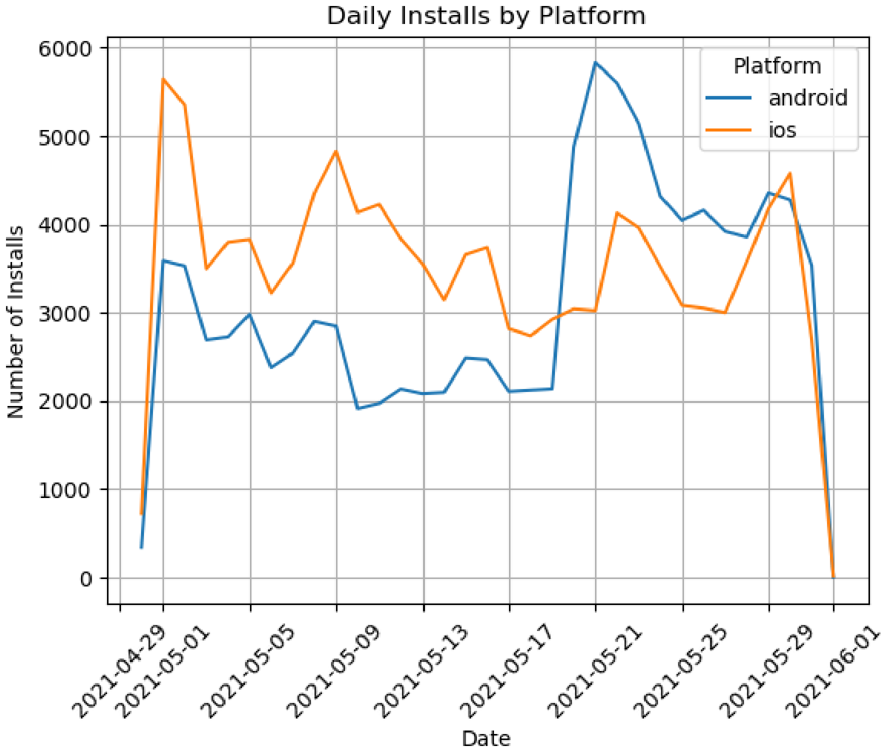
During certain periods, increases or decreases in downloads may be observed in some countries. These trends can be associated with local events, holidays, or marketing campaigns. By understanding the differences in downloads between different countries, country-specific marketing strategies can be developed. For example, if there are low download rates in a particular country, more intensive marketing campaigns can be conducted in that country.

3.1.6.Hourly Installs By Country



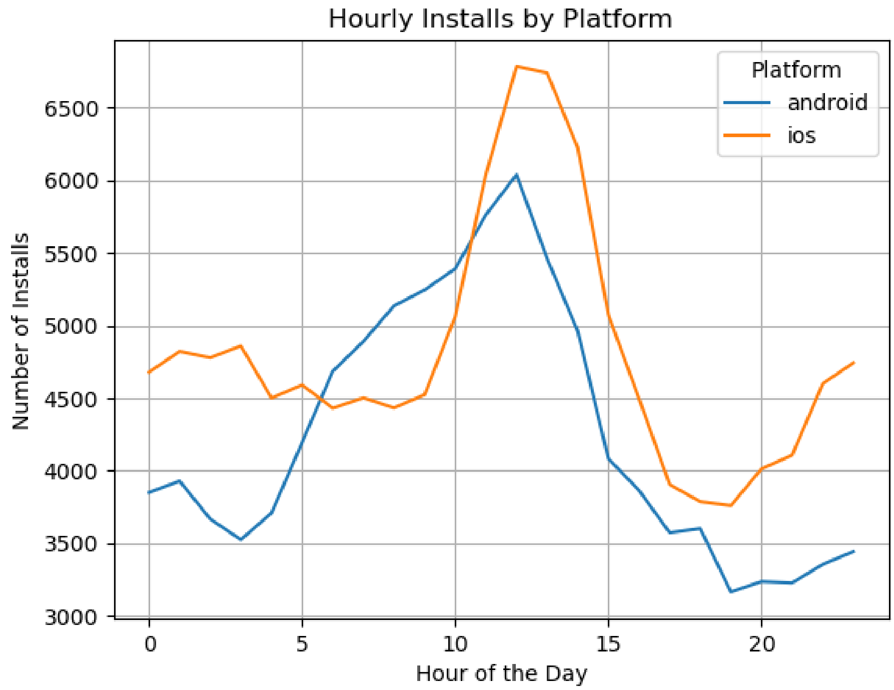
The presence of countries in different time zones leads to natural variations in download times. Countries with high downloads at certain hours indicate that users are more active during those time periods.

3.1.7.Daily Installs By Platform



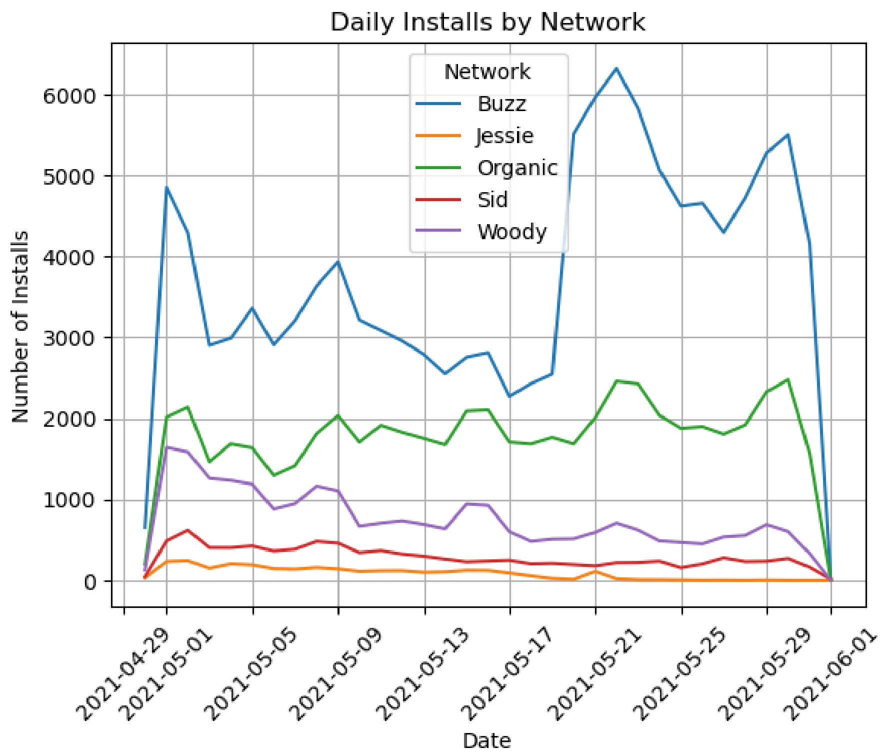
This graph shows the daily downloads of the game over time from different platforms (e.g., iOS, Android). During certain periods, increases or decreases in downloads may be observed on some platforms. These trends can be associated with platform-specific updates, advertising campaigns, or technical issues.

3.1.8.Hourly Installs By Platform



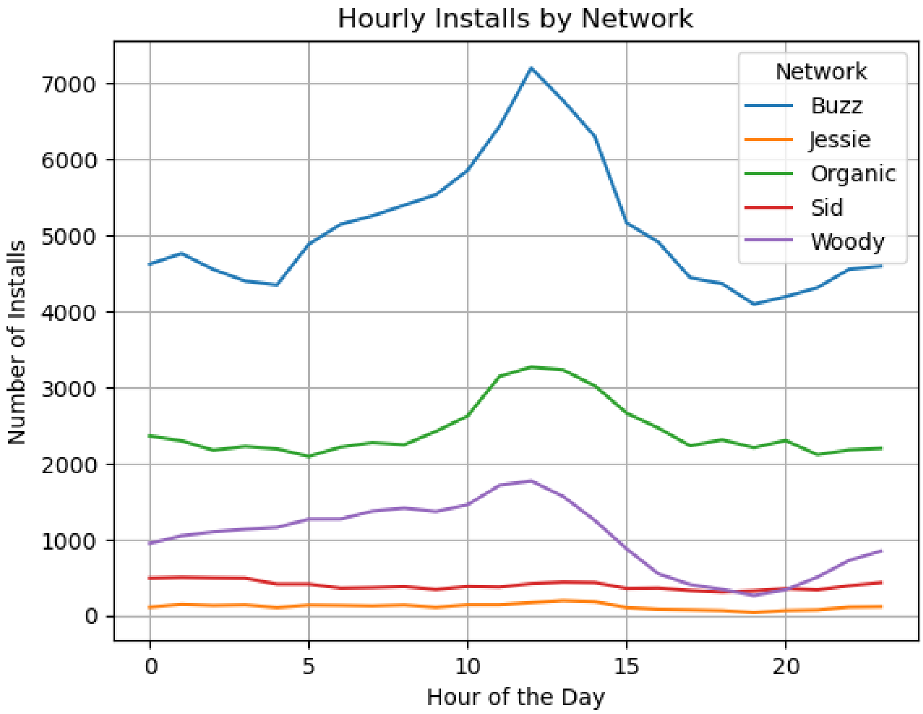
This graph shows the hourly downloads of the game from different platforms. Increases in downloads at certain hours on specific platforms may reflect platform-specific user behaviors. These differences can be used to develop platform-specific strategies.

3.1.9. Daily Installs By Network



This graph shows the daily downloads of the game over time from different advertising networks or marketing channels. The significantly higher downloads from certain networks indicate that these networks are the most popular channels for the game.

3.1.10.Hourly Installs by Network



Bu grafik, oyunun farklı reklam ağları veya pazarlama kanalları üzerinden saatlik yüklemelerini göstermektedir. Belirli saatlerde yüklemelerin yüksek olduğu networkler, bu saat dilimlerinde kullanıcıların daha aktif olduğunu gösterir. Farklı networklerdeki kullanıcı davranışlarını karşılaştırarak, kullanıcıların hangi saatlerde daha aktif olduğunu ve hangi networklerde bu saatlerde daha fazla yükleme yapıldığını anlayabilirsiniz.

3.1.11.Improvement Suggestions

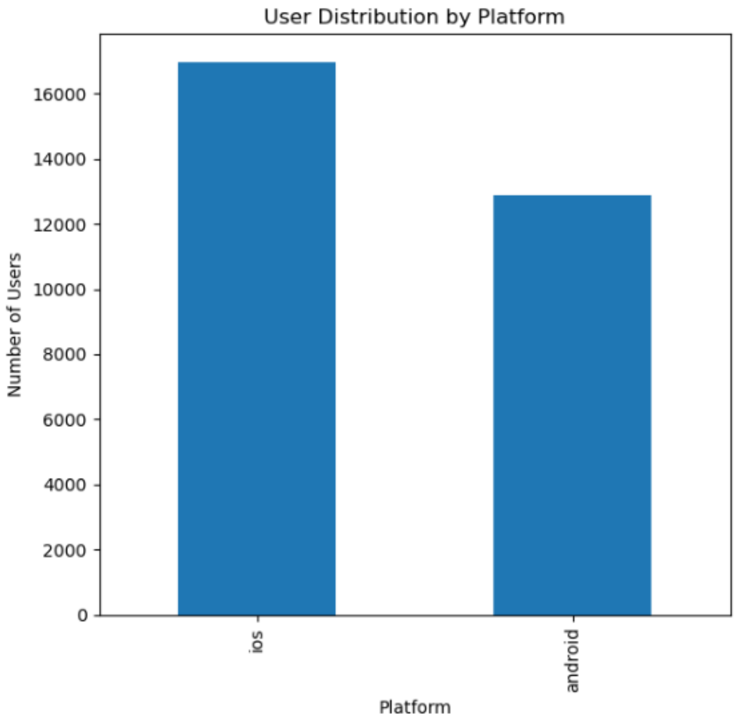
1. Track the steps users take after downloading the game. For example, by monitoring steps such as registration and the first game session, you can identify where user drop-off occurs.
2. Collect additional information on which devices users are downloading the game from (e.g., phone model, operating system version). This can help you make device-specific optimizations.
3. Organize special events and campaigns during specific time periods (e.g., holiday seasons, major sports events). This can increase user interest and attract new users.
4. Ensure that the game and marketing materials are adapted to different regions and languages. This can help you better respond to the needs of local markets and cultural differences.
5. Review the advertising budgets allocated to networks and adjust them based on the number of users downloading the game.

3.2.Dataset Session

This dataset contains detailed event data recorded for each user session in the game. It is crucial for understanding user interactions and behaviors within the game. By examining users' in-game behaviors, it is possible to conduct platform-based performance evaluations, analyze the in-game economy, and perform user engagement and level progression analyses.

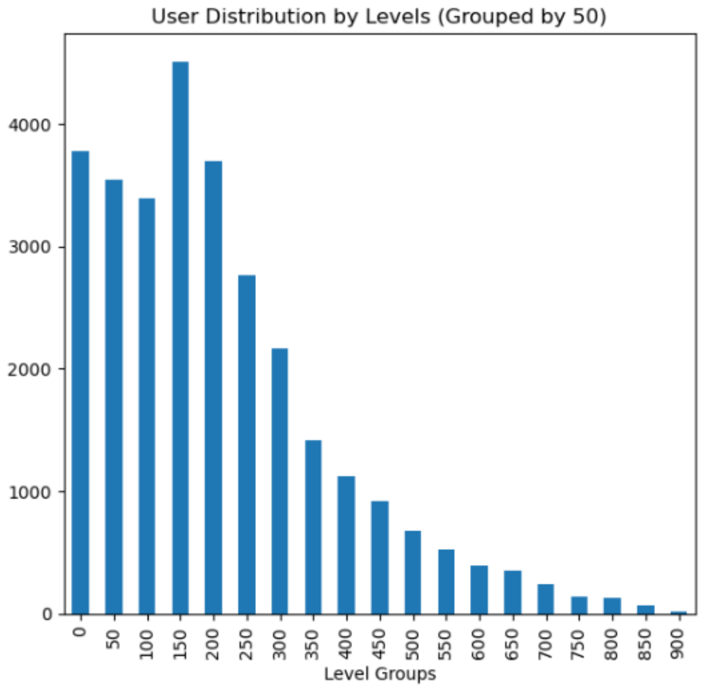
Due to the large amount of data in this dataset, a random sample of 1 in 10,000 of the total data has been taken.

