COOKING CRUSH

BUSINESS ANALYTICS

Final Project

Prepared By : Group 5

Aimen Arif 23110275
Aminah Haq 23110108
Mehr Shahzad 23110205
Omer Bin Rashid 23110061
Saman Ejaz 23110305

Background

A publisher of mobile games, FlowMotion Entertainment, is committed to providing its ardent followers with the greatest casual, female-oriented entertainment options available worldwide. Over 60 million users have downloaded the company's games. FlowMotion was established in 2014 with a base in Vancouver, Canada, and today has teams worldwide. Its goal is to be among the top mobile publishers in the world. The company's mission to give back to the neighborhood has evolved along with it. Some of the top mobile games in the world are published by FlowMotion. These casual-style titles are predominantly targeted at female consumers, a market category that is neglected and whose audience represents a vast untapped opportunity. Our project is aimed specifically at the "Cooking Crush: cooking games" where you have to "Become the best culinary master in exciting free cooking games & time management games." In our project, we have concentrated on using the available data to advise FlowMotion Entertainment on how they may maximize the amount of income they generate from user transactions.

Literature Review

The market for mobile applications is constantly expanding.The number of app downloads is rising in tandem with the army of developers. Without a doubt, the amount of money made by the mobile application sector breaks all records. In an effort to increase their revenue, many start-ups and business owners have followed this trend and switched to mobile applications (*How much money can an app make you in 2022?* 2022). The velocity of this exponential growth and the possibilities of market growth in the domain can be catered by the fact that by 2023, mobile apps are projected to generate more than $935 billion in revenues via paid downloads, subscriptions, and in-app advertising (*How much money can an app make you in 2022?* 2022). In forming categories, the majority of these profit shares, based on revenues and downloads, on smartphones are accounted for video games.Even though the mobile gaming industry is only a decade old, mobile games accounted for 80 billion downloads out of 218 billion total downloads of mobile apps in 2020, or 36% of the total. Users played mobile games for 296 billion hours in the same year, up 35% from the 222 billion hours they played in 2019. It is predicted that by 2021, mobile gaming would account for more than $ 120 billion (an increase of 20% from 2020). That is 50% larger than the combined size of the console, PC, Mac, and portable markets (*Video games for smartphones: Pros and Cons of Android vs. iOS* 2022).

Occupying a significant chunk of the the market in this lucrative industry and having over 60 million downloads globally, The goal of FlowMotion Entertainment, a mobile game publisher, is to provide its loyal fans with the best casual, female-oriented entertainment games available anywhere in the globe. With a staggering 4.7/5 star rating and over 10 million downloads, Cooking Crush is one such mobile gaming app introduced by FlowMotion Entertainment. In this restaurant game, you receive bonuses for breathing, meditating, and loving yourself while you unlock new habits as you play along to enhance your life (Entertainment., *Our story*).

Having been through a thorough analysis of the data acquired from Cooking Crush game coupled with our secondary research, it is our understanding that in the age of big data and vast, complex integrated global technological networks, more and more data is being gathered with each and every online transaction, like downloads, in-app purchases, push notifications etc. This data, hence, can be used to identify a number of helpful behavioral patterns, insights, and trends that can serve as the foundation for strategy development for corporations and app developers. It is often claimed that due to variations in market share, purchasing power, and platform popularity, the platform choice i.e. Android or iOS, can have a considerable impact on revenue possibilities (*How much money can an app make you in 2022?* 2022). This project aims to further expand on this claim whilst simultaneously building upon and linking it to consumer buying behaviors, demographics like gender, location and age. Furthermore, we will also delve into customer segmentation based on income levels and through identification of regional hotspots. All of this will be done, in order to help FlowMotion Entertainment better understand their target market and how to better devise their marketing strategies to increase customer retention and maximize profits on Cooking Crush.

The Problem

This project will address a significant challenge FlowMotion Entertainment faces. As a first step, their management wants to know which countries are the most profitable for them. In addition, we would conduct external research in order to find out what the demographics of those countries are like. As of right now, they are unable to segment the advertisements properly so that they can be shown to the right customers. It is costing them money in advertisement costs and opportunity costs which would be avoided if the correct ads were shown to the right audience. Ultimately, the goal is to find out which factors affect the revenue generated by FlowMotion and eventually, and how we can increase the revenue generated by users.

Data Selection

The data was obtained from TA Hassan, who works at FlowMotion Entertainment company. The dataset contains mainly user data and the transactions that took place due to in-game user purchases. The data was given to us in a CSV format.

Explanation of Raw Dataset:
With 61490 rows and 56 columns, our data collection contains the following variables in their raw form:

event_id	occured_at	date	app_id	app_name	app_version
first_app_version	downloaded_content_version	gan_user_pseudo_id	user_id	developer_user_id	session_id
install_source	country_name	country_code	country_tier	device_platform	occured_at_user_local_time
user_age_days	gan_screen_id	iap_product_id	iap_product_name	iap_revenue_usd	iap_revenue_user_currency
user_currency	validated	session_elapsed_time_secs	User_purchase_seq_number_this_session	user_num_purchases_this_session	user_purchase_number_to date
user_lifetime_number_of_purchases	user_purchase_number_to date	user_lifetime_number_of_purchases	user_seconds_in_app_todate	user_lifetime_seconds_in_app	user_ltv_todate_usd
user_ltv_lifetime_usd	user_currently_active	session_started_at	session_ended_at	session_time_seconds	user_session_number

last_level_played_todate	ads_watched_todate	games_played_todate	user_attribution_source	user_attribution_medium	user_attribution_campaign
user_cohort	device_category	device_is_limited_ad_tracking	device_language	device_mobile_brand_name	device_mobile_marketing_name
device_mobile_model_name	device_mobile_os_hardware_model	device_operating_system_version	_synced_at		

At first, every variable is in the general format. Null values were mostly seen in 3 columns (developer_user_id, gan_screen_id, and, validated)

Each variable has unique problems that were dealt with by utilizing various codes. Throughout the paper, we will outline both their obstacles and their resolutions.

Data Processing

1. **Extracting clean, relevant data by removing unnecessary variables**

Since our original dataset contained 61490 observations and 56 variables, it was quite thorough and thus contained a lot of redundant information. After having decided our hypothesis and analyzing the dataset in detail we decided to first clean the dataset by removing the irrelevant variables (columns) so that the relevant columns for analysis can be identified.

By using Rstudio's built in NULL function we removed three redundant variables i.e., developer_user_id, gan_screen_id and X_synced_at. These variables were selected not only on the basis of value addition to the analysis but also because most, if not all of the values it contained were either redundant or displayed N/A.

2. **Formatting the date column into separate columns for date and time**

Our original dataset contained one variable i.e., "ocured_at" containing both time and date. This format was restrictive in a way that it didn't allow us to carry out time series analysis on our dataset. So, we divided the variable into two, one for time and one for date. By using Rstudio built in functions, as.Date for date and as.POSIXct for time (formatting time in hours, minutes and seconds), we were able to create two separate variables. This distinction allowed us to carry out time series analysis based on regional monthly sales .

Once the two variables for date and time were created, for minimizing redundancy we removed the ocured_at, date_time and install_source variables from our dataset.

3. **Handling of empty strings (NA) in "validated"**

The variable "validated" in the original dataset contained two values i.e., NA and 1. By using ifelse and is.na commands we replaced the NA values with 0 so that the variable now contained 0s and 1s.

4. **Factoring data**

For ease of analysis and better understanding we converted the "validated" and "device_platform" variables into factors by using R's built in function, as.factor. Since our entire analysis was based on the choice of platform and how it is linked with revenue generation and consumer buying behaviors, this step was crucial to find categories and carry out in-depth analysis.

5. Filtering data for "Crush Food Games"

Our original dataset contained entries for FlowMotion Entertainment 's two cooking games i.e., "Crush Food" and "Story Kitchen Diary" games. Since our analysis was only centered around crush food games, by using library dplyr, filter and grpel functions we filtered the two datasets out. This narrowed our entries from 61,490 to 58,254. This also shows that Story Kitchen Diaries had very few entries and removing them did not really impact overall analysis. We felt it would be smarter to focus on the better performing game, Crush Food.

6. Calculating tier wise total revenues

Our main hypothesis and the entire project analysis was centered around region wise revenue generation and how it can be maximized based on various sub-hypothesis. By first factoring the country_name variable and then by using group_by function we were able to create sub-groups based on tiers, where tier 1 represented high income, tier 2 mid-income and tier 3 low income countries. The grouping coupled with the forward pipe operator helped us sum the revenues (iap_revenue_usd) of each tier and display which tier contributed to the highest earnings.

7. Separating tier wise relevant dataset

For hypothesis testing and analysis, we created a separate dataset containing all of the relevant tier wise information required. Other than the new column, country_name_count (containing the total count of sessions from each country), this dataset contained country_tier, country_name, revenue and revenue_per_count (average revenue per country).

8. Separating user wise relevant dataset

The purpose of creating this separate dataset was to identify different consumer segments and hence expand on different consumer buying patterns and/or behaviors. From the original dataset we identified and extracted 15 relevant variables that were specific to each unique user session and would help us in further expanding on our hypotheses. The creation of this subgroup allowed us to build upon sub-hypotheses like what factors impact customer retention, choice of platform based on the region, identification of regional hotspots etc.

