MSMI 604 - Survey Design & Data Collection

Section 1 Group 3: Airbnb

Market Research Report: Airbnb

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Completed For: MSMI Survey Design & Data Collection Class

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1. Executive Summary

1.1 What were the Key Findings from the Research Study?

Our key findings from the research study stemmed from five categories (consumer insights, app interface, price, promotion, and safety/security). We found that the accuracy of post descriptions, lack of effective communication with the host, overpricing of properties, lack of discounts, frequency of scams, cleanliness and safety in the property were the major issues leading to the decline in popularity of Airbnb among the target market.

2. Description of the Study Goals

2.1 Research Objectives

The main objective of our survey was to gain consumer insights and decide whether to continue or improve different aspects of the Airbnb app such as pricing, promotions, safety / security, and the app interface. We want to gauge customer satisfaction or dissatisfaction with the Airbnb platform following the epidemic and offer workable ideas and marketing tactics to help the company reclaim its former brand quality.

2.2 What were the Key Questions?

Our target was individuals who were aware of the Airbnb app and had used the app in some way. Some key questions that were answered by our research study include:

- How did the COVID-19 pandemic expose or create new challenges for Airbnb? Did this affect customer perceptions and usage of the platform?

- Who is our target market and what are their characteristics?

- Where do our prospects position Airbnb in the market?

- Do considerations like how the property is used, the price, the process of booking through Airbnb, the safety/security of the guests and their personal data, and discounts/promotions have an impact on customer satisfaction?

- Do consumer demographics like income, age, or geographic location impact their contentment with Airbnb?

- What competitive advantage can Airbnb gain by improving their customer satisfaction?

3. Research Design & Methodology

3.1 Research Methodology

Our research started right after we decided on choosing Airbnb as our topic. We defined our survey goals and divided each survey goal into topic categories. Then, each team member drafted ten questions related to Airbnb and created a codebook (see Appendix) which stated each survey question and the corresponding variable name, response options and the measurement scale (ordinal, nominal, ratio or interval). From a pool of 50 questions we collectively came up with, the best ones were chosen to be in our final survey questionnaire and integrated into a Qualtrics[1] survey (see Appendix). We proceeded to create a Data Analysis plan (see Appendix) which captured how we will approach analyzing our survey results. We also wrote down the types of analyses we would conduct in RStudio[2] (such as chi-square tests, ANOVA, multiple regression etc.) that were best aligned with our data types (such as categorical or quantitative data) stemming from our survey questions. Once we received responses from our survey, we began cleaning and analyzing the data.

3.1.1 Problem Statement:

How has the pandemic unveiled imperfections of the Airbnb business model and what efforts could improve their customer experience and brand perception?

3.1.2 Type of Data:

We collected **primary data** which means we gathered all the information that was

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[1] *Qualtrics is a web-based software that allows users to create and send out surveys to respondents and receive reports of the data. Previous programming knowledge is not required to utilize the software.*

[2] RStudio is an integrated development environment for R, a programming language for statistical computing and graphics.

crucial to the research ourselves. Qualitative and quantitative data were both taken into consideration.

3.1.3 Research Sample and Method of Data Collection:

'Survey' is the method we chose for collecting our data. The survey consisted of 39 questions and used a mix of 'agreement scales' , 'frequency scales', 'dichotomous' and a few 'nominal' questions. We aimed to conduct a survey of people who were familiar with the platform and had booked a stay with Airbnb at least once. We received a total of 348 responses, out of which a few got dismissed as they did not pass the screener questions and some who did not complete the survey 100%. After cleaning the data, we received 157 valid responses for our analysis.