3.2.1.User Distribution by Platform



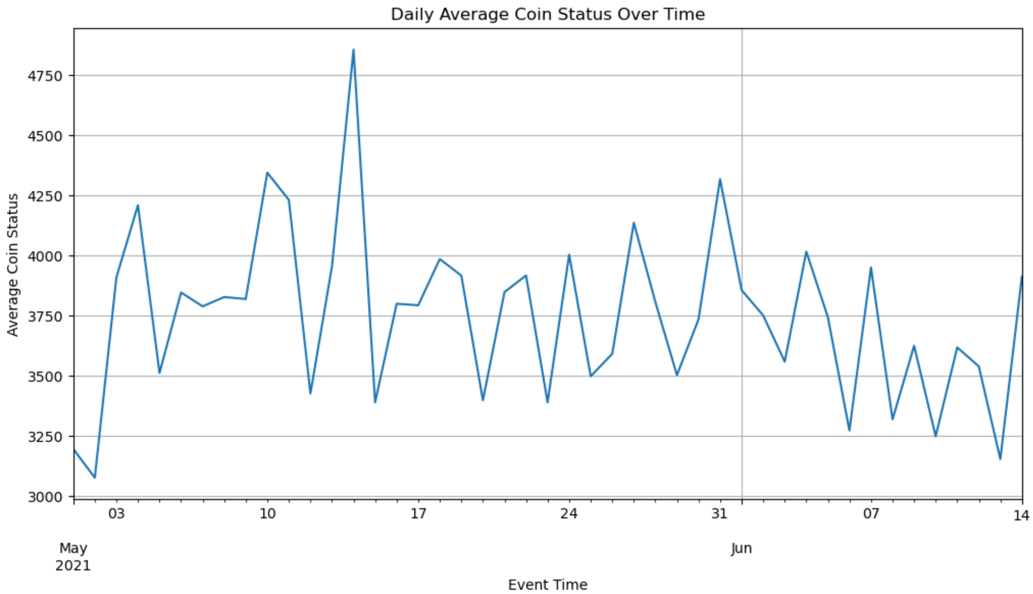
There are more users on the iOS platform compared to the Android platform. The lower number of Android users may be related to user experience issues. Therefore, the user experience on the Android platform should be improved, and potential issues should be resolved. Considering the differences between iOS and Android users, platform-specific content or events can be organized.

3.2.2.User Distribution by Levels



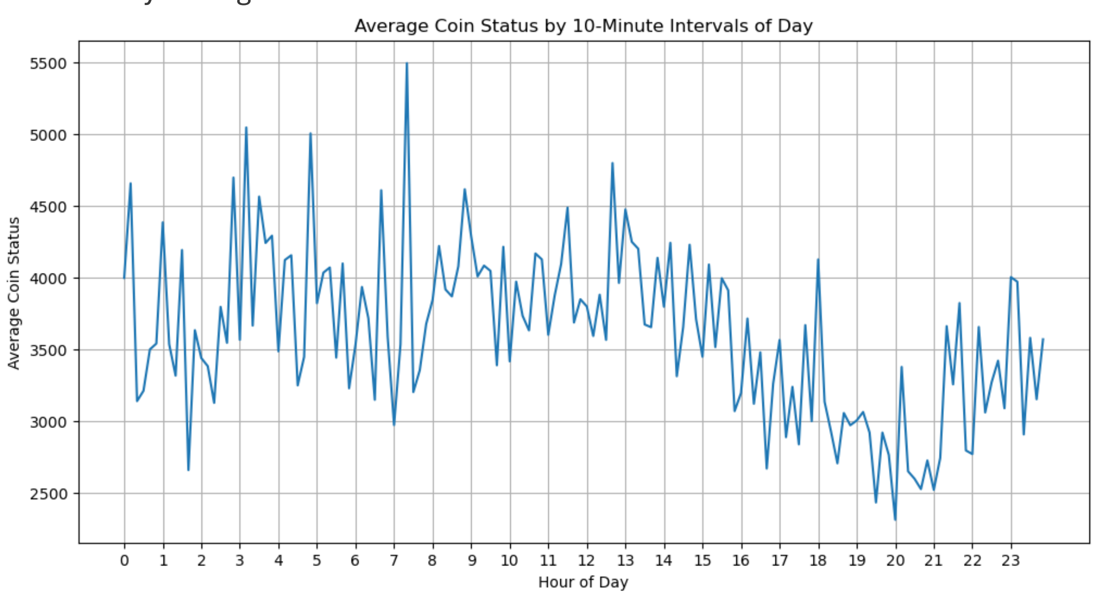
This graph shows the distribution of users in the game by level. On the X-axis, users' levels are grouped in increments of 50, while the Y-axis shows the number of users in each level group. The number of users is high in the first 200 levels, followed by a decline. The decrease in the number of users after a certain level may be related to how new the game is, or users may be disengaging after the 200th level. User behaviors at these levels should be examined in detail. As the level group increases, especially after the 200th level, a significant drop in the number of users is observed.

3.2.3. Daily Average Coin Status



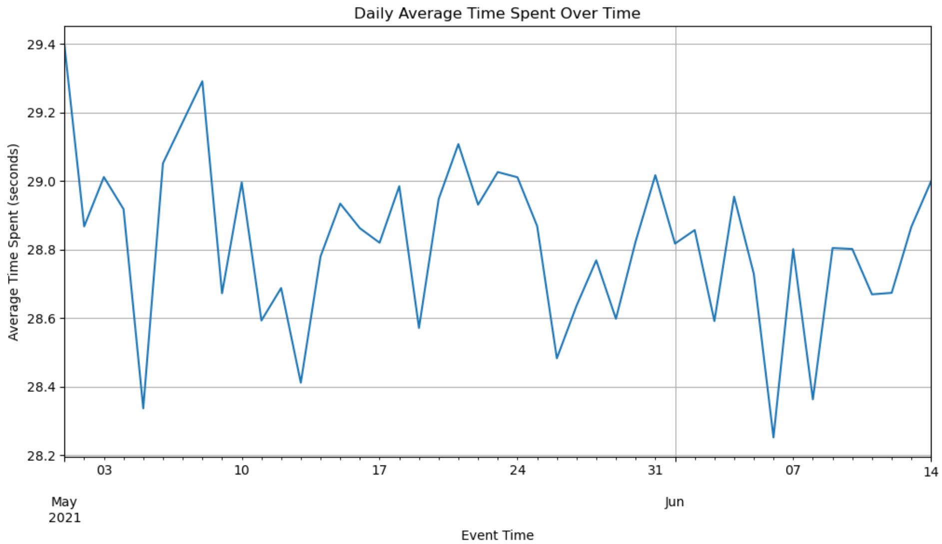
In this graph, the daily average coin status (coin amount) over a specific time period is shown. The fluctuations are quite irregular and do not follow a specific trend. Sudden increases may indicate in-game events, rewards, or periods when users collectively accumulate coins. For example, in-game events or bonuses may have been offered to users on certain days.

3.2.4. Hourly Average Coin Status



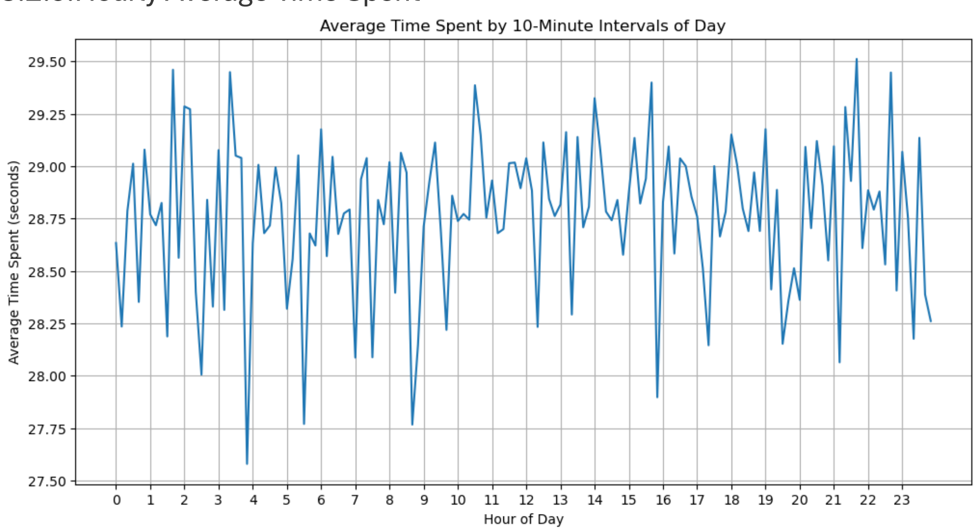
In this graph, the average coin status (coin amount) is shown for each 24-hour time period. Higher average coin status values are observed in the early morning hours (0-6) and evening hours (17-24). A decline in average coin status values is observed in the midday hours (12-16). The increase in coin status values in the early morning and evening hours may indicate that users are more active during these times. The midday declines could suggest that users have less time to play due to work or school commitments.

3.2.5.Daily Average Time Spent



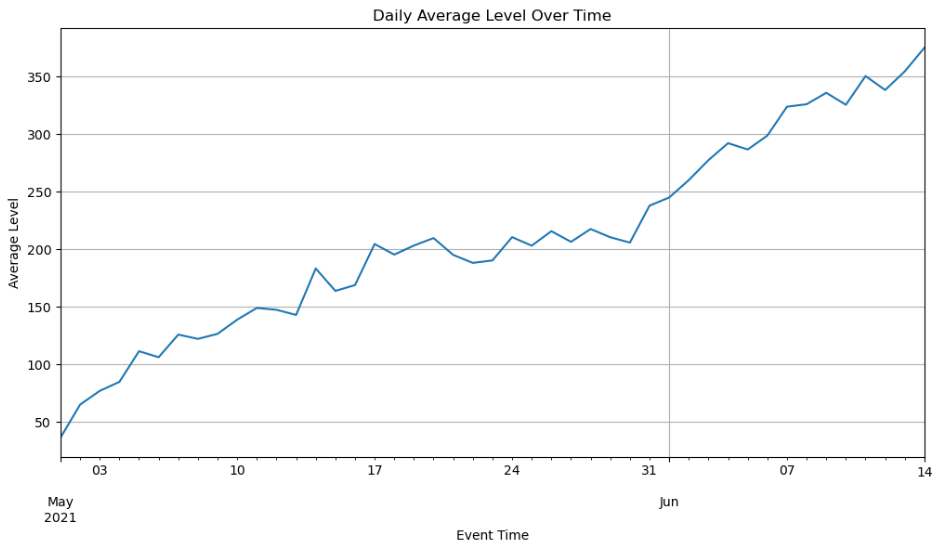
This graph shows the daily average time spent over a specific time period.

3.2.6.Hourly Average Time Spent



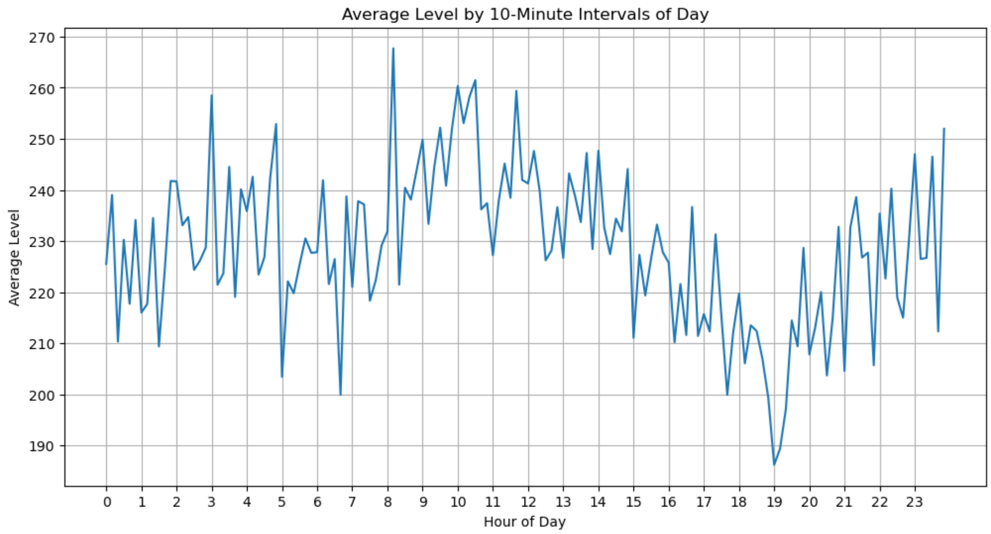
This graph shows the average time users spend in the game for every 10-minute time interval throughout the day. It is observed that users spend more time in the game during the early morning hours (0-6) and evening hours (18-24). This indicates that users are more active and spend more time in the game during these hours. A decline in the time spent in the game is observed during midday hours (12-16). These hours may be when users have less time to play due to work or school commitments.

3.2.7.Daily Average Level



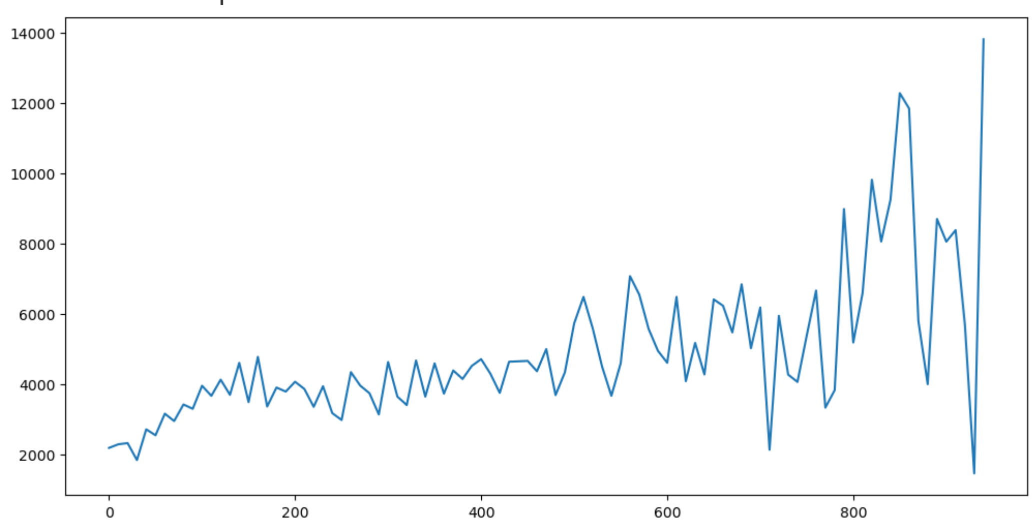
This graph shows the daily average level over a specific time period. A consistent upward trend in users' average levels indicates that the game is regularly played by users and that progress is being made in level advancement. Periods where the rate of increase slows down may suggest that users are spending less time on the game or that progressing becomes more challenging. This could be related to increasing difficulty levels in the game or a decline in user interest.