Lastly, in creating this dataset by running the command each_userdata[!duplicated(each_userdata$user_id),] we ensured that each user was accounted for only once in the separated user dataset and all of the repeated/duplicate User IDs were removed, making the analysis carried out later less prone to error and more rigid.

9. Calculating willingness to purchase

To better gauge buying behaviors and underlying patterns associated with in-app purchases we created a separate variable/column i.e., willingness_to_purchase, in our dataset. Analyzing the iap_revenue_usd variable we concluded that if the value is > 20 then the willingness to purchase is "High" else its "Low". Once this distinction was made, by using a simple as.factor command the data in the column was categorized into factors for better analysis. Since, statistical modeling is one of the most crucial applications of factors; as categorical variables are entered into statistical models differently than continuous variables, storing data as factors ensures that the modeling functions will treat such data appropriately.

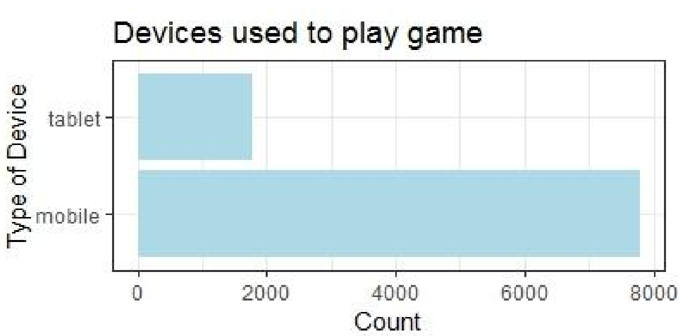
10. Formatting "each_userdata" Dataset

We formatted the above mentioned dataset to have a better understanding of our dataset and to carry out analysis with less noise and unnecessary entries in the dataset. By running the command with the code: each_userdata[each_userdata==''] <- NA, we were able to change all the empty cells to then be null values, or in this case, NA. Then after running the "na.omit" command, we got our dataset returned with incomplete cases removed. The function/command to change empty cells to return as NA were applied to 3 columns, which were "country_tier", "device_category" and, "user_currently_active". 7 other columns were then also factored using the as.factor function; These 7 columns include: user_id, country_name, country_tier, user_currently_active, device_category, user_currency and install_source. After this was done, the "unique" function was run to remove duplicate elements/rows. The "is.na" function is then run to indicate which elements are/were missing. Finally, the command "names(each_userdata)" is then run for R to then return or show us the finalized 17 columns for further data analysis and understanding.

Data Exploration

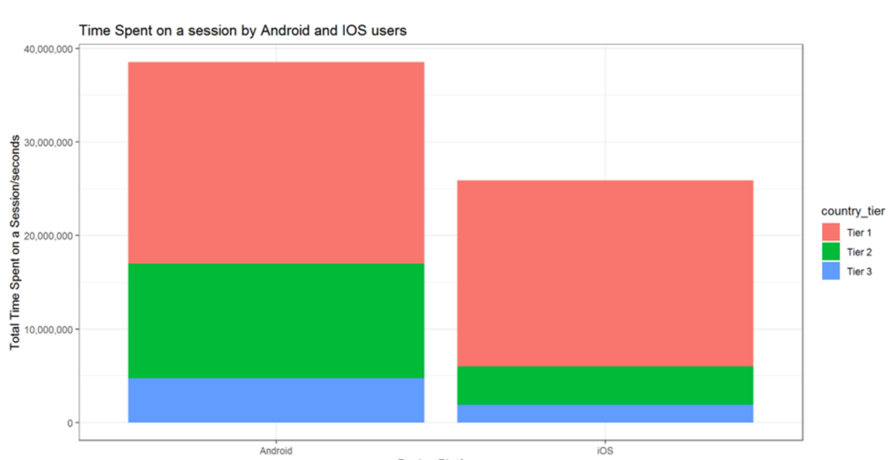
To delve deeper into our data and identify any correlations between different variables in our data set, we decided to construct various visualizations primarily using ggplot2. This phase of data exploration allowed us to come up with potential hypotheses on which we could specifically focus. However, our major purpose remained to detect any patterns and important relationships in our data.

Graphs
In this section, we will be inserting some graphs that we obtained through visualizations by ggplot2.



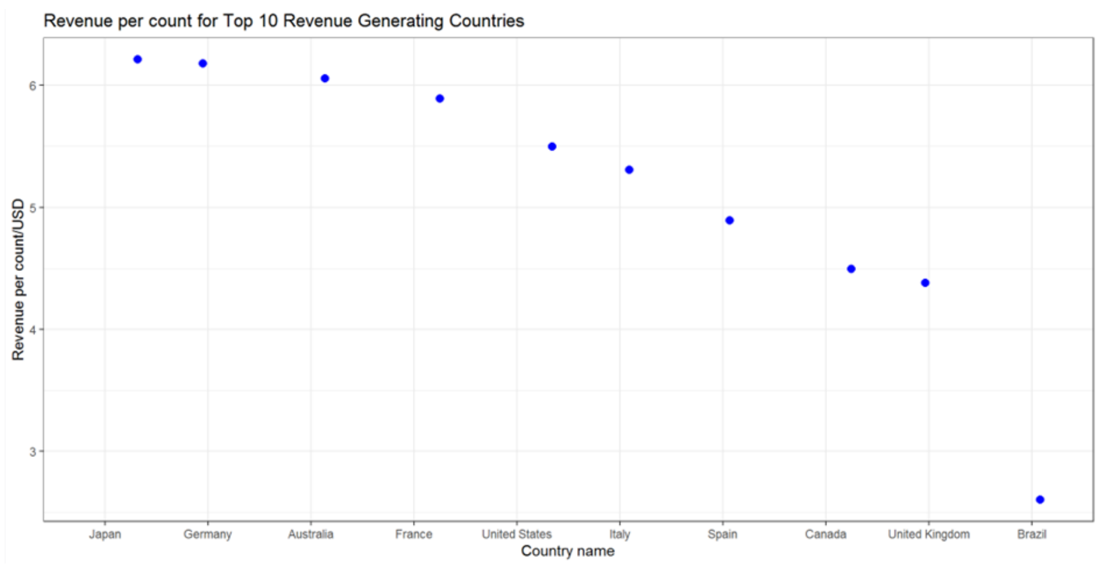
To explore our data, we constructed a bar chart to visualize the proportion of devices that players use to play cooking crush and found that roughly 7700 players use mobile devices while approximately 1800 players play the game on tablet.

Through the chart on the left, we attempted to visualize the time spent on one session by Android versus iOS users. We also segmented on the basis of whether the players belonged to countries in tier 1, 2, or 3.



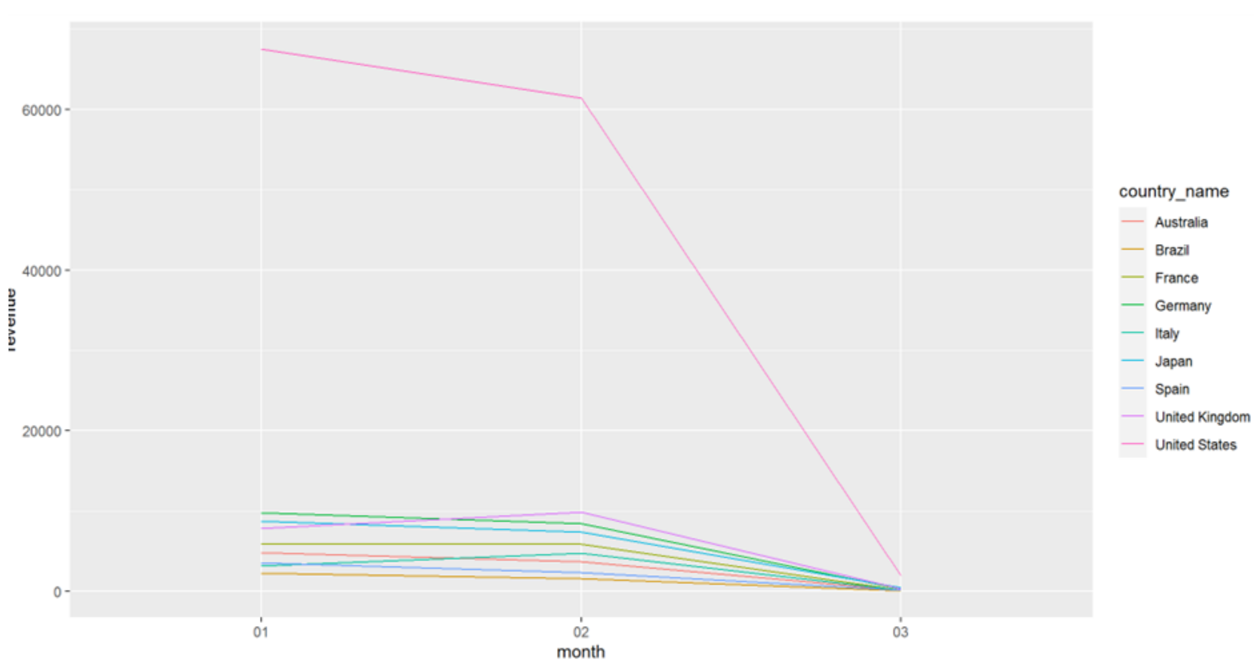
The second graph shows us the total number of seconds spent by users on the app respective to their tier and platform.As was the case with the previous graph, we can see that Android users spend a significantly longer time than iOS users on the app with, again, Tier 1 being the top contributor. This again points towards the fact that there are a lot more Android users than iOS users playing the game, hence, having more minutes on the application.