3.1.4 Research Design:

The survey consisted of 39 questions and used a mix of 'agreement scales', 'frequency scales', 'dichotomous' and a few 'nominal' questions. The survey was designed to cover 5 categories:

1. *Consumer Insights*: This section asked general questions related to the purpose of stay, how often Airbnb was used to book a stay, post descriptions, and the types of places customers preferred for overnight stays.
2. *App Interface*: In this section, we wanted to know how easy the Airbnb app was to navigate, to book stays, whether customer reviews influenced booking, level of satisfaction or dissatisfaction with specific features on the app and communication with the host.
3. *Price*: This section asked general questions about Airbnb's pricing strategy. We wanted to know how satisfied or dissatisfied customers were with base prices of properties and the additional fees charged, whether they negotiated prices,

what factors were responsible for customers booking from competing platforms and how often they shopped around for best deals.

4. *Promotion*: This section aimed to ask consumers how often they look for discounts when booking stays, their most preferred platform to receive promotions, their opinion on Airbnb launching a rewards program, and what kind of promotions customers were more inclined towards.
5. *Safety/Security*: In this section we wanted to identify how important or unimportant the property's security and cleanliness is when customers booked a stay and if getting scammed on the platform affects booking.

3.1.5 Methods of Data Analyzation:

Upon receiving the data set from Qualtrics, we cleaned the data in Microsoft Excel. We deleted columns that contained irrelevant information for our study such as IP addresses, start date and end date, response IDs, duration time of the survey, distribution channels, and user language. Responses that failed to pass the two screener questions were also discarded. We created separate Excel sheets for each of the five categories and exported them as csv[3] files (to be imported into RStudio).

Next, we began coding in RStudio using the correlation plot function (corrplot) to create a visualization plot with a correlation matrix that supported automatic variable reordering to help detect hidden patterns among variables in each of the five categories listed above. Then, we used a correlation function (lm) to run a correlation analysis for each category. Lastly, we used an anova function (ANOVA) to run a single anova analysis. This test yielded p-values for each variable which we then assessed as being

[3] *CSV (Comma Separated Values) format is a plain text format in which values are separated by commas. Each line of the CSV file is a data record and allows the user to import the file into an Excel spreadsheet or other software programs.*

greater than or less than 0.05. This determined if the variables were statistically significant or insignificant and if we could reject or fail to reject the null hypothesis.

3.1.6 Data Tools:

Qualtrics, RStudio, Tableau and Microsoft Excel (details in appendix)

3.1.7 Future Research:

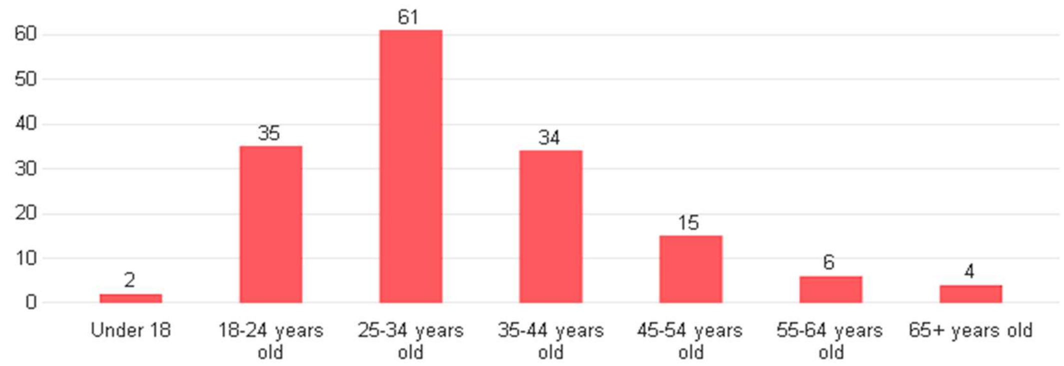
Since more than half of the total survey respondents said that they look around for best deals in addition to using Airbnb, we would like to target those consumers and probe for more information. We would want to know what factors are responsible for making them shop around and later, recommend strategies to Airbnb to create a better brand loyalty.