3.2.8.Hourly Average Level



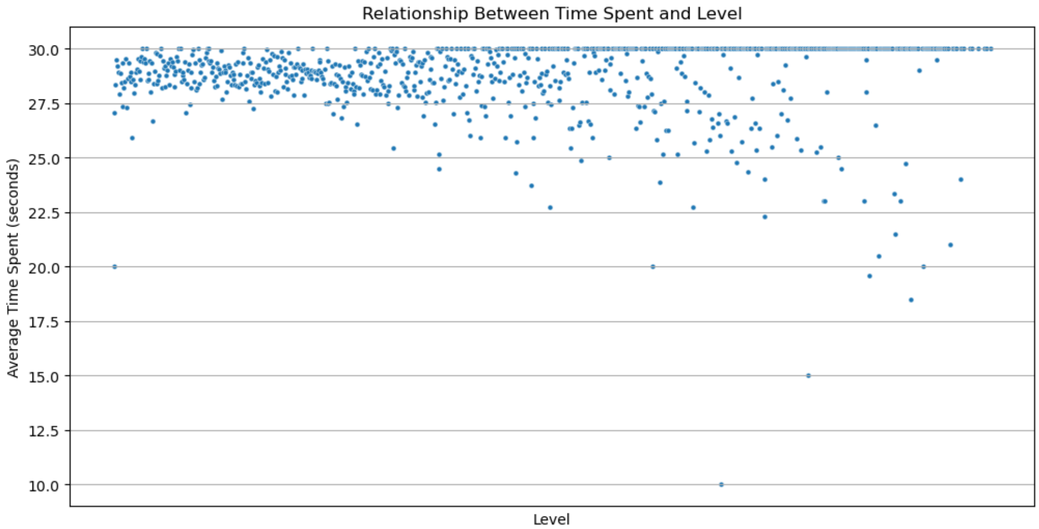
This graph shows the average levels achieved by users in 10-minute intervals throughout the day. Notable increases in average levels are observed during early morning and evening hours. These times may be when users are more active and making more progress. A decline in average levels is observed during midday hours (12-16). During these hours, the rate of new users downloading the game is high. Naturally, the number of level 1 players increases, which lowers the average level.

3.2.9.Relationship Between Coin Status and Level



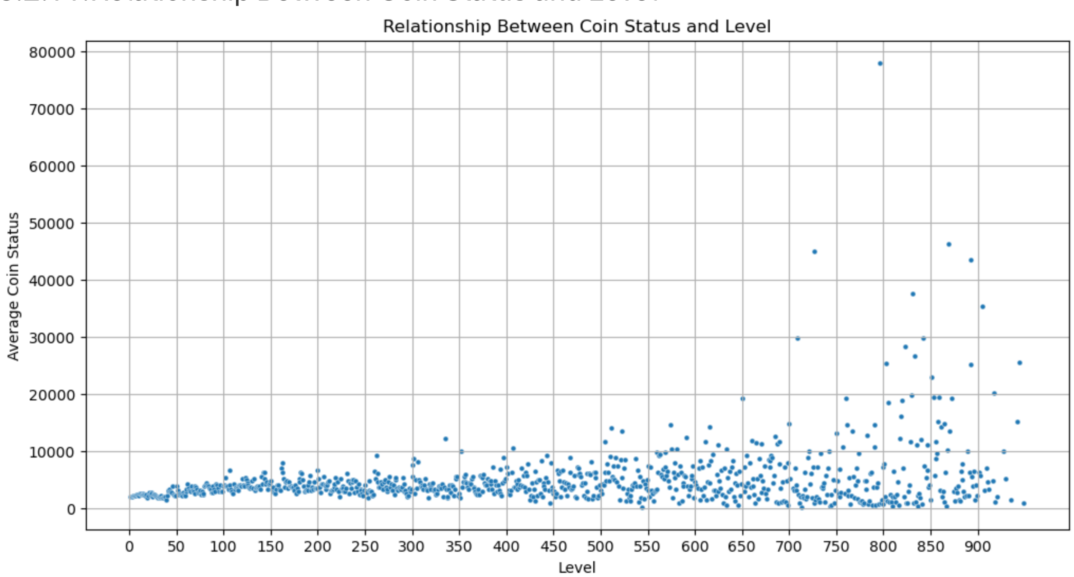
This graph shows the relationship between coin status and level. The general upward trend in coin status values as the level increases may indicate that users accumulate or spend more coins as they progress in the game. Users who spend a lot of coins as their level increases have a higher risk of leaving the game entirely, so these users can be grouped and given special coin rewards. Additionally, sudden increases and decreases at certain levels may be related to in-game events or level-up bonuses.

3.2.10.Relationship Between Time Spent and Level



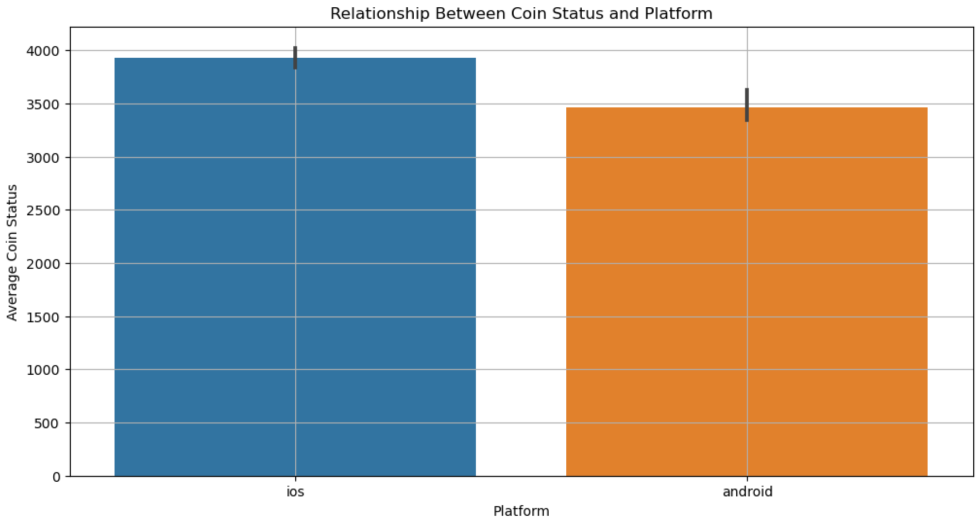
This graph shows the relationship between the average time spent by users at certain levels and their level. A wider time distribution at lower levels may indicate that users are progressing at different speeds or are in the process of learning the game. Occasional drops in time spent at higher levels may mean that some players are advancing through levels more quickly as they become more familiar with the game, or they may be leaving the game. In general, the average time spent at higher levels is 30. Players who fall below this threshold should be examined, and appropriate strategies should be applied based on their risk of disengagement from the game.

3.2.11.Relationship Between Coin Status and Level



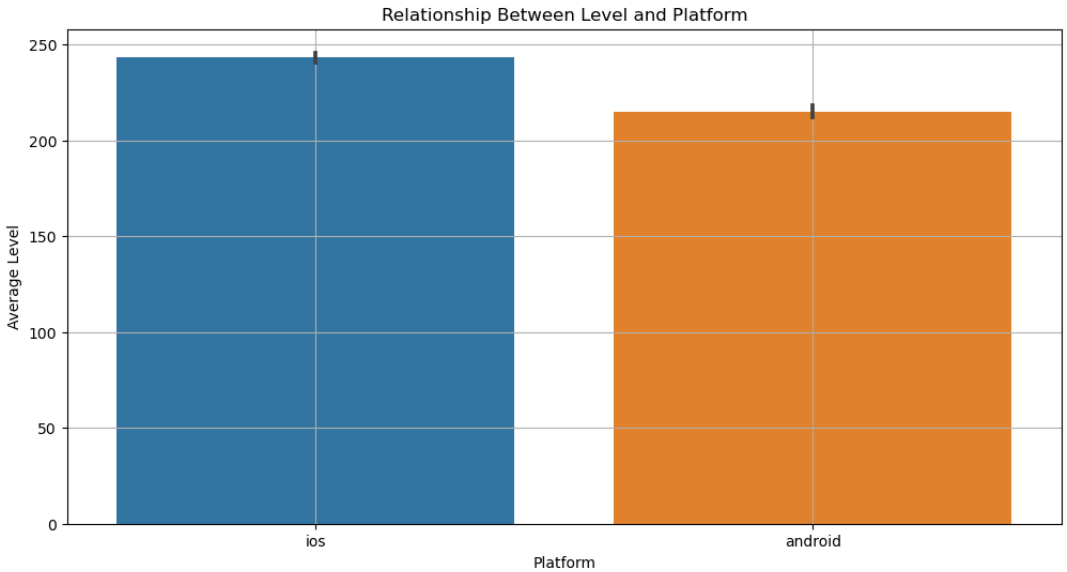
This graph shows the relationship between users' coin status and their levels. It is observed that coin status values are quite low and have a tighter distribution at lower levels. As the levels increase, coin status values spread over a wider range and show an upward trend. At higher levels (especially 500 and above), some users have very high coin status values.

3.2.12.Relationship Between Coin Status and Platform



This graph compares the average coin status values of users on iOS and Android platforms. The higher coin status values of iOS users may indicate that these users are more active in in-game activities or spend more on in-game purchases. Special promotions, bonuses, or events can be organized to further encourage Android users. This could increase in-game spending by Android users.

3.2.13.Relationship Between Level and Platform



This graph compares the average level values of users on iOS and Android platforms. The higher average level values of iOS users may indicate that these users progress further and reach more levels in the game. This could suggest that iOS users are more engaged with the game or spend more time playing. Additionally, it may indicate that iOS users have a better device experience, leading to a higher level of engagement compared to Android users.

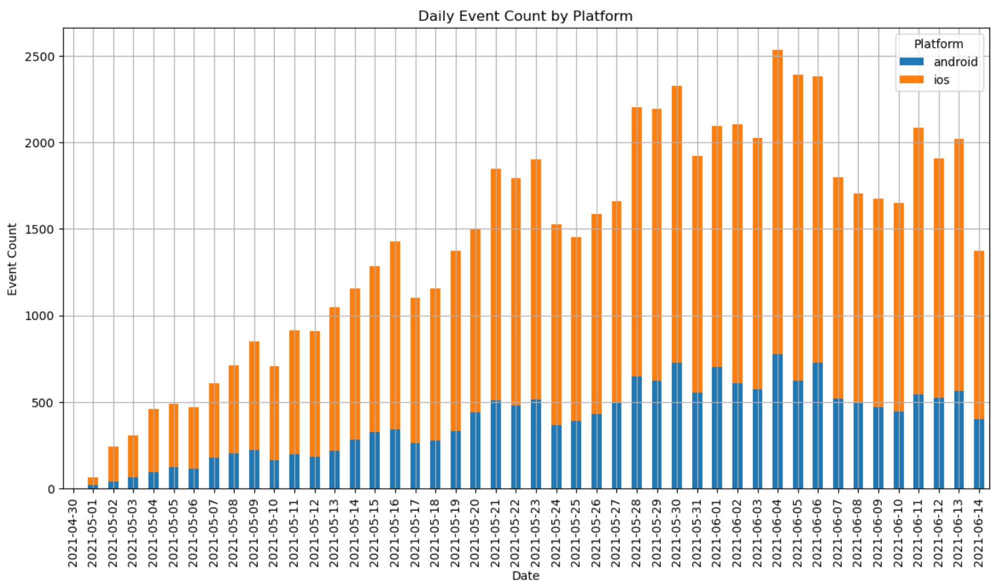
3.2.14.Improvement Suggestions

1. Machine learning models can be developed to predict or classify user behaviors. For example, future spending can be predicted based on users' levels in the game.
2. Analyzing the reasons why users quit the game can help develop strategies to reduce user churn. This analysis can help you understand at which stages and why users abandon the game.
3. Analyzing the reasons why users quit the game can help develop strategies to reduce user churn. This analysis can help you understand at which stages and why users abandon the game.
4. Players can be evaluated in different groups based on certain metrics, and in-game strategies can be implemented to increase game time and the number of players.

3.3.Dataset Revenue

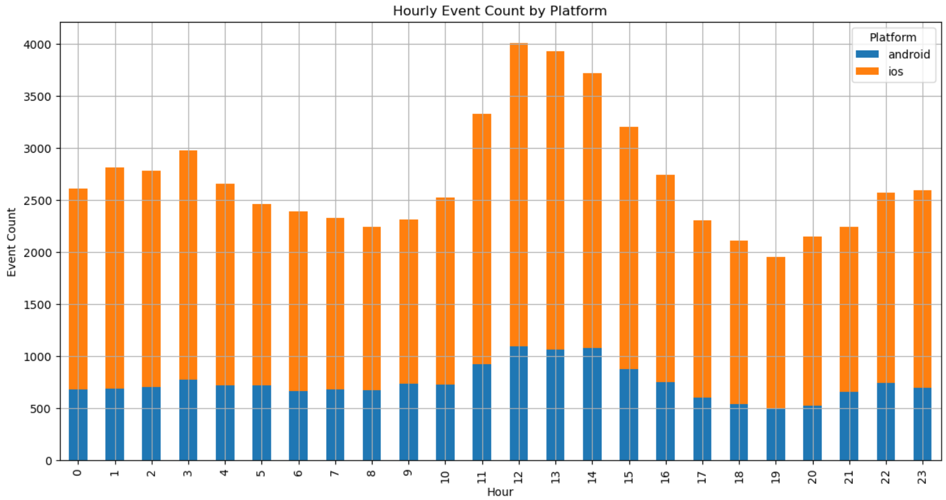
The dataset used in the analyses contains comprehensive information reflecting users' in-game behaviors and spending habits. These datasets include various metrics such as user IDs (user_id), purchase times (event_time), platform types (iOS and Android), types of purchased packages (package_type), and revenue obtained (revenue). Analyzing these datasets is critical for evaluating the game's performance and understanding user behaviors. Revenue distribution analyses over time intervals help us understand the relationship between purchase frequency and revenue. The frequency of users' purchases and its effects on average revenue allow the development of strategies such as loyalty programs and recurring offers. These analyses can help develop strategies that encourage users to make purchases more frequently. Revenue per user analyses identify the game's most valuable users and how much revenue they generate. Graphs of the highest spending users reveal the impact of high-spending users on the game's economy. This information enables the development of special strategies to retain and reward high-spending users.