Additionally, to take our exploratory analysis further, we constructed a descending order jitter plot to visualize revenue per count against the top 10 revenue generating countries for FlowMotion. Interestingly, the findings yielded that the revenue per count was highest for **Japan** closely followed by **Germany**.



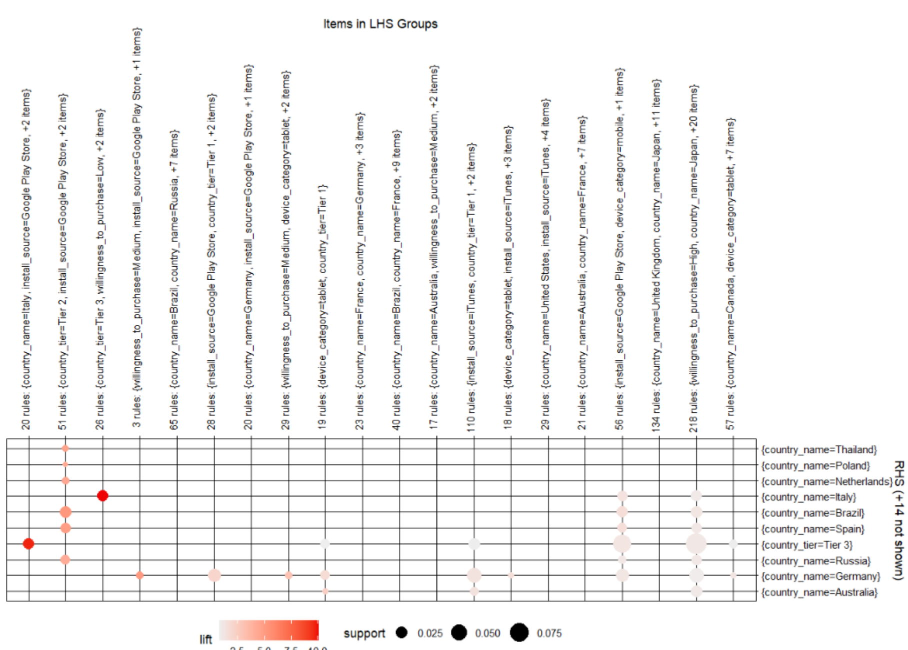
In the exploration phase, we also constructed a time series graph to visualize the general trend in total revenue generated across the three month time frame (January, February, March) by the top 10 revenue generating countries. We gained some interesting insights. For instance, we found that the **United States** contributed the highest overall revenue relative to the other countries in the set. However, there was a gradual decline in overall revenue generated from January to February and a **steep decline** in revenue from February to March. Since the United States is the highest revenue generating country for the app, this information could prove helpful in identifying causal factors for the steep decline in revenue generation.

Another notable change was the gradual increase in revenue generated by the United Kingdom from January to February. A general trend noted for all the countries was the decline in overall revenue generated from February to March.



Association Rules (ARules)

For the purpose of exploring the data and the various associations in it we decided to run arules on our data. This was primarily used to see the type of relations our data makes and the support, confidence and lift values for those relations. The arulesViz library was used to test which rules work best for our dataset. The graph above shows that we experience high lift values when support is kept to a minimum and confidence values are either 1 or 0.25. So we used a very low value for our support like 0.0000011 and 0.25 to test association rules. Our aim was to test willingness to buy on the rhs with the remaining correlated variables like device platform, install source, tier of the country which impacts the willingness. One limitation that we faced was that our data was immensely skewed towards the 'low' willingness to pay which was impacting our results adversely. We however still decided to go ahead with conducting this preliminary analysis for our data. The results however were not exactly satisfactory. We can see that support from our results is very little and when our subrules were sorted by lift, only 24 sub rules were seen. The lift values were obnoxiously high with the highest value greater than 44. This showed us that these association rules were not the right analysis for our data. They did not give us any predictive or associative model for our data.



Decision Tree- Predictive Analysis

We wanted to conduct predictive modeling on our data set to test our variables. We used the decision tree for this however, due to pre pruning in R our decision tree did not show satisfactory results (referred to in the appendix) and the number of n was too large. It only displayed a single node and we were unable to form a prediction about the model, nevertheless, we used other data exploratory analysis to gauge our results and linked them with external research.

Hypothesis and Analysis

Following an analysis of the data, we developed two hypotheses. To support our assertion, each hypothesis may or may not result in a sub-hypothesis.

1. **Hypothesis 1: Which Countries in each tier and across trier contribute most to revenue generation?**

The following sub-hypothesis must also be investigated in order to test the main hypothesis:

- Which tier contributed most to revenue?
- Which top 10 countries contributed most to revenue generation and which tier did they belong to?
- Within each tier, which countries contribute the most to total revenue generated?
- Which countries and tiers did the top 250 users which watched most ads belong to?

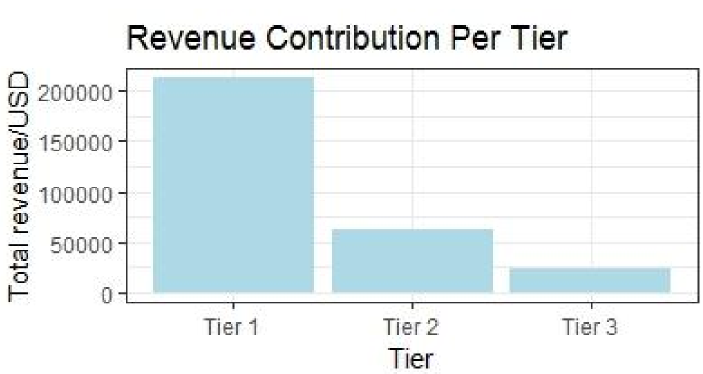
2. **Hypothesis 2: iOS users generate more revenue for FlowMotion through Crush Food than Android users.**

The following sub-hypothesis must also be investigated in order to test the main hypothesis:

- Do Android or iOS users make more purchases?
- Are users of the top ten performing countries Android or iOS users?
- Which platform is used in top 10 performing countries of Tier 2 and 3?
- Which platforms did the top 250 users which watched most ads use?

Hypothesis 1 Analysis:

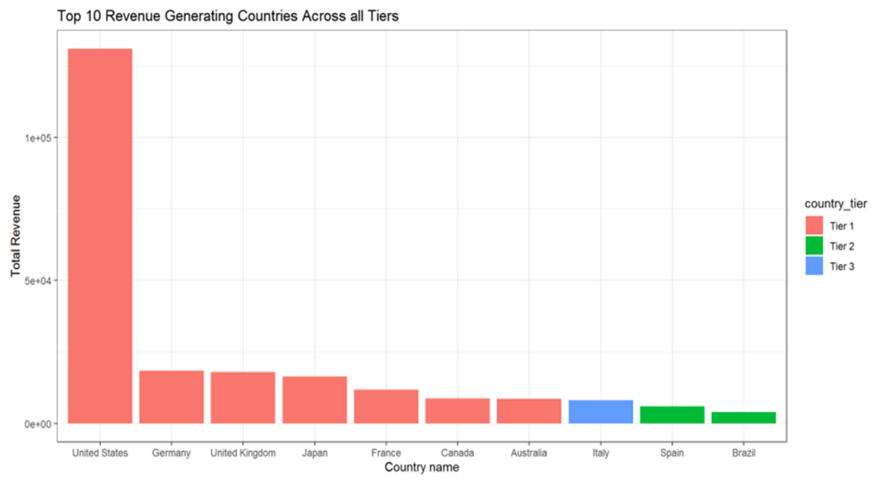
- **Sub- hypothesis 1: Which tier contributed most to revenue?**



To test our hypothesis, we constructed some specific visualizations that would help us gain insights about how revenue contribution was divided on the basis of tier wise segmentation. Accordingly, we found that tier 1 countries contributed the most to total revenue generated by the game exceeding **$200,000** revenue in the 3 month time frame relative to **$60,000** contributed by tier 2 countries and approximately **$25,000** generated from countries in tier 3. The significantly higher revenue contribution of countries in tier 1 may arise from the fact that players from first world countries generally possess a higher disposable income and are hence able to make more in-app purchases and ultimately make greater contributions to total revenue generation.

- **Sub-Hypothesis 2 : Which top 10 countries contributed most to revenue generation and which tier did they belong to?**

To gain a more holistic picture, we also constructed a plot of the top 10 revenue generating countries across all tiers. This enabled us to identify the geographic regions which contributed most significantly to overall revenue generation. Confirming the findings of the tier 1 graph shown below, we see that the highest total revenue contribution comes from the United States. Moreover, the least amount of revenue in the chart is generated by Brazil which belongs to tier 2. An interesting observation is that Italy contributes more revenue though it belongs to tier 3. We can also see the top seven well- performing countries all belong to tier 1 whereas two belong to tier 2 and one to tier 3.