4. Research Study Results

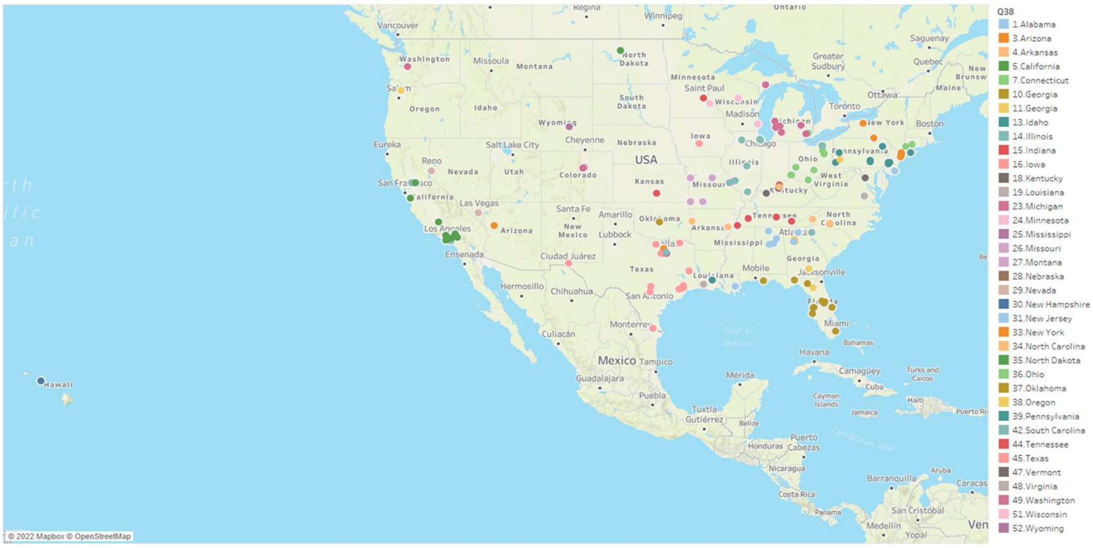
4.1 Descriptive Statistics

We aimed to conduct a survey of people who were familiar with the platform and had booked a stay with Airbnb at least once. We had an overall sample size of 348 responses from November 26, 2022 to December 2, 2022. Upon analysis of the survey responses, we received 157 valid responses who had passed the screener questions (Q1. Are you aware of the Airbnb platform? and Q2. Have you booked a stay on Airbnb?). From the graphs below, we can see three distributions. Firstly, 82.8% of the respondents are 18-44 years old, mostly from age 25-34 years old with 61 respondents (38.8%). Secondly, 29.9% of the respondents are from Florida, Illinois, Ohio, and Texas. 9.5% of the respondents from Texas, which is the biggest group of respondents Lastly, 67.5% of the respondents have $10,001 to $75,000 yearly income. Most of the respondents are $25,001 to $50,000 with 42 respondents (26.7%).

Age of Respondents



States Where Respondents Reside



Household Income of Respondents

4.2 What were the Results?

4.2.1 Findings:

We found that in each of the five categories (consumer insights, app interface, price, promotion, and safety/security) there were variables that correlated with each other (highlighted in yellow). As seen in our Data Analysis Plan, we chose one variable in each of the categories and compared it to the other variables in that same category. By conducting an ANOVA test on R, we were able to see the p-values, assess whether they were greater than or less than 0.05 and determine if they were statistically significant or insignificant.

In Category 1 - Consumer Insights (ci_), we found that whether the photos of the property match the customer's expectations of the actual space (ci_photogenuity) and the accuracy of post description (ci_postdescription) affected how often customers booked stays with Airbnb (ci_booking). The purpose of the stay (ci_purpose), what customers deem as the most important factor (ci_decision) and the type of place customers stay overnight (ci_overnight) did not affect how often customers booked stays with Airbnb.