3.3.1. Daily Event Count by Platform



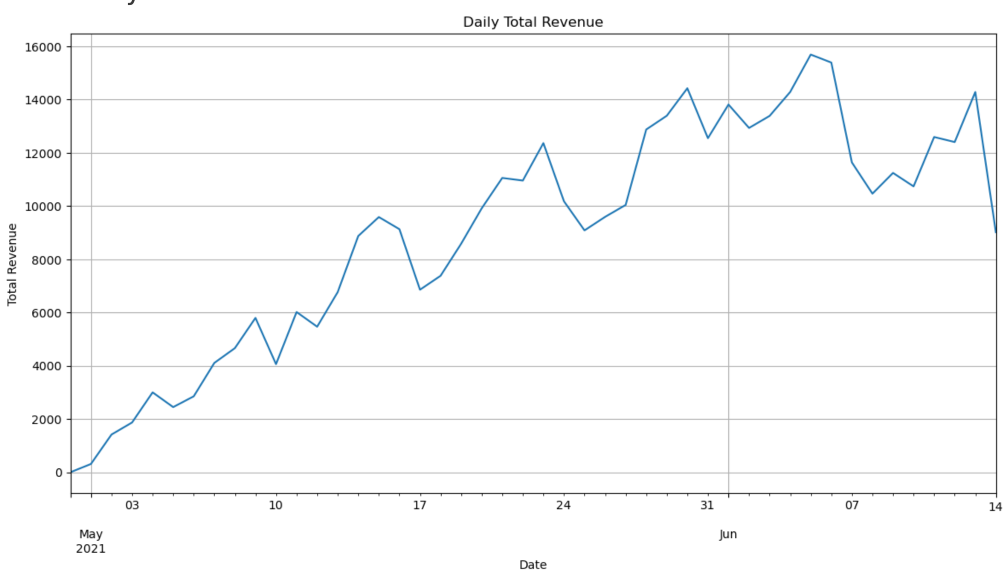
The graph shows a clear upward trend in the total number of events over time. This may indicate that the game's user base is growing or that users are engaging more with the game. During the period from early May 2021 to mid-June 2021, the number of events increased steadily on both platforms. This could suggest that the game gained popularity during this time or that a successful marketing campaign was conducted. The iOS platform (shown in orange) generally has a higher number of events compared to the Android platform (shown in blue). This could mean that iOS users play the game more or show more interest in the game than Android users.

3.3.2.Hourly Event Count by Platform



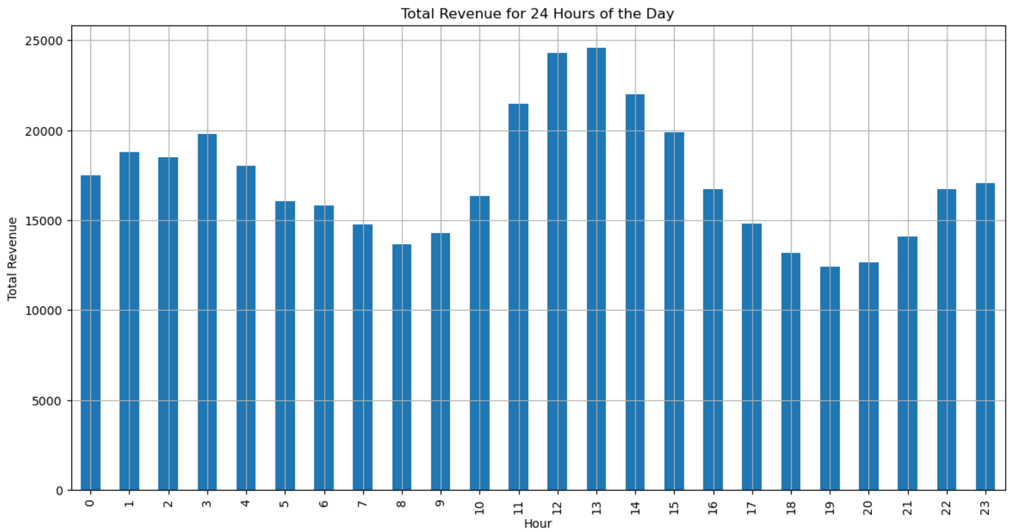
This graph shows the number of events occurring each hour of the day on iOS and Android platforms. A significant increase in the number of events is observed between 10:00 AM and 2:00 PM. During this time period, both iOS and Android users play the game more frequently. These hours are when users are most active. The number of events remains high between 11:00 PM and 3:00 AM as well. This may indicate the presence of users who play the game late at night.

3.3.3.Daily Total Revenue



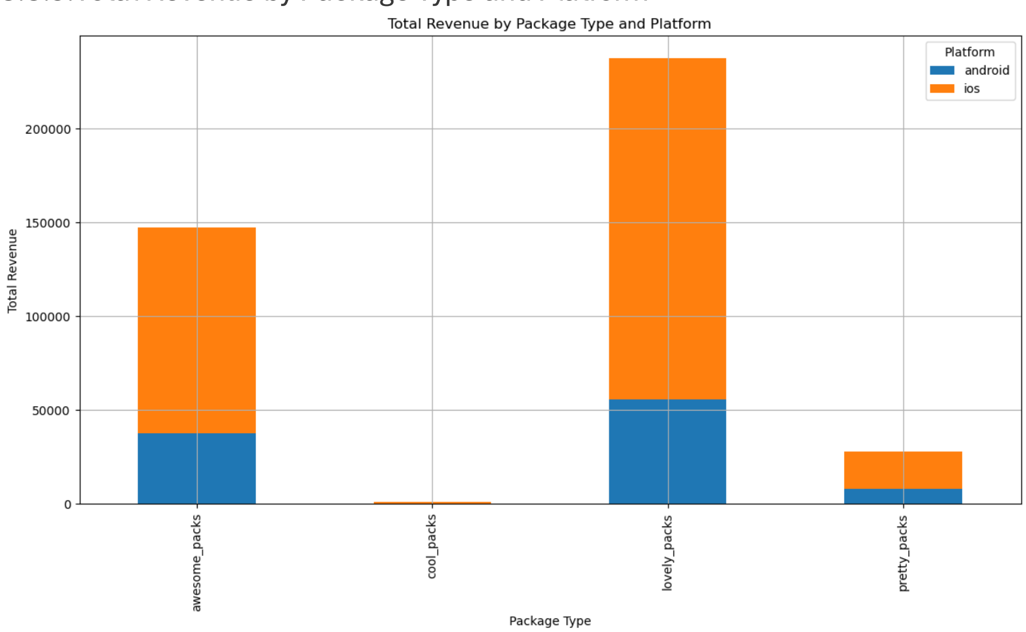
This graph shows the total daily revenue over a specific time period. Overall, the graph indicates a clear upward trend in total revenue over time. This may suggest that the game's user base is growing or that users' in-game spending is increasing.

3.3.4. Total Revenue for 24 Hours of the Day



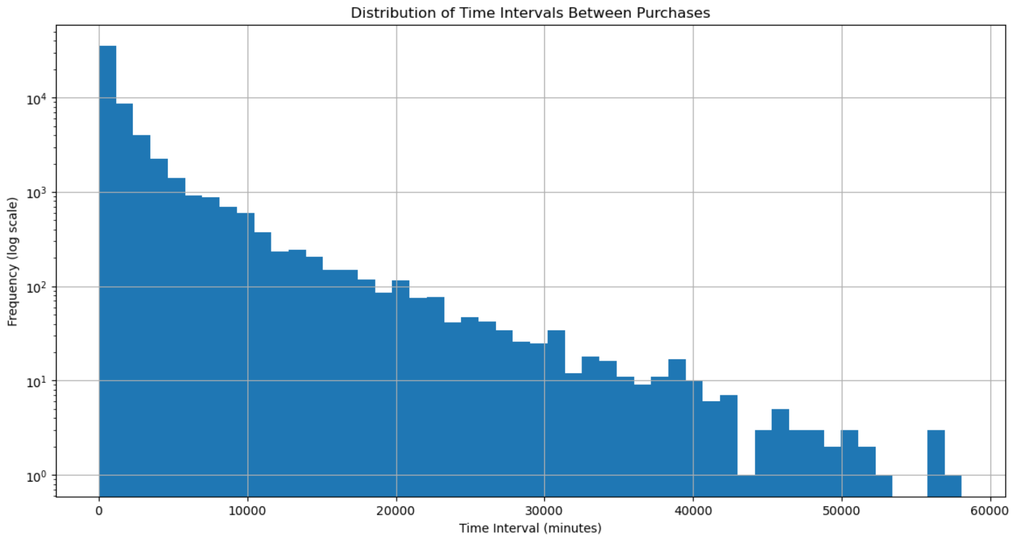
This graph shows the total revenue generated each hour of the day. Naturally, this graph closely resembles the purchase count graph.

3.3.5. Total Revenue by Package Type and Platform



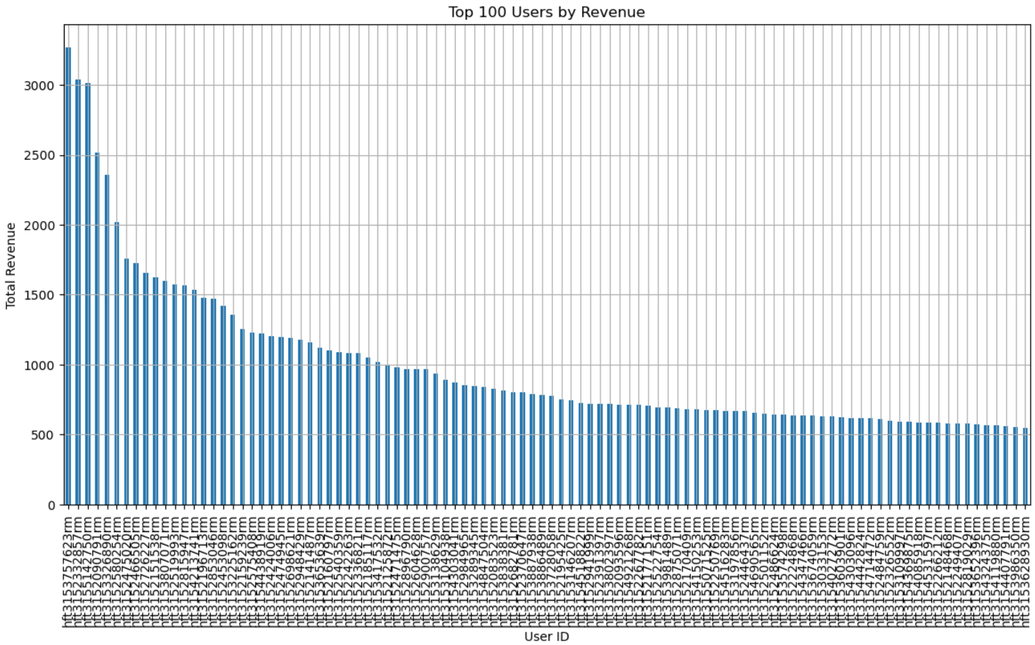
This graph shows the total revenue generated by different package types and platforms (iOS and Android). The graph indicates that the "awesome_packs" and "lovely_packs" package types generate significantly higher revenue compared to other package types. The iOS platform (shown in orange) generally generates more revenue than the Android platform (shown in blue). In the "awesome_packs" and "lovely_packs" package types, iOS revenue is significantly higher than Android revenue.

3.3.6.Distribution of Time Intervals Between Purchases



This graph shows the distribution of time intervals between users' purchase transactions. The graph indicates that the frequency of purchases made within short time intervals (e.g., within a few minutes) is very high. This suggests that users tend to make consecutive purchases within short periods. As the time interval increases, the purchase frequency decreases. In other words, users generally make repeat purchases within short periods, and as this interval lengthens, the purchase frequency drops. Given th e high frequency observed within short time intervals, strategies to encourage more spending during these periods can be developed. For example, offering discounted deals shortly after the first purchase could be effective.

3.3.7.Top 100 Users by Revenue



This graph shows the top 100 highest-grossing users in the game and the total revenue generated by each user. The purchasing behavior of these players can be examined specifically. By analyzing the differences in total revenue in detail and creating an environment that encourages these players to make more purchases, an increase in revenue can be observe

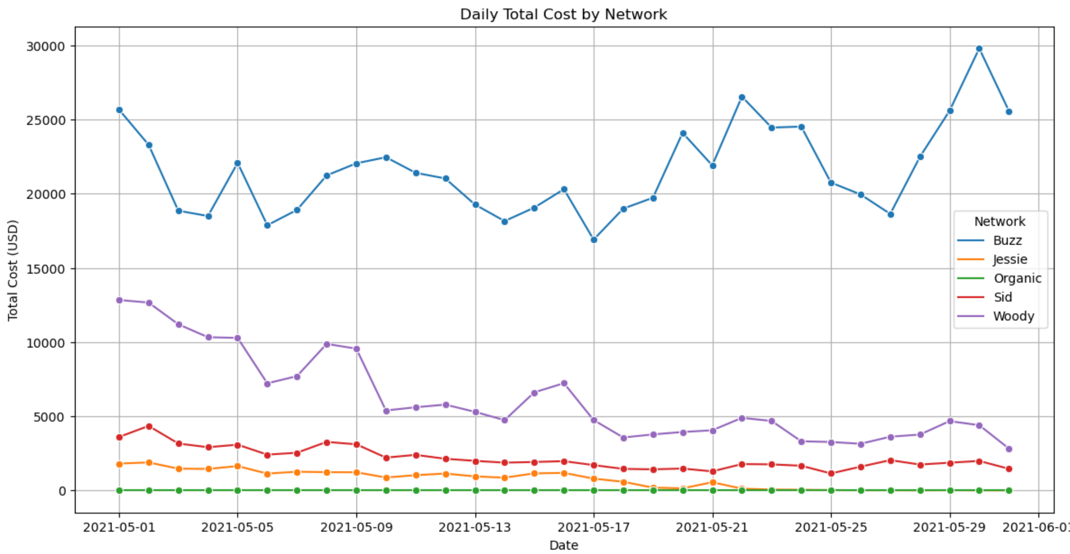
3.3.8.Improvement Suggestions

1. It has been observed that players are more active at certain hours and days. Special events and advantageous packages can be offered during these times to generate more revenue.
2. Special benefits can be provided to high-spending players to encourage other players to spend more.
3. Underperforming packages can be reviewed and, if necessary, their content and names can be changed.
4. Continuously review data collection processes to gather more user behavior data. Users can be grouped and appropriate sales strategies can be applied to each group.
5. Since total purchases on Android devices are much lower than on iOS, purchasing advantages for Android devices can be increased.