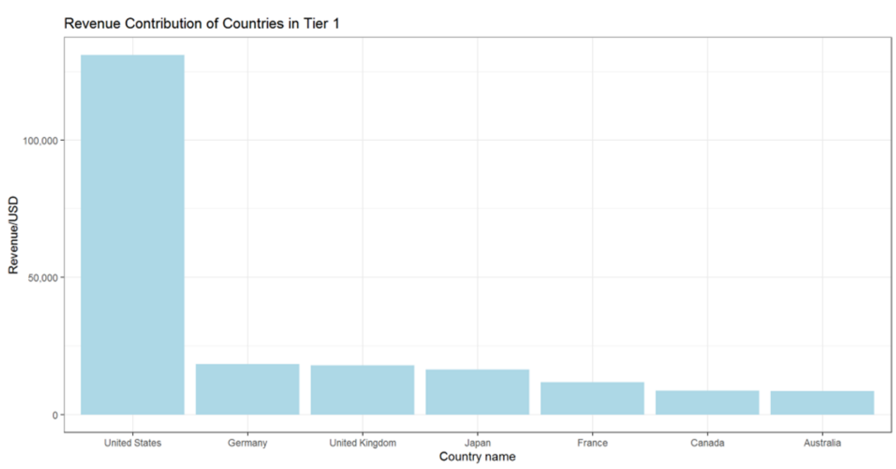


- **Sub-Hypothesis 3: Within each tier, which countries contribute the most to total revenue generated?**

Additionally, we wanted to gauge further insights by analyzing the revenue contribution of countries within each tier. For these purposes, we used ggplot2 to construct the following bar charts for top 10 revenue generating countries in each of tier 1, 2, and 3.

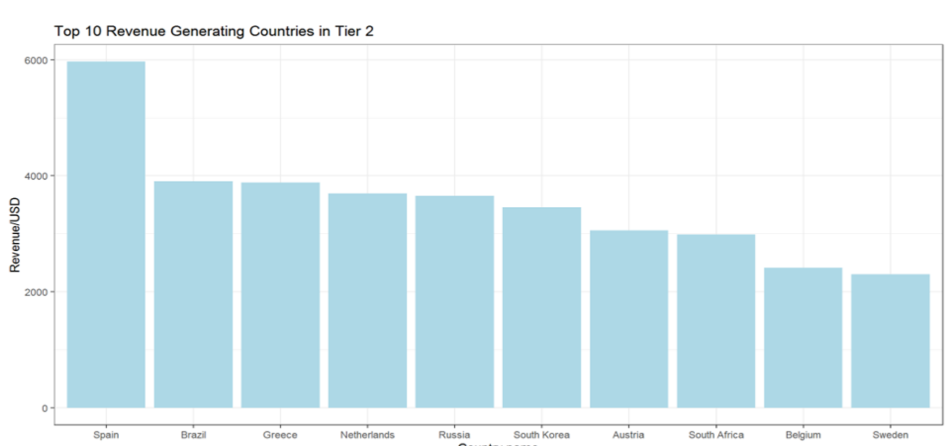
Tier 1

Since tier 1 comprises only 7 countries, we constructed a descending order bar chart to analyze the revenue contribution of each country in the tier. We see that the highest revenues, at approximately $150,000, are generated by the United States while the least amount of revenue in the tier is contributed by Australia.

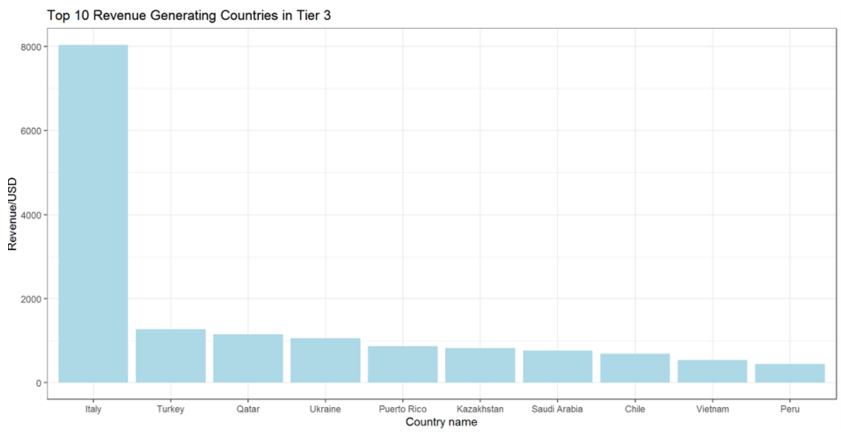


Tier 2

Constructing the same chart to visualize revenue contribution for countries in tier 2, we observed that Spain generated the highest revenue, roughly **$5900**, while Sweden contributed the least to total revenue generated by the cooking game relative to the other countries in the tier. These findings are corroborated by



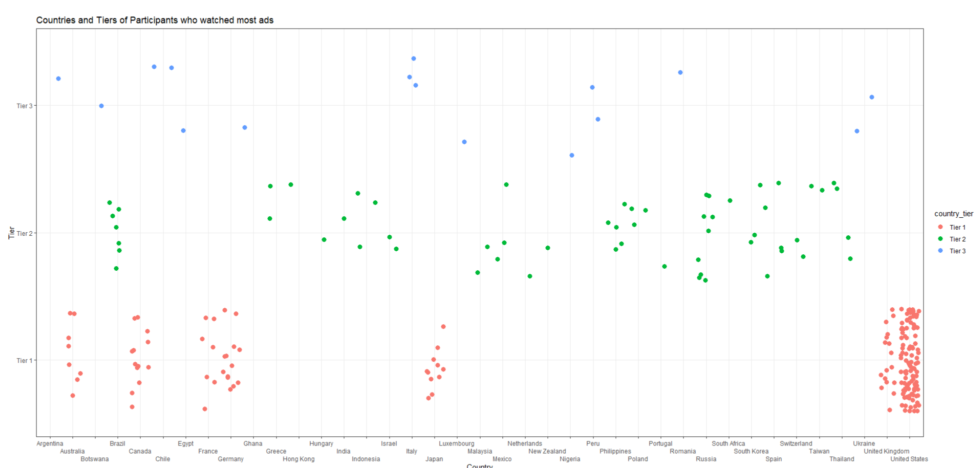
external research which confirms the rapid growth of the mobile gaming segment in Spain. Additionally, in terms of global mobile game revenue, the segment is projected to grow by **6.5%** in the years following 2022-2027. (Statista)



Tier 3

Lastly, we constructed a bar chart to identify the top 10 revenue generating countries in the third tier. It was interesting to note that Italy, the highest revenue generating country in the tier, contributed roughly **4 times more** than the second highest revenue contributing country in the descending order chart. Additionally, Peru contributed the least to total revenue generation at less than **$500**.

- **Sub Hypothesis 4: Which countries and tiers did top 250 users which watched most ads belong to?**



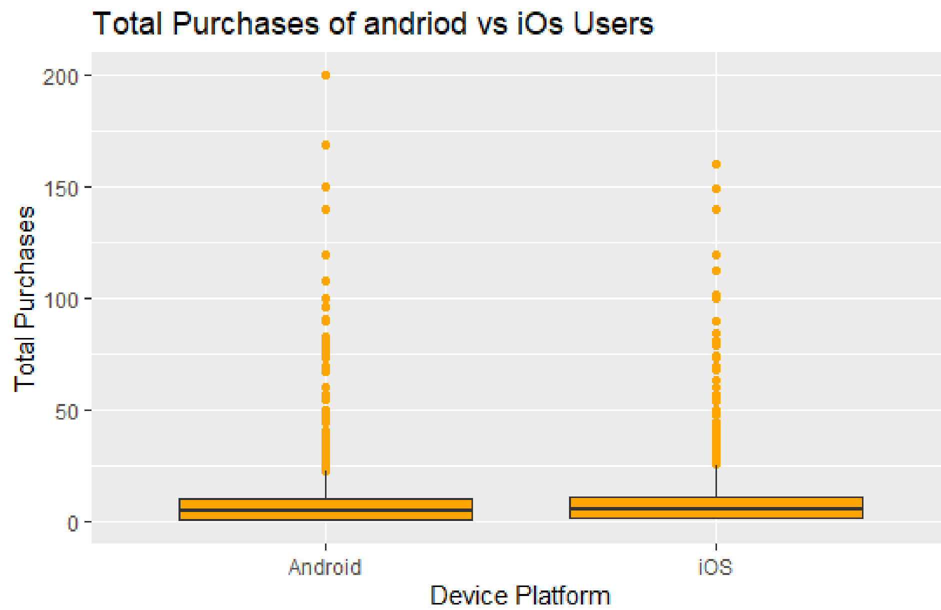
Looking at this graph, which shows the countries and tiers of the participants who watched the most ads. It clearly shows a concentration at the US and UK section in Tier 1, leading us to the point that these countries contribute the most ad-generated revenue for FlowMotion Entertainment. We can also deduce from this graph that Tier 1's participants watch the most ads by the number of points for each Tier. We can also tell that countries belonging to Tier 2 contributed more than tier 3 for revenue generation through ads. Users from Brazil and Russia also contributed to ad revenue. In tier 3, most ads were watched by users in Italy.