- **Category 1: Consumer Insights** - comparing ci_booking with:
  - ci_photogenuity: p-value= 0.00013 < 0.05 so fail to reject null hypothesis
  - ci_postdescription: p-value= 0.00433 < 0.05 so fail to reject null hypothesis
  - ci_purpose: p-value= 0.22217 > 0.05 so reject null hypothesis
  - ci_decision: p-value= 0.18350 > 0.05 so reject null hypothesis
  - ci_overnight: p-value= 0.24424 > 0.05 so reject null hypothesis

In Category 2 - Airbnb app interface (app_), we found that being able to effectively communicate with the host under any circumstance (app_hostcommunicate) and customer satisfaction or dissatisfaction with the self-check in feature (app_selfcheck) affected whether the booking of a property on Airbnb was effortless (app_booking). The user reviews of properties (app_reviews), a better sort feature (app_sortfeature), frequency of glitches (app_glitch) and being able to see listings from third-party sites (app_thirdparty) did not affect the effortless booking of a property on Airbnb.

- **Category 2: App Interface - comparing app_booking with:**
    - app_hostcommunicate: p-value= 0.0000425 < 0.05 so fail to reject null hypothesis
    - app_selfcheck: p-value= 0.0445 < 0.05 so fail to reject null hypothesis
    - app_reviews: p-value= 0.0572 > 0.05 so reject null hypothesis
    - app_sortfeature: p-value= 0.2871 > 0.05 so reject null hypothesis
    - app_glitch: p-value= 0.7659 > 0.05 so reject null hypothesis
    - app_thirdparty: p-value= 0.5377 > 0.05 so reject null hypothesis

In Category 3 - Price (price_), we found that the base price of properties (price_base) and expensive fees such as cleaning, service, occupancy, taxes etc. (price_fee) affected whether customers shopped around for best deals in addition to using the Airbnb platform (price_bestdeals). A customer's willingness to pay a higher price for a highly rated property (price_frequency), willingness to pay higher prices for superhosts (price_superhost), frequency of customers negotiating the price of their stay (price_negotiation) and a price hike on the platform (price_hike) did not affect whether customers shopped around for best deals in addition to using the Airbnb platform.

- **Category 3: Price - comparing price_bestdeals with:**
    - price_base: p-value= 0.000511 < 0.05 so fail to reject null hypothesis

  - price_fee: p-value= 0.003947 < 0.05 so fail to reject null hypothesis
  - price_frequency: p-value = 0.423325 > 0.05 so reject null hypothesis
  - price_superhost: p-value = 0.095563 > 0.05 so reject null hypothesis
  - price_negotiation: p-value = 0.135895 > 0.05 so reject null hypothesis
  - price_hike: p-value = 0.154069 > 0.05 so reject null hypothesis

In Category 4: Promotion (promo_), we found that gaining reward points on a credit card (promo_creditcard) and the frequency of significantly discounted rates on weekdays (promo_flexibility) affected how often customers looked for discounts while booking travel accommodations (promo_discount). Customers most preferred channel to receive discounts (promo_channel), receiving monthly promotions to encourage booking (promo_monthlypromo), offering extra amenities such asb access to pool, a jacuzzi, washer dryer etc. at no charge on top of the discounts on the overall reservation amount (promo_amenities) and launching a rewards program to encourage customers to book stays (promo_rewards) did not affect how often customers looked for discounts while booking travel accommodations.

- **Category 4: Promotion - comparing promo_discount with:**
  - promo_creditcard: p-value= 0.0019 < 0.05 so fail to reject null hypothesis
  - promo_flexibility: p-value= 0.0047 < 0.05 so fail to reject null hypothesis
  - promo_channel: p-value = 0.2907 > 0.05 so reject null hypothesis
  - promo_monthlypromo: p-value = 0.0908 > 0.05 so reject null hypothesis
  - promo_amenities: p-value = 0.1137 > 0.05 so reject null hypothesis
  - promo_rewards: p-value = 0.5096 > 0.05 so reject null hypothesis

In Category 5: Safety/security (ss_), we found that properties that did not follow safety protocols, such as broken fire alarms/smoke/carbon monoxide detectors, improper maintenance of gas appliances, etc. (ss_protocols) and the frequency of customers getting scammed on the platform (ss_scam) affected the importance customers placed on security when reserving a stay through Airbnb (ss_security). Customer satisfaction or dissatisfaction with the cleanliness of the property (ss_cleanliness) did not affect the importance customers placed on security when reserving a stay through Airbnb.