3.4.Dataset Cost

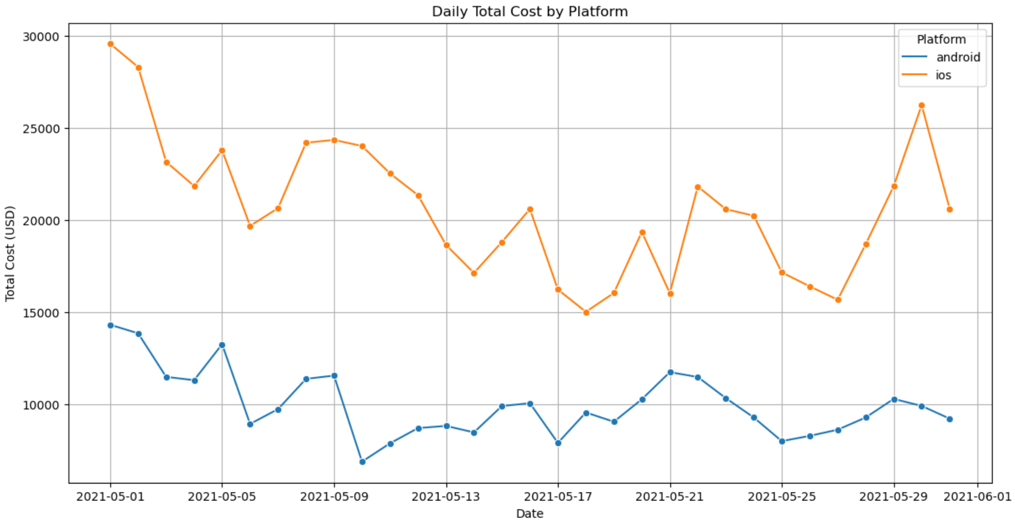
This dataset includes expenses for user acquisition. It contains the total cost and the number of observations based on specific dates, networks, platforms, and countries. Expenditures on different advertising networks have been examined. For example, differences may be observed between expenditures on networks such as Facebook or Google Ads. Using this dataset, country and network-based strategies can be focused on. Different marketing strategies can be applied to networks and countries with low user returns.

3.4.1.Daily Total Cost by Network



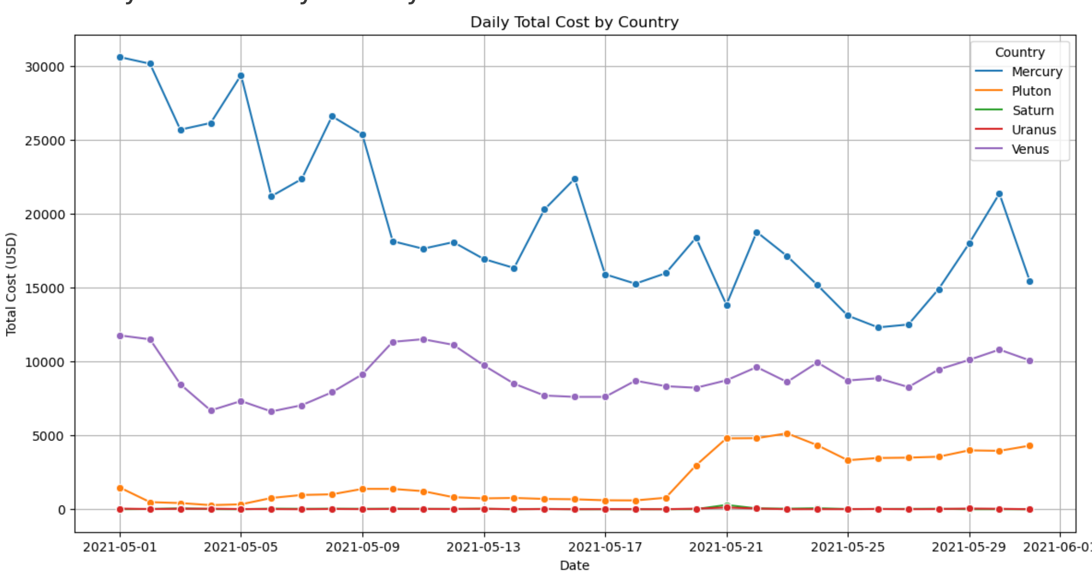
This graph shows the total costs of different advertising networks on a daily basis. It is important to analyze the returns of the high costs for Buzz and Woody networks. It should be ensured that high-cost networks provide higher-yield users. By analyzing the quality of users brought by low-cost networks (Jessie, Organic, Sid), it can be determined whether to increase investments in these networks. Fluctuation periods can provide insights into the timing of campaigns. Especially the periods when costs increase indicate times of more intensive marketing activities.

3.4.2. Daily Total Cost by Platform



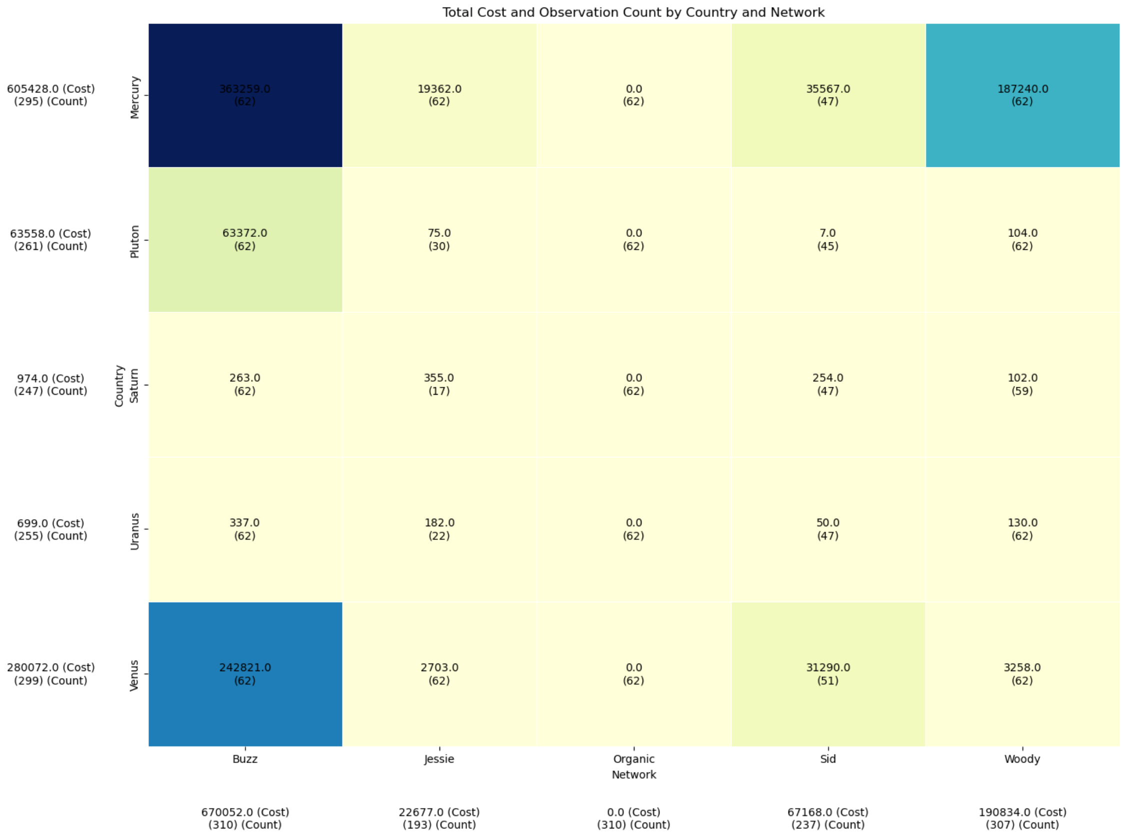
This graph shows the total costs of different platforms (Android and iOS) on a daily basis. Higher expenditures on the iOS platform may indicate that this platform is more lucrative or targets a more specific market. This suggests that future marketing budgets might be allocated more towards iOS. Low-cost user acquisition strategies on the Android platform can continue with the goal of reaching a broader audience. However, additional strategies can be developed to increase the value of these users.

3.4.3. Daily Total Cost by Country



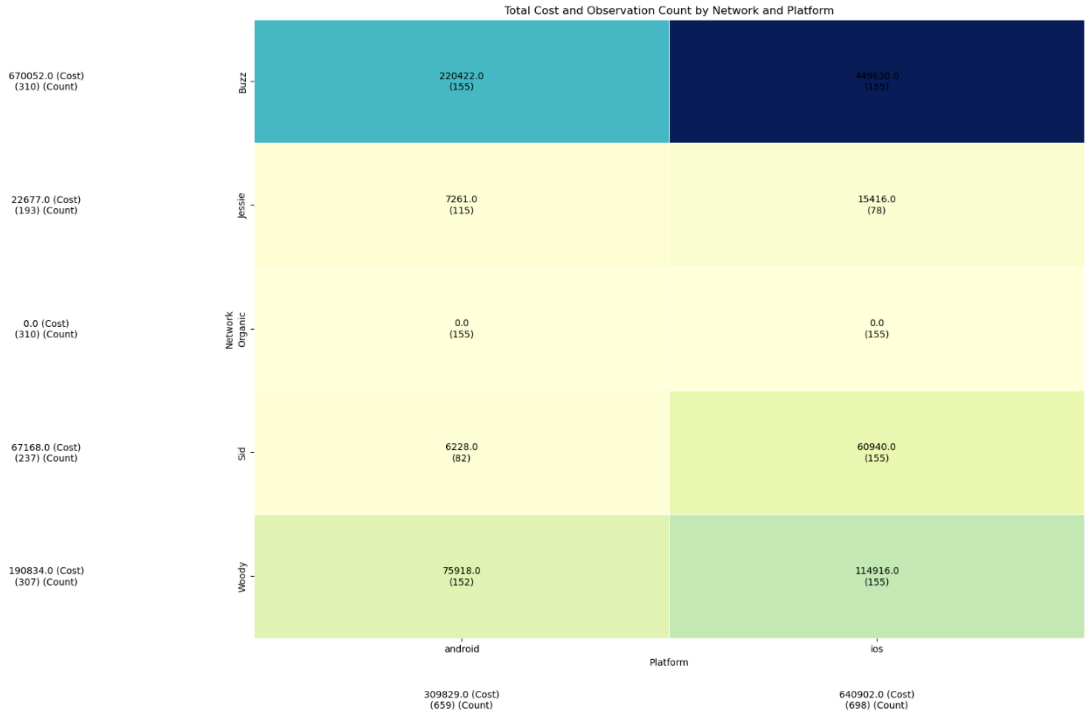
This graph shows the total costs of different countries on a daily basis. Expenditures in the country of Mercury are significantly higher compared to other countries. This indicates that Mercury is a primary target market and that user acquisition in this country is more expensive. The high expenditures in Mercury may suggest that users in this market generate higher revenue or that a more aggressive marketing strategy is being implemented. Saturn may be a market where the lowest cost user acquisition strategies are applied. This could mean that the marketing budget is lower, or that this country is a lower priority target.

3.4.4. Total Cost and Observation Count by Country and Network



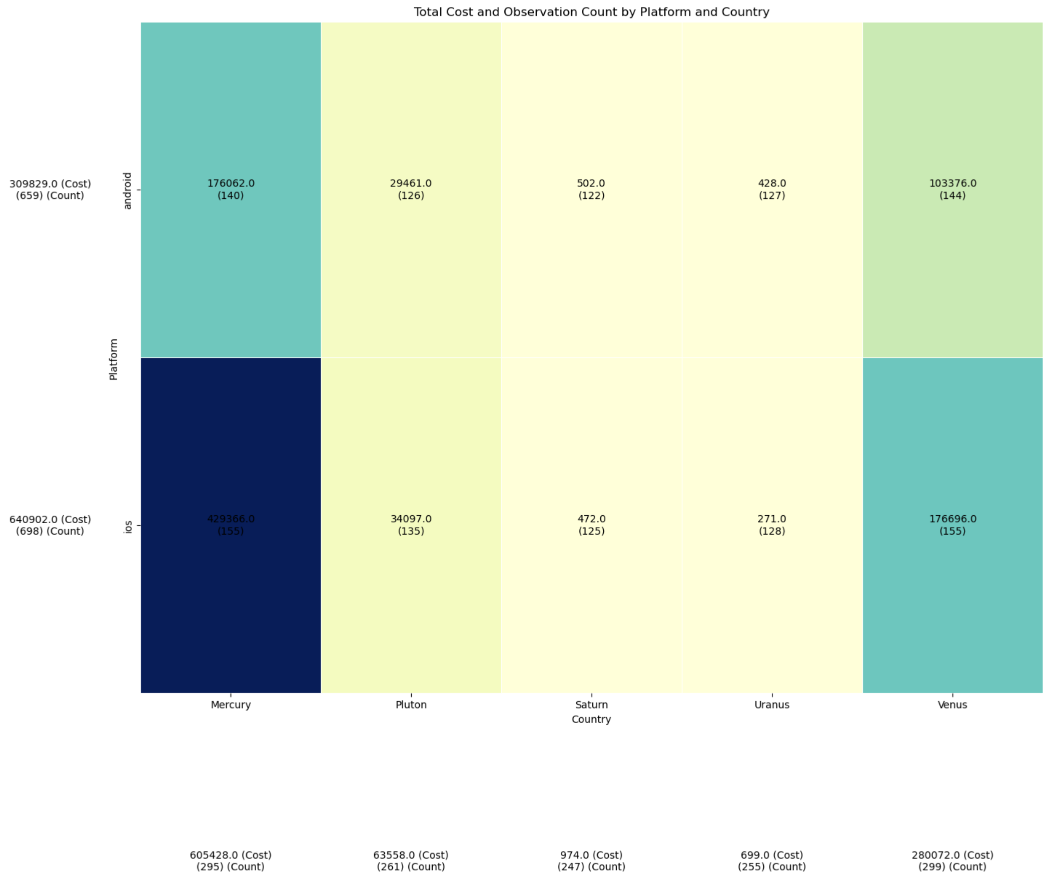
This graph is a heat map showing the total cost and the number of observations by country and network. The Buzz network stands out as a high-cost but high-yield network. Detailed analyses should be conducted to understand how efficiently the budget allocated to this network is used. Mercury shows significant user acquisition costs through the Buzz network. This indicates that Mercury is a primary target market and that the Buzz network is effective in user acquisition in this market. The cost of the Organic network appears as 0. This could mean that this network is used by users to download the game without seeing ads.