Hypothesis 2 Analysis:

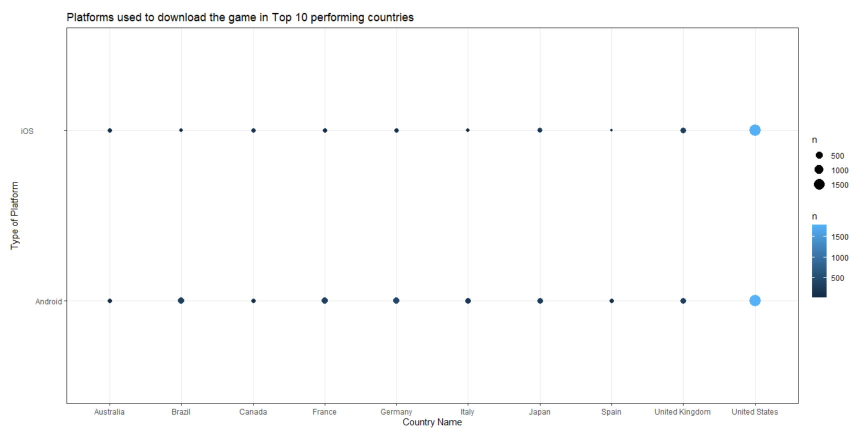
To test our hypothesis, we constructed different visualizations to gauge the proportion of total revenue generated by Android versus iOS game players.

- **Sub Hypothesis 1 : Do Android or iOS users make more purchases?**

The following boxplot depicts the total number of in-app purchases made by iOS and Android users of the game. We can see that Android users have made a higher number of purchases relative to iOS users. The purchases of Android users go to the maximum value 200 US dollars whereas those of iOS are approximately 30-40 dollars below. This insight is further supported by Figure 1 of the Appendix, which shows us that Android users (approximately $43,000) generate more revenue than iOS users (approximately $33,000).



- **Sub-Hypothesis 2: Are users of top ten performing countries Android or iOS users?**

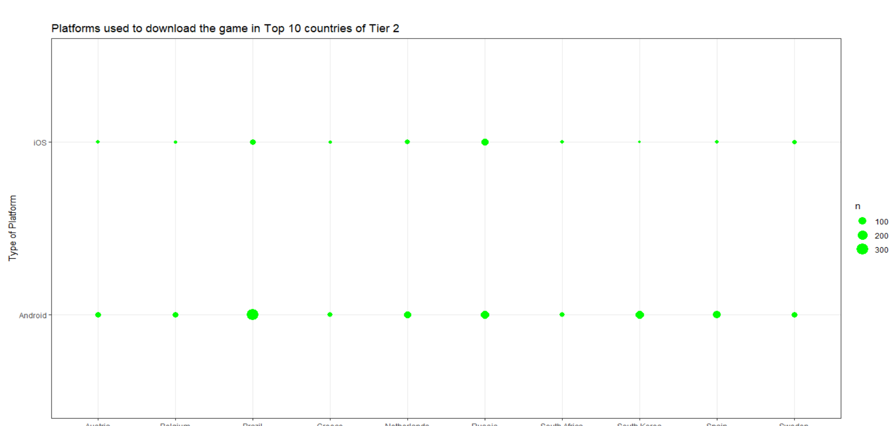


In order to understand which platforms were being used by the top 10 performing countries we used geom_count to visualize two categorical variables. As we can see, the proportion of Android and iOS users in the United States and Canada is equal whereas the United Kingdom and Australia have slightly more iOS users meaning that there is more purchasing power in such countries, therefore an equal number of purchases are made through each platform. This is indicative of the purchasing power of these countries, therefore allowing FlowMotion to better understand users in which countries are more willing to purchase. However, we see that in the rest of the countries such as Brazil, France, Italy, Japan and Spain have relatively more Android users, this could be less purchasing power in these countries due to which more Android users exist in these countries compared to iOS. To further support this we can see that in Figure 2 of the Appendix that Google Play Store is more frequently used overall and specifically in the above mentioned countries. Our results also reinforced the statistic that Android users constitute 71% of the market showing there are also generally more Android users compared to Apple (Laricchia, *Global Mobile OS Market Share 2022* 2022).

- **Sub-Hypothesis 3: Which platform is used in top 10 performing countries of Tier 2 and 3?**

**Since Tier 1 contains 7 countries and all of them constitute the top 10 performing countries overall we will not do Tier 1 analysis as they have been analyzed above*

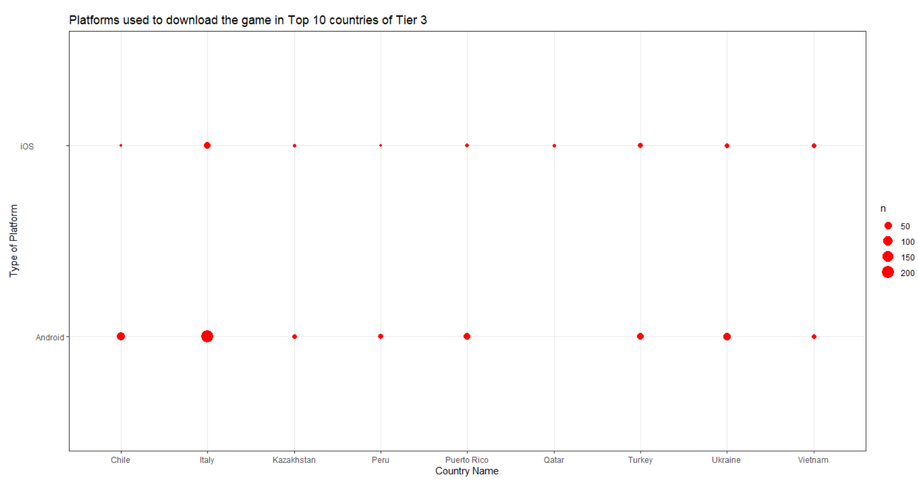
Tier 2



This graph was constructed using geom_count in order to accurately visualize two categorical variables.

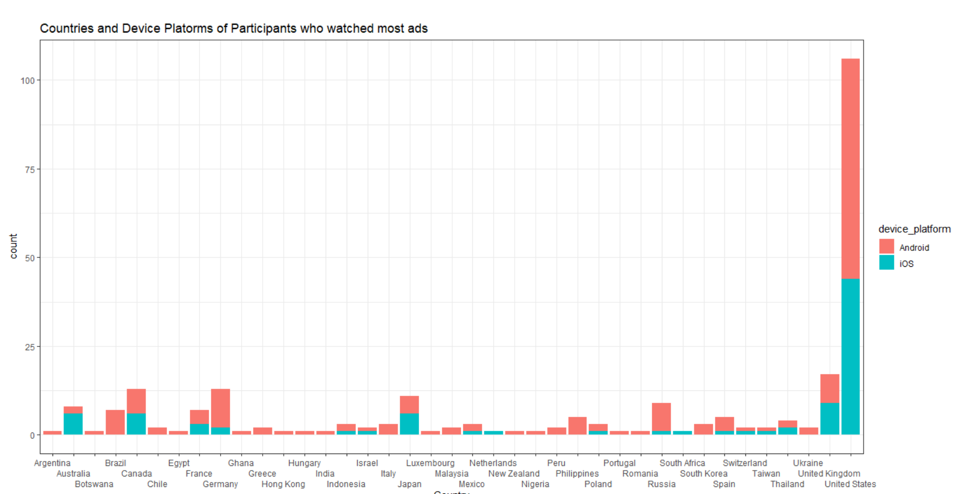
From the graph we can deduce that all top performing countries in this tier are using Android more than iOS, this is essentially due to cheaper availability of Android devices comparatively and as some of these countries fall into slightly lower income brackets. However, though South Korea is a high-income country we see a huge disparity in its Androids vs iOS users, this is indicative of the fact that the telecom infrastructure of South Korea allows Android apps to earn more revenue comparatively. Another interesting observation that can be made is that Brazil has the most Android users, however Spain is the most revenue generating country in this tier. This can be justified from the Revenue per count graph shown above, showing that the revenue generated per download in Spain is higher comparatively. Another observation shows that Russia has much higher iOS users compared to the rest of the countries in this graph.

Tier 3



The graph for tier 3 shows us that Vietnam had an equal number of iOS and Android users compared to the rest of the countries, all of which had more Android users. An interesting observation that can be made since Qatar appears to be an outlier was less than 50. This could be accounted for by the fact that the share of Android devices of the Qatar mobile operating systems has been decreasing over the years while iOS has been increasing and now contain 22% of the market share (Published by Statista Research Department & 12, *Qatar: Mobile Operating Systems Market Share 2020* 2022). Furthermore we can see that Italy which is the 7th most revenue generating country has more Android users, however compared to the rest of the countries it also has the most amount of iOS users. Peru and Chile, have very few iOS users downloading the game.