3.4.5.Total Cost and Observation Count by Network and Platform



This graph is a heat map showing the total cost and the number of observations by network and platform. It indicates significant user acquisition costs through the Buzz network on the iOS platform. iOS users typically may generate higher revenue, which could explain the greater investment in this platform. The Android platform targets a broader audience and provides user acquisition at relatively lower costs. The Buzz network has been effectively used here as well.

3.4.6. Total Cost and Observation Count by Platform and Country



This graph is a heat map showing the total cost and the number of observations by platform and country. Higher expenditures on the iOS platform indicate that this platform is more lucrative or targets a more specific market. Especially the countries Mercury and Venus stand out as significant user acquisition regions on the iOS platform.

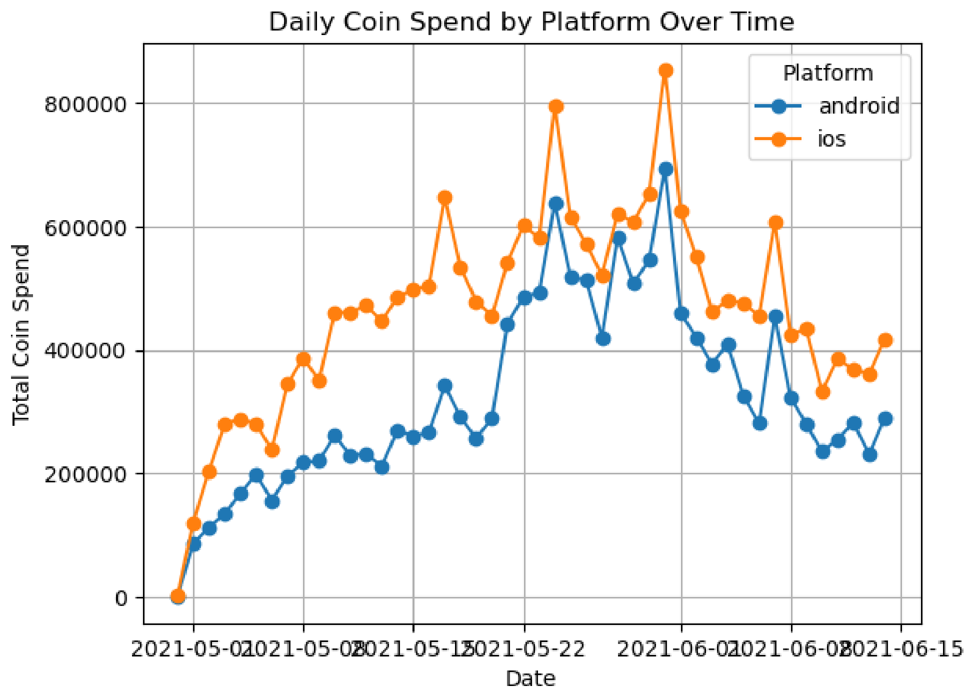
3.4.7. Improvement Suggestions

1. Analyze the returns on expenditures for different networks and platforms. These analyses can help determine which campaigns are more efficient and whether high-cost campaigns provide the expected returns.
2. Conduct time series analyses to examine spending trends and seasonal effects over time. These analyses help understand cost changes during specific periods.
3. Analyze correlations and cause-and-effect relationships between different variables. For example, examine cost differences between certain platforms or networks and how these differences impact user behavior.
4. Implement dynamic budget management to adjust the marketing budget based on performance. Allocate more budget to high-performing campaigns to increase efficiency.

3.5.Dataset Coin Spend

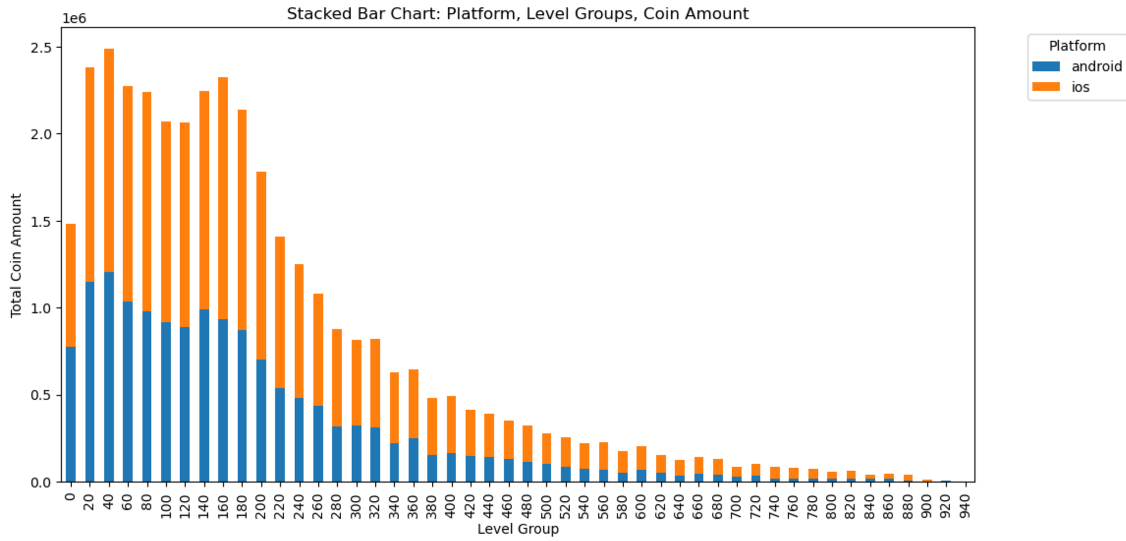
This dataset is used to track users' coin spending activities in a game. A random sample of 1% of the data has been taken for analysis. This dataset includes each spending event and related information. Understanding which levels and spending types users spend more coins on can be used to improve game design and user experience. Comparing the coin spending behaviors of users on different platforms can be used for platform-specific optimizations. By analyzing whether users spend more coins at certain levels, it is possible to assess the difficulty of those levels.

3.5.1.Daily Coin Spend by Platform



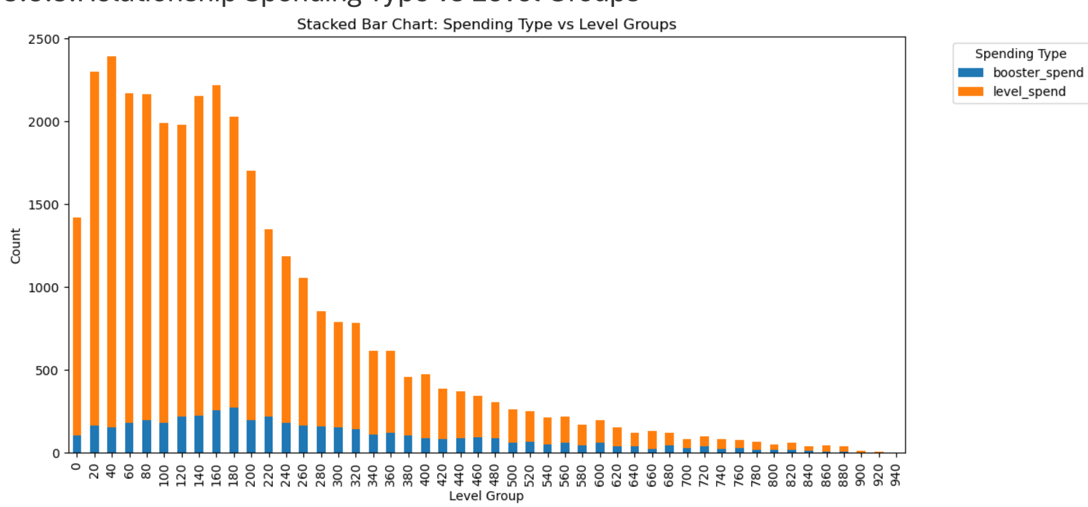
The graph shows a general increase followed by a decrease in coin spending for both platforms. This indicates that users' coin spending increased over a certain period and then decreased. The daily total coin spending on the iOS platform is generally higher than on the Android platform. There are daily fluctuations on both platforms. These fluctuations may indicate that users spend more coins on certain days or that specific events are more frequently held on these days.

3.5.2.Relationship Platform, Level Groups, Coin Amount



The graph shows that total coin spending decreases across level groups. Initially higher spending decreases as level groups increase. In level groups where total coin spending is high, it is likely that the number of users is also high. This means that more users are present at these levels, thereby increasing the total spending amount. On the iOS platform, high total coin spending at low and medium levels may indicate that more users are active at these levels. Similarly, high spending at low levels on the Android platform may suggest a larger number of users at those levels.

3.5.3.Relationship Spending Type vs Level Groups



This graph shows the total number of spendings for different spending types by level groups in stacked bars. In this graph, level spendings are significantly higher compared to booster spendings. This may indicate that users use their coins more for advancing levels.

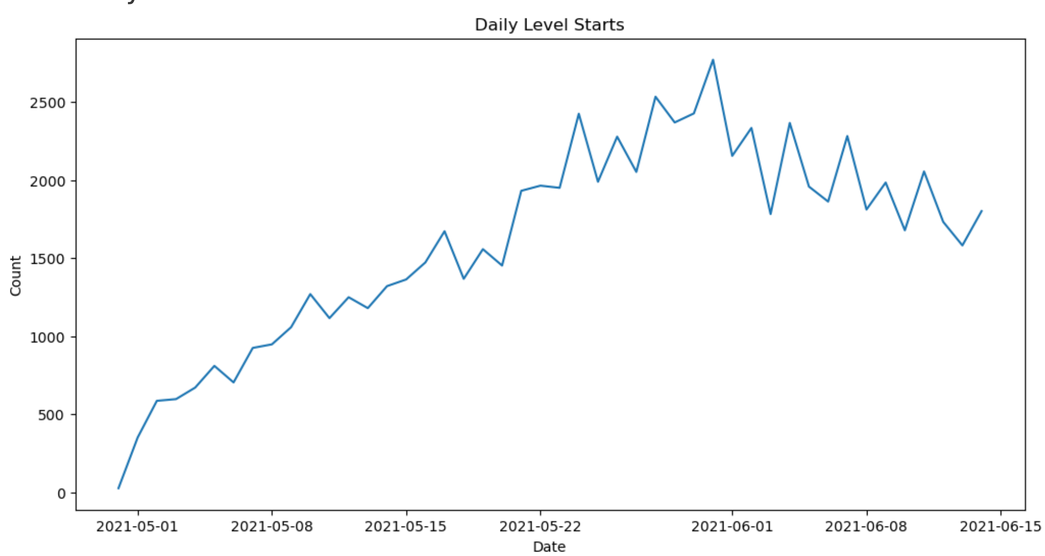
3.5.4.Improvement Suggestions

1. Segment users based on their spending behaviors and analyze the different characteristics and behaviors of each segment. This can be useful for developing personalized marketing strategies. For example, identify low, medium, and high-spending user groups and organize special campaigns for each group.
2. Conduct A/B tests on different spending types and promotion strategies to determine which strategies are more effective.
3. Compare the spending behaviors of users on different platforms to create platform-specific marketing and development strategies.
4. Considering that iOS and Android users may have different spending tendencies, offer special deals for each platform.
5. Identify levels where users spend more coins and optimize the difficulty of these levels. This can help keep users engaged in the game longer and encourage more spending.

3.6.Dataset Level Start

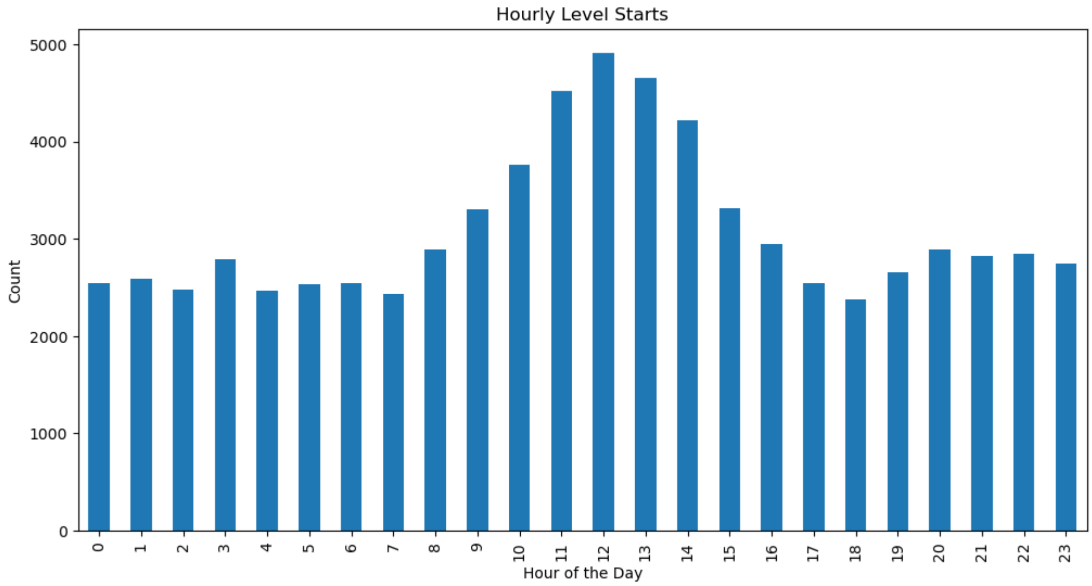
This dataset shows the level at which users start the game. A random sample of 0.1% of the total data has been taken for analysis. It indicates the platform from which users enter the game. This dataset shows how many users started the game within specific time periods. With this data, the times users enter the game can be analyzed.