- **Sub Hypothesis 4: Which platforms did the top 250 users which watched most ads use?**



Looking at this graph, which shows the countries and the platforms of the participants who watched the most ads, we can say that for at least the US, UK, Thailand, Canada and,France, the platform divide for ads watched is around 50/50 but for the other countries, the clear contributor was Android with some countries' penetration being all from Android. The only outlier is Australia, which has more users from iOS watching ads. This again points towards the fact that there are a lot more Android users than iOS users playing the game leading to having more minutes on the application which then leads to more minutes spent on watching ads.The graph also shows us that 17 of these countries had only Android users.

Limitations & Conclusion

Assumptions:

- We are not accounting changes in revenue for inflation in the short term.
- When we group the data by each user, we are assuming that the user is located in the same geographical location, using the same currency and belongs to the same tier etc.
- We assumed certain variables which were not explicitly identified. For example, in install sources, we took manual install as Google Play Store. Lenovo and Oppo phones were also associated with Google Play Stores because they are Android.
- We assumed it would be beneficial for the company to get insights in USD so that is a standard we used to calculate.

Limitations:

- The data set we collected was from the past 3 months.With data relating to mobile applications a lot of factors come into play which can lead to fluctuation in the results. For example, the company could have made some marketing efforts that might have skewed results in one month.
- Data set lacked any demographic information of the customers like their age, gender, income etc which restricted us in terms of clustering. Buying behaviors could not be tested based on characteristics of our users.
- Some user IDs were missing which resulted in loss of data at the time of overlap.
- The country data was not noted in a format that was readable on the “world map” of R which led to restrictions in visualizations.

Conclusion & Recommendations:

After evaluating all the graphs and visualizations, it is clear that countries with comparable economic backgrounds and tiers do have a significant role in the income earned by players, whether it is from in-game purchases or advertisements. As a result, while developing marketing strategies, these aspects should be concentrated on within particular nations. These nations obviously have elevated amounts of mobile gaming engagement; therefore, marketing efforts should take this into account. It is evident that Tier 1 expenditure differs significantly from the spending of the other two tiers, particularly when looking at the first two sub-hypotheses of the first main hypothesis. Players from first-world nations often have larger disposable incomes, which enables them to make more in-app purchases and, as a result, contribute more to overall revenue generation. These can account for the tier 1 countries' much higher revenue contribution. The possibility for further penetration is advised, but FlowMotion Entertainment should also concentrate on Tier 1 nations like Japan and Brazil from Tier 2 and even Tier 3 countries where the mobile gaming market is unmatched, such as India and China, where the demand is still substantially stronger. Speaking in terms of conversion and generating revenue from users, the subsequent conversion is far more likely after the first. They should encourage their users to take that initial step by doing so, therefore. Push, in-app, and email marketing that highlights the advantages and makes tempting offers should be prepared to launch. Use push and email to re-engage consumers and use in-app messaging to direct them around problem spots in the purchasing process. When speaking about advertisements and the revenue generated from them, The US and UK continue to dominate in terms of the number of advertisements viewed and the money made from them, with a greater concentration in Tier 1 than in Tier 2 and 3. Dynamic in-game advertising is an effective strategy, it seems. In-game advertising enables advertisers to reach their consumers where they are most active and engaged, thanks to its interactive capabilities and flexibility. Additionally, it is becoming more crucial for advertisers to make sure their ads are pertinent to the local experience and their target demographic as consumers continue to consume various sources of entertainment at once.

As the results of hypothesis 2 show us, most revenue generation is accumulated through Android users. The main reason for this primarily is due to the fact that Android devices are manufacturers all over the globe as opposed to iOS is only manufactured by Apple.Since, we have concluded that most revenue in the top performing countries across tiers and within tiers are largely Android users since most purchases are made by them and they contribute the most to ad - generated revenue as well, therefore it would be more wise for FlowMotion to concentrate on Android users compared to Apple users. Therefore, it is more essential that they should dedicate more of their marketing budget on App Store Optimization of Google Play Store, more than iTunes in order to increase revenue especially through those countries which have more Android users. Spending more money on the app store optimization of Google Play Store will then allow them to improve the visibility of Cooking Crush : Cooking Games and will ensure that it reaches the relevant segment which is also more willing to make the purchase. It will also allow them to increase organic app downloads, increased conversion rate and hence revenue all the while ensuring that that app reaches the global audience, it will also help reduce the costs associated with user acquisition. It will also ensure that the app will remain in high ranking.

Appendix A

Figure 1

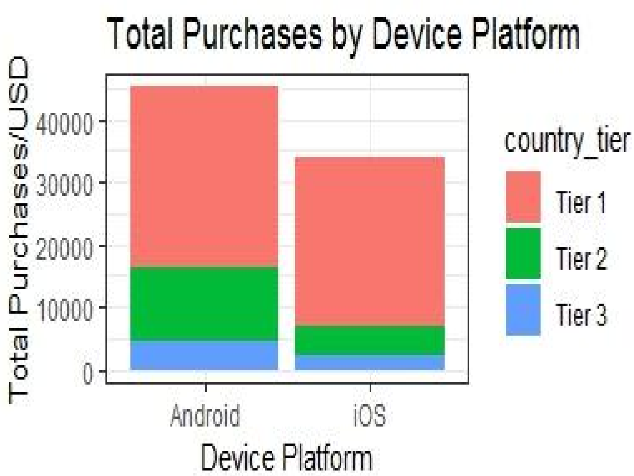


Figure 2

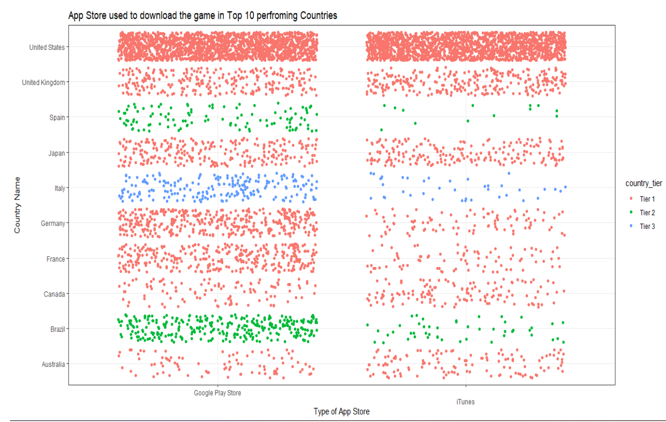


Figure 3 :

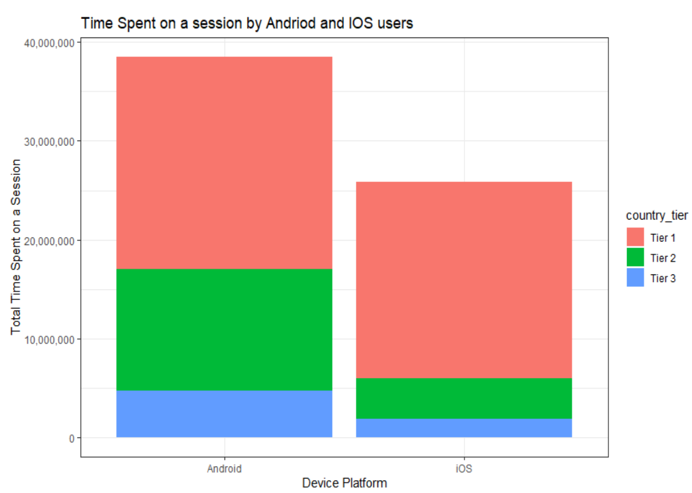


Figure 4

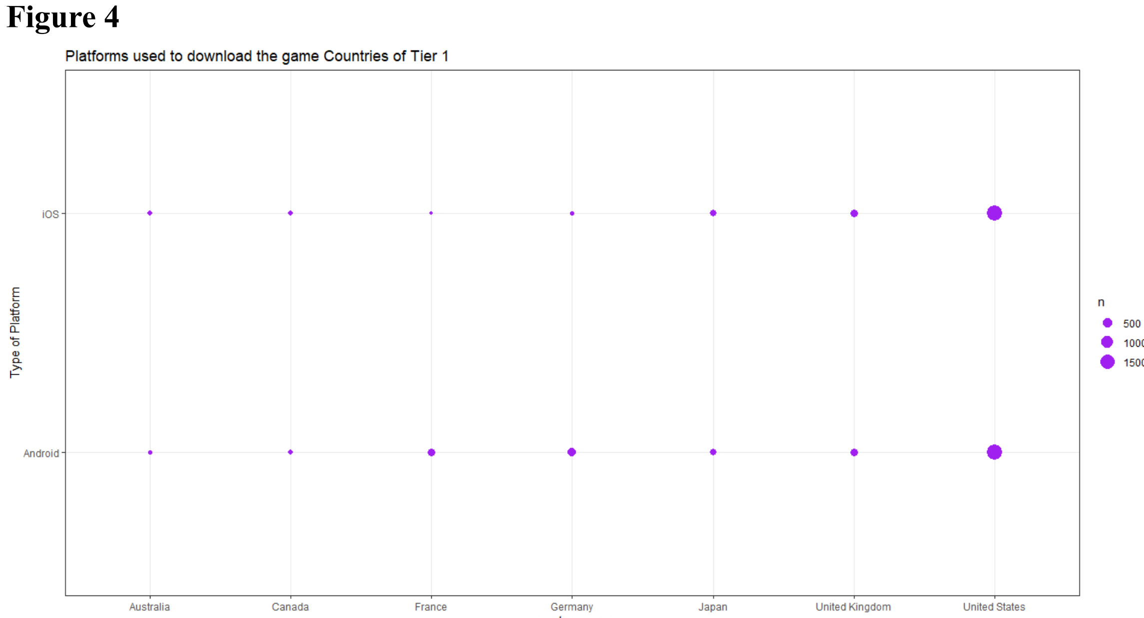


Figure 5

```
> inspect(sort(willingness_subrule, by = "lift"))
     lhs                                    rhs                               support confidence     coverage     lift count
[1]  {country_name=Faroe Islands}        => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[2]  {country_name=Faroe Islands,
      country_tier=Tier 3}               => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[3]  {country_name=Faroe Islands,
      install_source=iTunes}             => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[4]  {device_category=mobile,
      country_name=Faroe Islands}        => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[5]  {device_category=mobile,
      country_name=Bahrain}              => {willingness_to_purchase=High} 3.435246e-05  1.0000000 3.435246e-05 44.40885     2
[6]  {country_name=Faroe Islands,
      country_tier=Tier 3,
      install_source=iTunes}             => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[7]  {device_category=mobile,
      country_name=Faroe Islands,
      country_tier=Tier 3}               => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[8]  {device_category=mobile,
      country_name=Faroe Islands,
      install_source=iTunes}             => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[9]  {device_category=mobile,
      country_name=Bahrain,
      country_tier=Tier 3}               => {willingness_to_purchase=High} 3.435246e-05  1.0000000 3.435246e-05 44.40885     2
[10] {device_category=mobile,
      country_name=Bahrain,
      install_source=iTunes}             => {willingness_to_purchase=High} 3.435246e-05  1.0000000 3.435246e-05 44.40885     2
[11] {device_category=mobile,
      country_name=Faroe Islands,
      country_tier=Tier 3,
      install_source=iTunes}             => {willingness_to_purchase=High} 1.717623e-05  1.0000000 1.717623e-05 44.40885     1
[12] {device_category=mobile,
      country_name=Bahrain,
      country_tier=Tier 3,
      install_source=iTunes}             => {willingness_to_purchase=High} 3.435246e-05  1.0000000 3.435246e-05 44.40885     2
[13] {device_category=mobile,
      country_name=Luxembourg,
      install_source=iTunes}             => {willingness_to_purchase=High} 8.588114e-05  0.5555556 1.545861e-04 24.67158     5
[14] {device_category=mobile,
      country_name=Luxembourg,
      country_tier=Tier 3,
      install_source=iTunes}             => {willingness_to_purchase=High} 8.588114e-05  0.5555556 1.545861e-04 24.67158     5
[15] {country_name=Luxembourg,
      install_source=iTunes}             => {willingness_to_purchase=High} 8.588114e-05  0.4166667 2.061147e-04 18.50369     5
```