3.6.1.Daily Level Starts



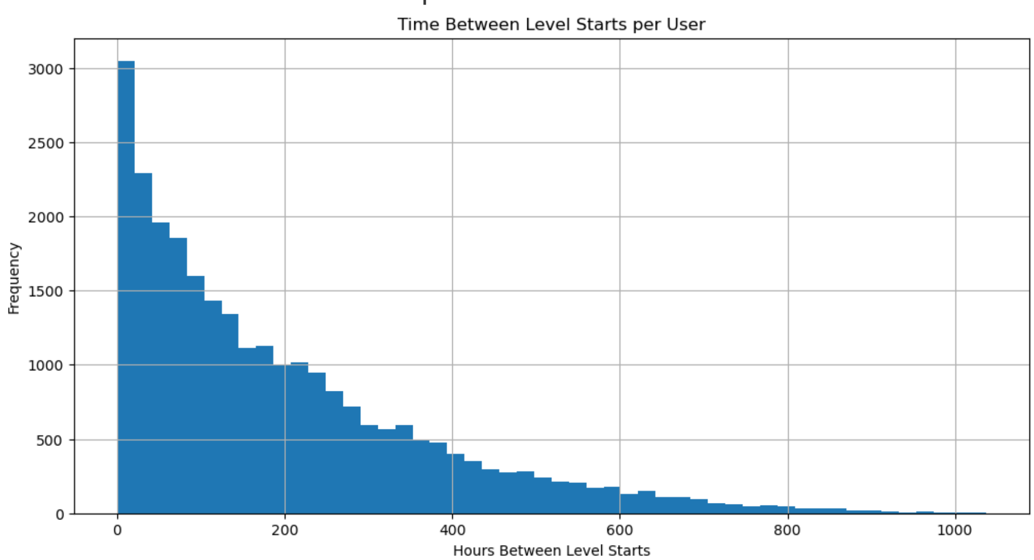
The graph allows for temporal analysis of the levels at which users in the dataset start the game daily. Given the increase in the number of users, the rise in level starts can largely be attributed to the participation of new users. By looking at this graph, the number of users playing the game can be observed.

3.6.2.Hourly Level Starts



The graph shows the distribution of level starts throughout the 24 hours of the day. This graph is useful for understanding at what times users are more active and start more levels in the game. Regularly monitoring the in-game behaviors and activity times of new and existing users is important for optimizing user engagement strategies.

3.6.3.Time Between Level Starts per User



The graph shows the distribution of time intervals between level starts among users. This graph is used to understand how frequently users play the game and how the time between level starts is distributed.

By analyzing this graph, values that encourage users to start new levels can be identified. This can help keep users engaged in the game for longer periods.

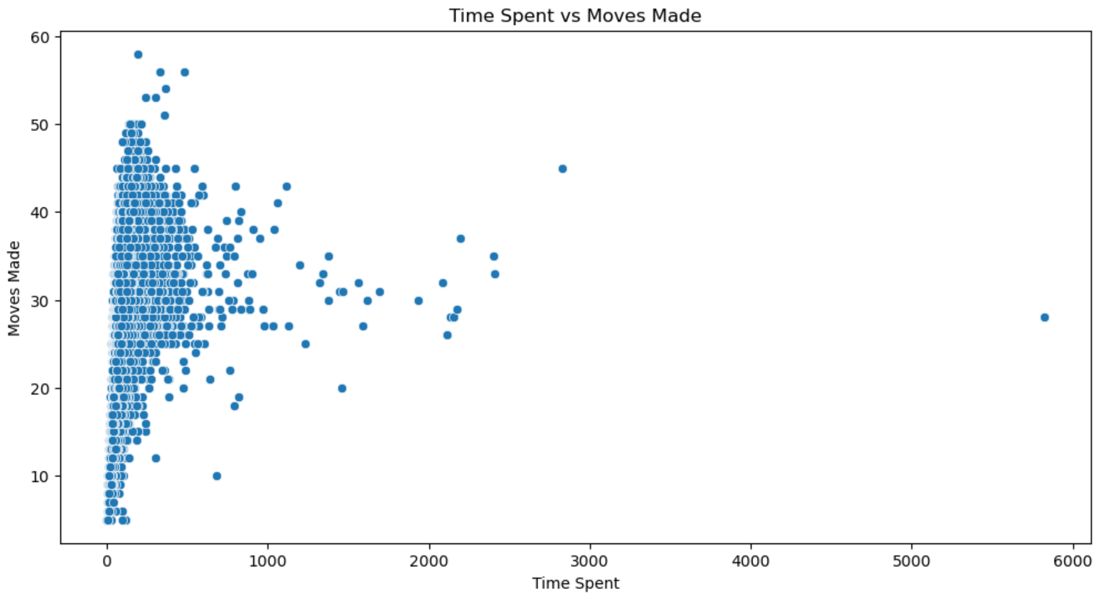
3.6.4.Improvement Suggestions

1. Reminder notifications and special offers can be provided to users who have long intervals between starting new levels.
2. Time series models can be used to predict future user activities. Models like ARIMA and Prophet can be used to forecast user activities and level starts.
3. Machine learning models can be developed to predict when users will return to the game or quit playing.
4. External data sources such as social media, customer support data, or user feedback can be integrated to analyze user behaviors more comprehensively.

3.7.Dataset Level End

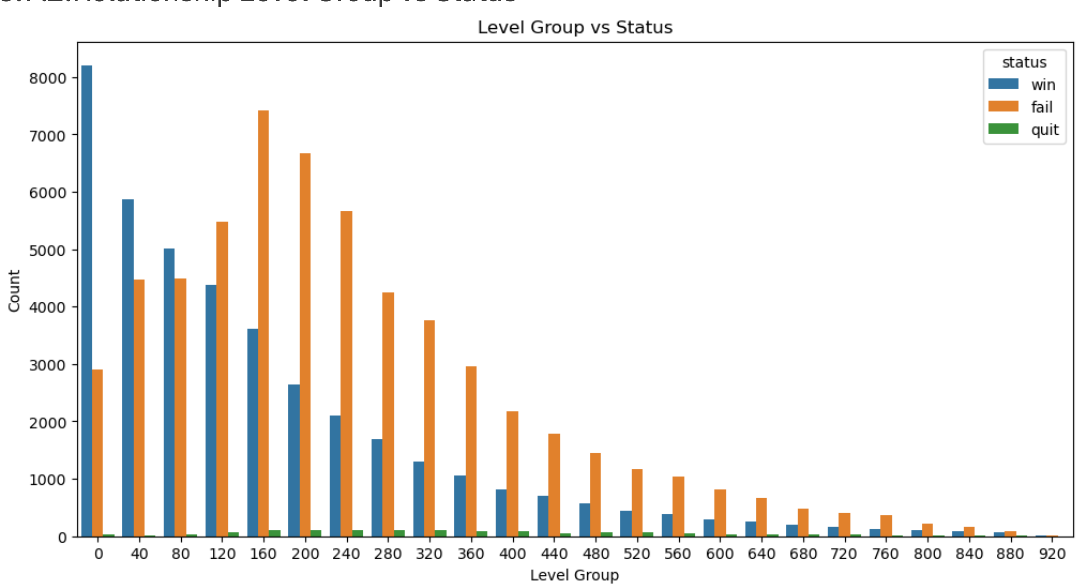
This dataset contains events related to the completion of in-game levels and creates a record each time a level is finished. It is highly valuable for understanding player behavior and the difficulty of game levels. The dataset includes information such as the timestamp of each event, user ID, game platform, completed level number, time spent to complete the level, how the user completed the level, number of moves made, and remaining moves. The relationship between the level number and the time spent, as well as the moves made, can be analyzed. This allows identification of which levels are more challenging and where players spend more time. For example, an increase in time spent and moves made at higher levels may indicate that these levels are more difficult.

3.7.1.Relationship Time Spent vs Moves Made



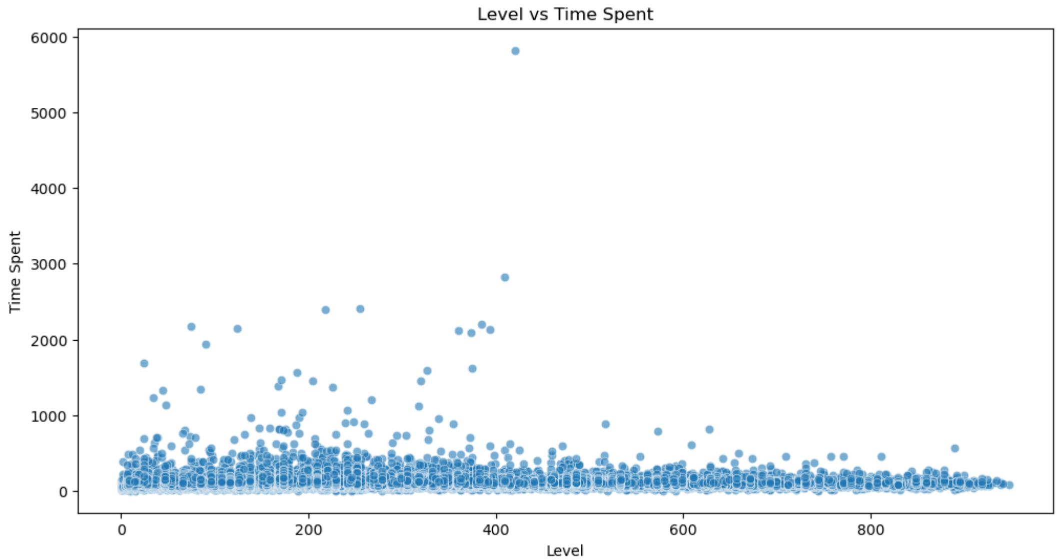
The graph is a scatter plot showing the relationship between time spent and moves made. Many data points are concentrated between 0 and 2000 seconds. This density indicates that most users complete the levels within this time range. There are some data points above 2000 seconds, especially around 4000, 6000, and 8000 seconds. More detailed analysis can be conducted to understand the reasons for these outliers. These users may have experienced difficulties during the game or encountered a bug.

3.7.2.Relationship Level Group vs Status



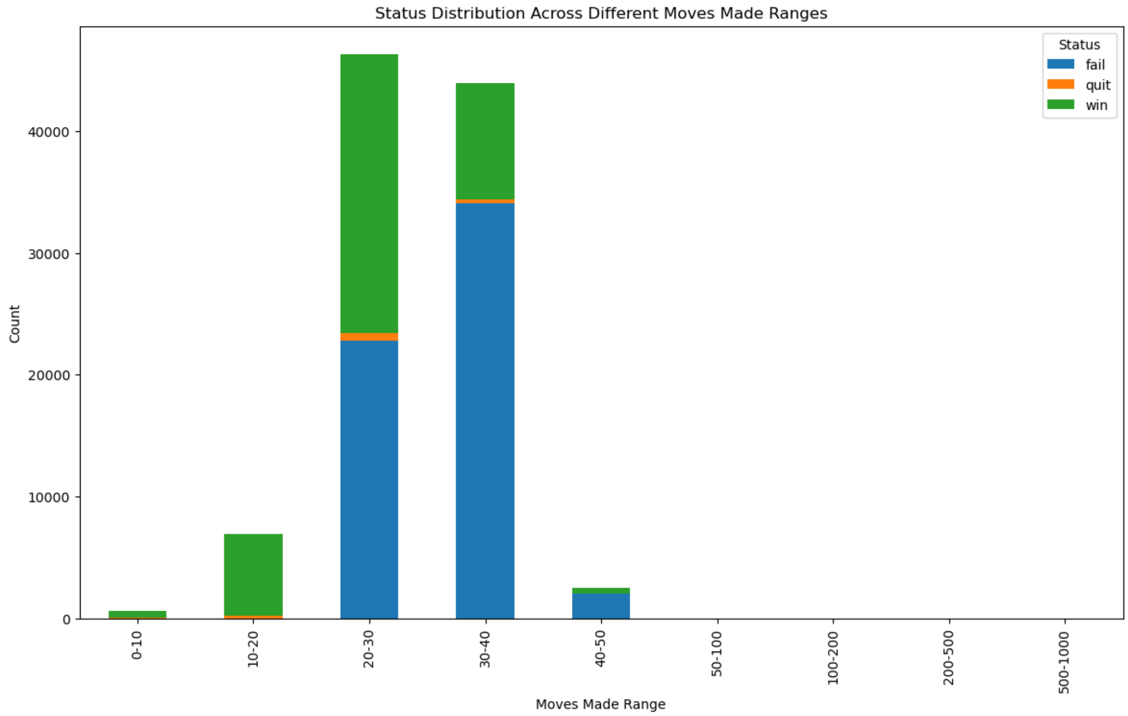
The graph is a stacked bar chart showing the relationship between Level Group and status. It visualizes the number of win, fail, and quit statuses for each Level Group. In most level groups, the number of fail statuses is higher than the number of win statuses. Quit statuses are quite low and almost similar in number across all levels. In the lower level groups (0-40, 40-80), win statuses are more or close to fail statuses. As the level groups increase, the number of fail statuses becomes significantly higher than the number of win statuses. Especially in the 120-240 level groups, fail statuses show a significant increase. Quit statuses are quite low across all level groups. This suggests that players generally try to complete the levels, but when they fail, they are more likely to quit the game at higher levels.

3.7.3.Relationship Level vs Time Spent



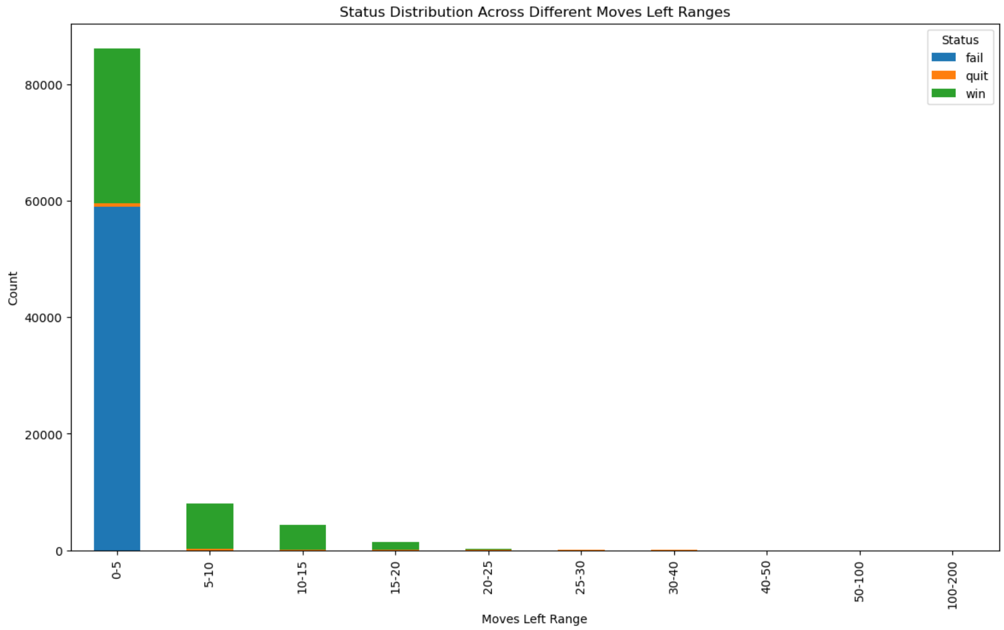
The graph is a scatter plot showing the relationship between level and time spent. At lower levels (especially between 0-200), the data points are quite dense, and most of the time is spent within the 0-1000 seconds range. It is observed that players spend more time at lower levels, but this time decreases after a certain level. A more detailed analysis can be conducted to understand why players spend over 2000 seconds. The challenges or game bugs these players encounter can be identified and necessary improvements can be made.

3.7.4. Status Distribution Across Different Moves Made Ranges



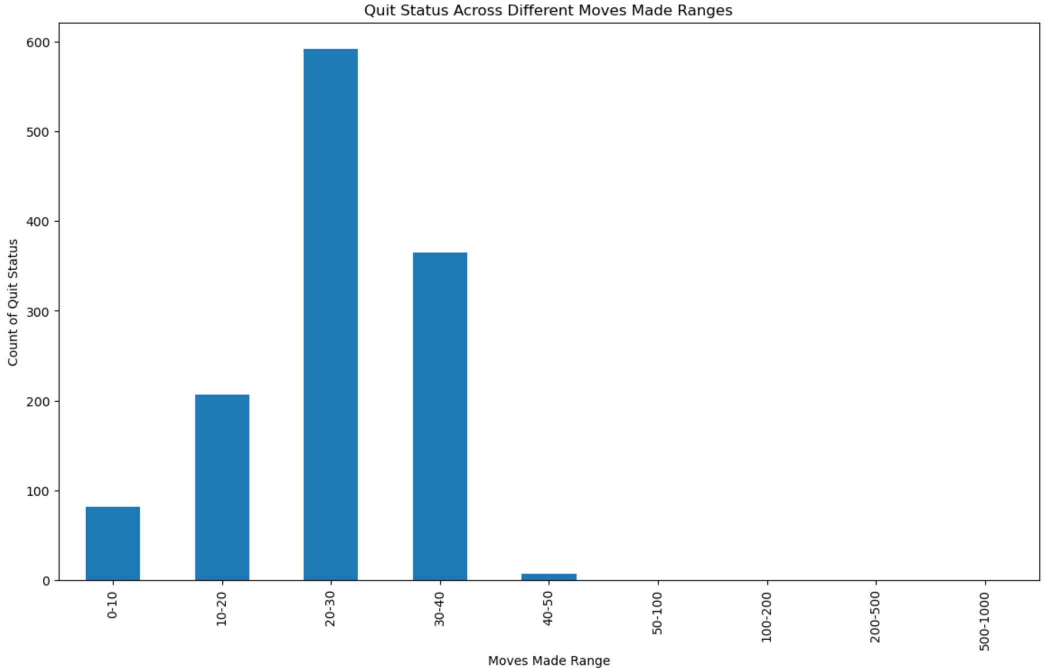
The graph is a stacked bar chart showing the relationship between Moves Made ranges and status (win, fail, quit). In the 0-10 moves range, win statuses are quite low, and there are almost no fail or quit statuses. In the 10-20 moves range, win statuses increase slightly, but fail and quit statuses remain very low. In the 20-30 moves range, win statuses increase significantly, but fail statuses are also high in this range. In the 30-40 moves range, win statuses remain high, but fail statuses are equally high. In the 40-50 moves range, win statuses decrease, and fail statuses increase. The low number of quit statuses indicates that players generally try to complete the game. However, analyzing the specific levels or move ranges that cause quit statuses can help prevent this issue.

3.7.5.Status Distribution Across Different Moves Left Ranges



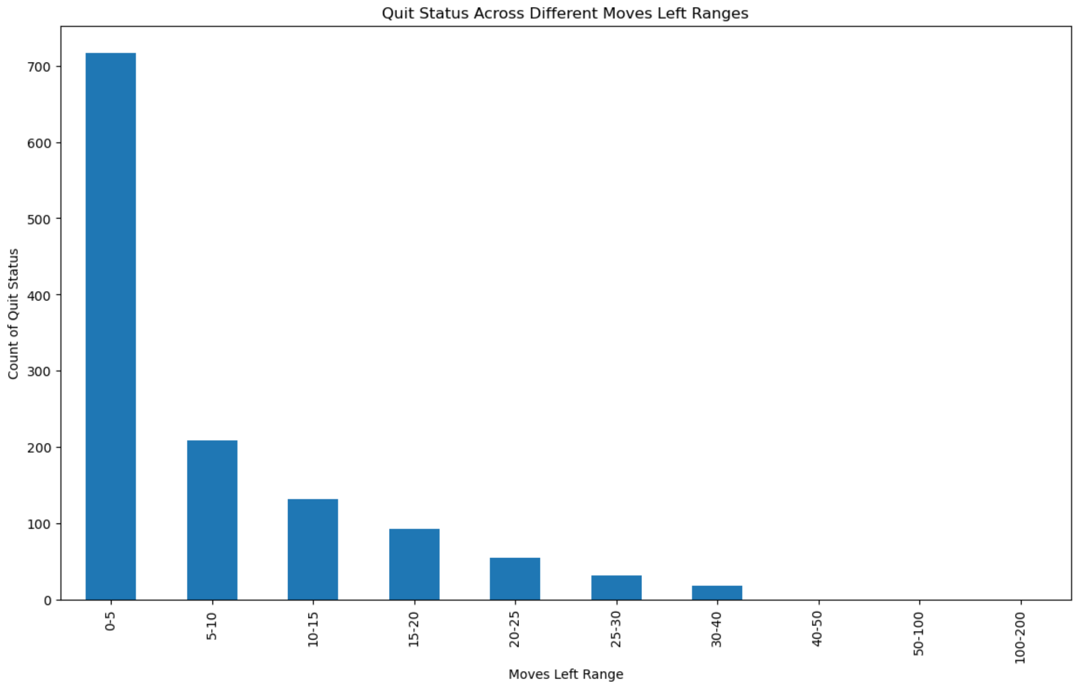
The graph is a stacked bar chart showing the relationship between Moves Left ranges and status (win, fail, quit). In the 0-5 moves range, the number of fail statuses is quite high. This indicates that players typically have very few moves left before completing the level and usually fail at this stage. In the 5-10 moves range, the number of win statuses increases, indicating that players are successful in completing the level with this many moves left. Win statuses are also seen in the 10-15 moves range but at a lower rate. In these ranges, fail and quit statuses are quite low, indicating that players complete levels when they have enough moves left. In the 15-20 moves range, win statuses are fewer, and fail statuses are very low. The data significantly decreases for 20 and more moves left, and there are almost no fail or quit statuses. This shows that players typically complete levels successfully with this many moves left.

3.7.6. Quit Status Across Different Moves Made Ranges



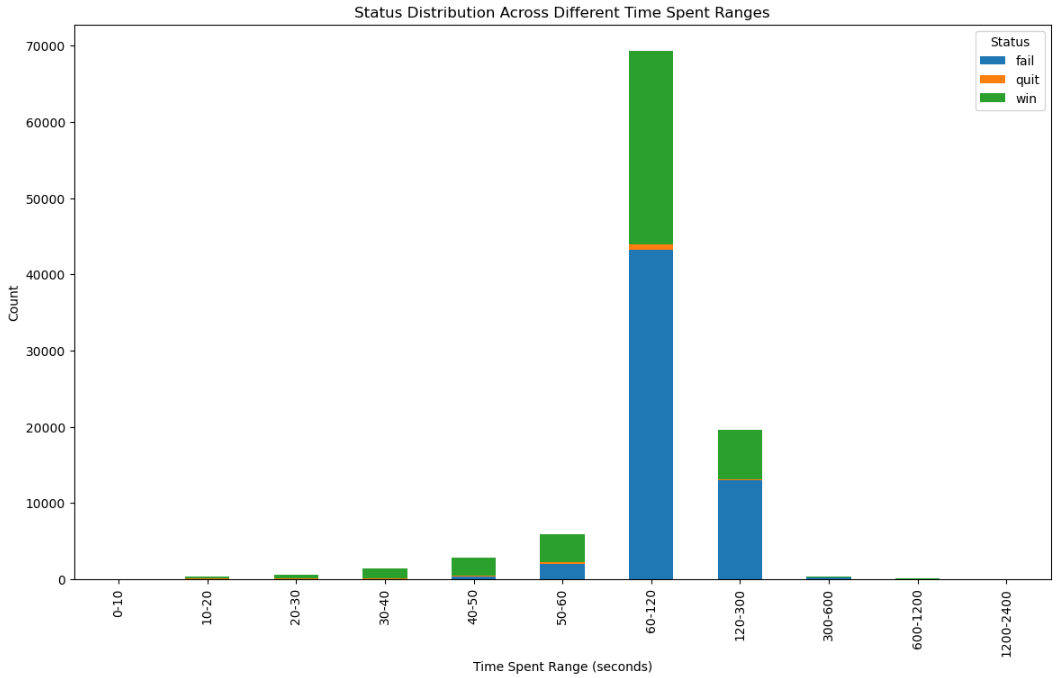
The graph is a bar chart showing the number of quit statuses in different Moves Made ranges. In the 0-10 moves range, the number of quit statuses is low. In the 10-20 moves range, quit statuses increase, indicating that players are more likely to quit the game at this number of moves. In the 20-30 moves range, quit statuses are at their highest level. This is the range where players are most likely to quit the game. The high number of quit statuses in the 20-30 moves range suggests that the difficulty level in this range needs to be reviewed. It is important to analyze why players are struggling and quitting the game at this stage.

3.7.7.Quit Status Across Different Moves Left Ranges



The graph is a bar chart showing the number of quit statuses in different Moves Left ranges. The high number of quit statuses in the 0-5 moves left range indicates that players find it difficult to complete levels with this many moves remaining. Additional help or hints can be provided to prevent players from quitting when they have very few moves left. Gathering feedback from players, especially in move ranges with high quit statuses (0-5), can help understand the reasons behind this behavior. This feedback can be used to improve game design. The decrease in quit statuses when there are 10-15 or more moves left shows that players are more willing to complete the game when they have enough moves remaining. Strategies that help players achieve a sufficient number of moves can be provided to maintain this motivation.

3.7.8.Status Distribution Across Different Time Spent Ranges



The graph is a stacked bar chart showing the relationship between Time Spent ranges and status (win, fail, quit). The high number of fail statuses in the 60-120 seconds range may indicate that players struggle during this time frame. The difficulty level of these stages can be reassessed. The low number of quit statuses shows that players generally try to complete the game. However, analyzing why quit statuses occur in certain time ranges can help prevent this issue.

3.7.9.Improvement Suggestions

1. The analysis showed that players struggle and fail more in certain levels. Balancing the difficulty levels in these stages can provide a smoother experience for players.
2. Collecting feedback from players is useful for understanding which parts of the game are challenging or frustrating. This feedback will be helpful for making improvements in game design.
3. Technical optimizations can be made to enhance game performance. Issues like high latency or low frame rates can negatively affect the player experience. Such technical problems should be addressed.

4.Level Dashboard

Detailed analysis and tracking of the levels users interact with in mobile games are critical for enhancing game performance and improving user experience. For this purpose, the level dashboard prepared for this game is designed to comprehensively monitor game performance, user behaviors, and revenue analysis. The metrics and visualizations used in the dashboard provide important insights into the current state of the game, allowing for strategic decision-making based on this information.

The metrics included in the level dashboard encompass fundamental indicators such as the total number of levels completed in the game, the number of levels currently being actively played by users, the number of levels successfully completed, and the number of levels that ended in failure. Additionally, detailed data such as the daily active user count (DAU), the average time users spend completing a level, and the average number of moves made are provided. Metrics like level transition rate and level completion rate are used to evaluate users' progress and success within the game.

Furthermore, special metrics such as difficult and easy levels indicate which levels pose more challenges for users or which levels are more easily completed. Financial metrics like average revenue and average coin expenditure analyze users' spending and the amount of coins spent at each level. Lastly, the user retention rate, shown through time series graphs, illustrates how long players continue to play the game.

Level Dashboard		
Metric	Description	Visualization Type
Total Levels	Total number of levels completed in the game	Number
Active Levels	Number of levels currently being actively played by users	Number
Completed Levels	Number of levels successfully completed	Number
Failed Levels	Number of levels that ended in failure	Number
Daily Active Users (DAU)	Daily active user count	Time Series Graph
Average Time Spent	Average Time Spent	Line Graph
Average Moves Made	Moves users make to complete a level	Line Graph
Level Transition Rate	Rate at which users move from one level to another	Line Graph
Level Completion Rate	Rate at which users complete the levels they start	Line Graph
Difficult Levels	Levels with the lowest completion rates	Bar Graph
Easy Levels	Levels with the highest completion rates	Bar Graph
Average Revenue	User spending at each level	Scatter Plot

Average Coin Spending	Amount of coins users spend at each level	Scatter Plot
User Retention Rate	Duration for which users play the game	Time Series Graph

5.Conclusion

In conclusion, the comprehensive analysis of the "Row Match!" game has provided significant insights into user behaviors, platform performance, and revenue generation. The analysis highlighted critical metrics such as Daily Active Users (DAU), Average Time Spent Per Level, and Average Revenue Per Level, offering a clear understanding of the game's current performance. The detailed examination of datasets revealed patterns in user acquisition, engagement, and spending, emphasizing the importance of targeted marketing strategies and platform-specific optimizations.

Key findings suggest that iOS users tend to be more engaged and spend more compared to Android users, indicating a need for platform-specific marketing and user retention strategies. The analysis of level completion rates and coin expenditures provided valuable information for balancing game difficulty and enhancing user experience. Additionally, the importance of adapting marketing efforts to regional differences was underscored, ensuring a more effective global reach.

The recommendations proposed in the report aim to address identified challenges and leverage opportunities for improvement. By implementing these strategies, "Row Match!" can enhance user engagement, increase revenue, and achieve sustainable growth in the competitive mobile gaming market. Continuous data analysis and adaptation to user feedback will be crucial in maintaining the game's success and ensuring a rewarding experience for players.

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