Figure 6

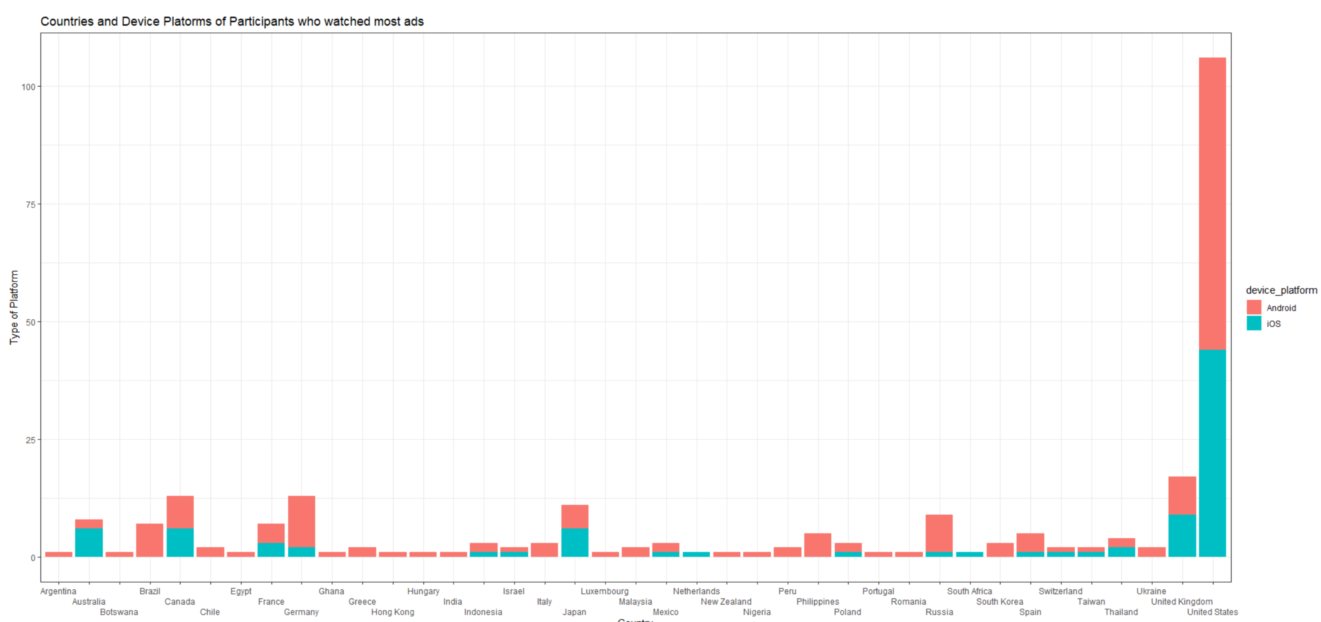


Figure 7

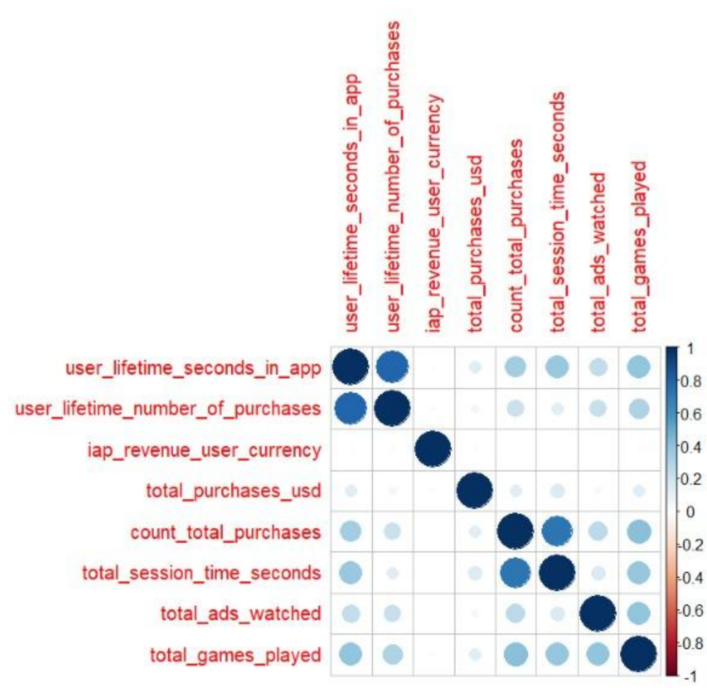


Figure 8

```
                                                                   call
 apriori(data = arules, parameter = list(support = 1.1e-05, conf = 0.25))
> inspect(Grules[1:41])
     lhs                                  rhs                                 support confidence     coverage      lift count
[1]  {}                                => {install_source=iTunes}            4.017863e-01  0.4017863 1.000000e+00  1.000000 23392
[2]  {}                                => {country_name=United States}       4.088114e-01  0.4088114 1.000000e+00  1.000000 23801
[3]  {}                                => {install_source=Google Play Store} 5.981278e-01  0.5981278 1.000000e+00  1.000000 34823
[4]  {}                                => {country_tier=Tier 1}              6.677430e-01  0.6677430 1.000000e+00  1.000000 38876
[5]  {}                                => {device_category=mobile}           7.970800e-01  0.7970800 1.000000e+00  1.000000 46406
[6]  {}                                => {willingness_to_purchase=Low}      8.586568e-01  0.8586568 1.000000e+00  1.000000 49991
[7]  {country_name=French Polynesia}   => {country_tier=Tier 3}              1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[8]  {country_name=French Polynesia}   => {willingness_to_purchase=Medium}   1.717623e-05  1.0000000 1.717623e-05  8.415727     1
[9]  {country_name=French Polynesia}   => {install_source=iTunes}            1.717623e-05  1.0000000 1.717623e-05  2.488885     1
[10] {country_name=French Polynesia}   => {device_category=mobile}           1.717623e-05  1.0000000 1.717623e-05  1.254579     1
[11] {country_name=Faroe Islands}      => {willingness_to_purchase=High}     1.717623e-05  1.0000000 1.717623e-05 44.408848     1
[12] {country_name=Faroe Islands}      => {country_tier=Tier 3}              1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[13] {country_name=Faroe Islands}      => {install_source=iTunes}            1.717623e-05  1.0000000 1.717623e-05  2.488885     1
[14] {country_name=Faroe Islands}      => {device_category=mobile}           1.717623e-05  1.0000000 1.717623e-05  1.254579     1
[15] {country_name=Congo [DRC]}        => {country_tier=Tier 3}              1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[16] {country_name=Congo [DRC]}        => {install_source=iTunes}            1.717623e-05  1.0000000 1.717623e-05  2.488885     1
[17] {country_name=Congo [DRC]}        => {device_category=mobile}           1.717623e-05  1.0000000 1.717623e-05  1.254579     1
[18] {country_name=Congo [DRC]}        => {willingness_to_purchase=Low}      1.717623e-05  1.0000000 1.717623e-05  1.164610     1
[19] {country_name=Iran}               => {country_tier=Tier 3}              1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[20] {country_name=Iran}               => {device_category=tablet}           1.717623e-05  1.0000000 1.717623e-05  4.928051     1
[21] {country_name=Iran}               => {install_source=iTunes}            1.717623e-05  1.0000000 1.717623e-05  2.488885     1
[22] {country_name=Iran}               => {willingness_to_purchase=Low}      1.717623e-05  1.0000000 1.717623e-05  1.164610     1
[23] {country_name=Trinidad and Tobago} => {country_tier=Tier 3}             1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[24] {country_name=Trinidad and Tobago} => {install_source=Google Play Store} 1.717623e-05  1.0000000 1.717623e-05  1.671884     1
[25] {country_name=Trinidad and Tobago} => {device_category=mobile}          1.717623e-05  1.0000000 1.717623e-05  1.254579     1
[26] {country_name=Trinidad and Tobago} => {willingness_to_purchase=Low}     1.717623e-05  1.0000000 1.717623e-05  1.164610     1
[27] {country_name=Guam}               => {country_tier=Tier 3}              1.717623e-05  1.0000000 1.717623e-05  9.616782     1
[28] {country_name=Guam}               => {install_source=iTunes}            1.717623e-05  1.0000000 1.717623e-05  2.488885     1
```

Appendix B

Variables	Description
user_id	This field shows the unique User ID that the player has been allocated
country_name	This field shows the country from which the player is playing from
country_tier	This field shows the respective tier where the origin country is allocated
user_currently_active	This field shows whether the respective user is currently using the app on their device
device_category	This field shows whether the player is playing from a mobile device or a tablet.
user_lifetime_seconds_in_app	This field shows the number of total seconds that the user has spent on the app
user_lifetime_number_of_purchases	This field shows the total number of purchases that the user has made over time.
user_age_days	This field shows the number of days that the user has spent after downloading the application
iap_revenue_user_currency	This field shows the total of the purchases that the user had made in their currency.
user_currency	This field shows the currency through which the user makes the in-game purchases with
device_platform	This field shows the operating system of the device on which the user is using the application.
install_source	This shows the platform or the gateway through which the user downloaded the application
total_purchases_usd	This field shows the total of purchases that the user has made over time in US Dollars.
count_total_purchases	This field shows the count of purchases that the user has made
total_session_time_seconds	This field shows the total number of seconds that the user has spent playing the game, in other words, time spent in a gaming session.
total_ads_watched	This field shows the total number of ads that the user has watched.
total_games_played	This field shows the total number of games that the user has played.

Appendix C

Figure 1

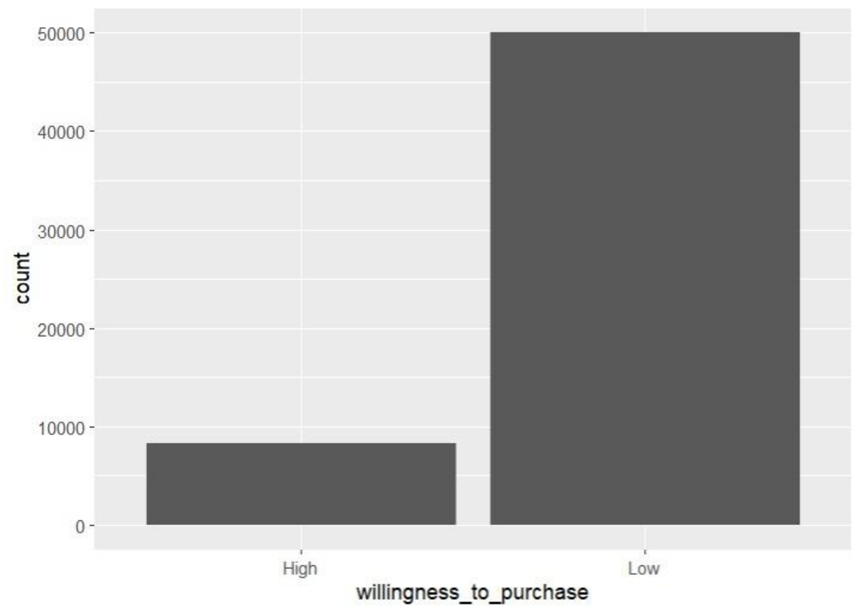


Figure 2

```
     High       Low
0.1413432 0.8586568
```

Figure 3

```
> tree_dt
n= 8659

node), split, n, loss, yval, (yprob)
      * denotes terminal node

1) root 8659 1228 Low (0.1418178 0.8581822) *
>
```

Figure 4

```
> train.set.var
      country_tier device_category device_platform    install_source games_played_todate
51089       Tier 1          mobile             iOS            iTunes        -0.443955347
55256       Tier 1          mobile         Android Google Play Store        -0.504648830
9219        Tier 1          mobile         Android Google Play Store        -0.150818738
54230       Tier 3          tablet         Android Google Play Store        -0.145653335
23944       Tier 2          mobile         Android Google Play Store         0.485817157
13428       Tier 1          tablet         Android Google Play Store        -0.488506946
5582        Tier 1          mobile             iOS            iTunes        -0.509814233
16583       Tier 3          mobile         Android Google Play Store        -0.224425728
23155       Tier 1          tablet             iOS            iTunes        -0.239921936
52742       Tier 1          mobile         Android Google Play Store        -0.452349126
41597       Tier 1          tablet             iOS            iTunes        -0.380679163
57954       Tier 1          mobile             iOS            iTunes        -0.310300549
56034       Tier 1          mobile             iOS            iTunes        -0.137905231
591         Tier 2          mobile         Android Google Play Store         1.231572186
13591       Tier 3          mobile         Android Google Play Store        -0.291575964
31493       Tier 2          mobile         Android Google Play Store        -0.081085800
10430       Tier 1          mobile             iOS            iTunes        -0.491089647
6250        Tier 1          tablet             iOS            iTunes         0.221090264
6748        Tier 1          tablet         Android Google Play Store        -0.334836213
28391       Tier 1          mobile         Android Google Play Store        -0.265748950
31478       Tier 3          mobile         Android Google Play Store        -0.541452325
14695       Tier 1          mobile         Android Google Play Store         0.002851995
36110       Tier 1          mobile             iOS            iTunes         0.194617574
45167       Tier 1          mobile         Android Google Play Store        -0.011352862
18833       Tier 1          tablet         Android Google Play Store         0.587833862
31509       Tier 1          mobile         Android Google Play Store         0.771851337
8962        Tier 1          mobile         Android Google Play Store        -0.244441664
27409       Tier 1          mobile         Android Google Play Store         0.108097077
7353        Tier 1          mobile         Android Google Play Store        -0.440726970
23411       Tier 1          mobile             iOS            iTunes         0.515518223
3214        Tier 2          mobile         Android Google Play Store        -0.185685207
29687       Tier 1          mobile         Android Google Play Store        -0.452994802
45907       Tier 2          mobile         Android Google Play Store        -0.200535740
33966       Tier 1          tablet             iOS            iTunes         0.385737478
27253       Tier 1          mobile             iOS            iTunes        -0.321277030
```

Bibliography

Entertainment., F.M. (no date) *Our story*, *FLOW MOTION*. Available at: https://www.flowmotionentertainment.com/our-story/ (Accessed: December 14, 2022).

How much money can an app make you in 2022? (2022) *MCRO*. Available at: https://mcro.tech/blog/app-revenue/#:~:text=Even%20though%20the%20number%20of,%25%20per%20year%20on%20Android (Accessed: December 14, 2022).

Laricchia, F. (2022) *Global Mobile OS Market Share 2022*, *Statista*. Available at: https://www.statista.com/statistics/272698/global-market-share-held-by-mobile-operating-systems-since-2009/#:~:text=Android%20maintained%20its%20position%20as,the%20mobile%20operating%20system%20market (Accessed: December 14, 2022).

Published by Statista Research Department and 12, S. (2022) *Qatar: Mobile Operating Systems Market Share 2020*, *Statista*. Available at: https://www.statista.com/statistics/612702/mobile-operating-system-share-in-qatar/#:~:text=Market%20share%20of%20mobile%20operating%20systems%20Qatar%202015%2D2020&text=In%20July%202020%2C%20Android%20held,22%20percent%20in%20July%202020 (Accessed: December 14, 2022).

Video games for smartphones: Pros and Cons of Android vs. IOS (2022) *Starloop Studios*. Available at: https://starloopstudios.com/video-games-for-smartphones-pros-and-cons-of-android-vs-ios/ (Accessed: December 14, 2022).