- **Category 5: Safety/Security - comparing ss_security with:**
    - ss_protocols: p-value= 0.0385 < 0.05 so fail to reject null hypothesis
    - ss_scam: p-value= 0.0473 < 0.05 so fail to reject null hypothesis
    - ss_cleanliness: p-value= 0.2263 > 0.05 so reject null hypothesis

4.2.2 Interpretation:

If the ANOVA test yielded a p-value less than (<) 0.05, the statistic was considered significant, the null hypothesis was rejected and the two variables in comparison were correlated in some way. If the p-value was greater than (>) 0.05, the statistic was not significant, the null hypothesis failed to reject and the two variables were not correlated to each other.

4.2.3 Implications:

Based on our findings, we found that there are some opportunities Airbnb can take advantage of and there are also some threats that the company should address.

1. Photos of the property and descriptions of the property uploaded by the Airbnb host heavily influenced whether customers booked Airbnb stays. From our survey results, we found that Airbnb was not providing customers with accurate property descriptions. This presents a threat and Airbnb should publish legitimate and correct photographs and descriptions of their properties to address the issue.

2. Being able to efficiently connect with the host under any circumstance and improving the self-check-in feature (available after reserving a stay on Airbnb) made the booking process effortless for respondents in our survey. This presents two opportunities for Airbnb to improve their platform. First, by bettering the communication between the customer and the property host before, during and after the booking can help the customer feel more confident utilizing the Airbnb platform. Also, conducting some more research as to why customers are dissatisfied with the current self-check-in feature can help boost usage of the platform when booking travel accommodations.

3. Base price of Airbnb properties and expensive fees (such as cleaning, service, occupancy, taxes) were factors that heavily influenced whether customers booked with Airbnb or searched for accommodation elsewhere. This presents a threat to Airbnb as brand loyalty decreases and they lose customers to competing websites. To combat this, the base price of properties advertised on Airbnb and any additional fees should be standardized and reasonable to the average Airbnb customer. The company can conduct further research to find a compromisable price so customers are satisfied and the platform still makes money.

4. Earning credit card reward points and booking at drastically reduced rates on weekdays encouraged consumers to utilize Airbnb. This presents two opportunities for the company. First, they can offer promotions during the weekdays to capture the interest of existing customers and attract new ones. Secondly, the company can establish relationships with credit card providers to issue reward points to Airbnb consumers who use their credit cards to make bookings.

5. Customers highly prioritized booking properties that adhered to safety protocols and the frequency of customers being scammed affected whether they booked a stay using Airbnb. This presents two threats to the company. First, Airbnb should mandate that property hosts conduct thorough safety exams and check for broken fire alarms/smoke/carbon monoxide detectors, improper maintenance of gas appliances, etc. in their properties. Additionally, Airbnb should follow up with monthly inspections and mandate monthly maintenance services for all properties listed on Airbnb. Secondly, to combat the frequent scamming attempts customers face, Airbnb should regularly scan the platform for fake users and hosts and doctored property photos. Additionally, users should only be allowed to pay via credit or debit card through the company's website and hosts should not be able to ask customers for other types of payment. Further research into the types of scams customers encounter frequently can help improve customer satisfaction and trust in the brand.

5. Recommendations

We came up with three main recommendations that address Airbnb's issues with customer satisfaction, brand loyalty and brand perception.

1. **Partnering with credit card companies:**
   - We found that if customers were able to earn reward points by using their credit card on Airbnb, they would book more often on the platform. We recommend the company partner with well-known credit card issuers (such as Mastercard, Visa, Chase etc.) and offer a rewards program where users can accrue points and get money back on Airbnb reservations.
2. **Making more trustworthy posts:**
   - Our findings made it clear that customers had expectations that were not met regarding the property photos and descriptions provided on Airbnb. In order to create more trustworthy property posts, Airbnb should take the initiative to monitor whether property hosts are consistently posting accurate photos which also match their descriptions. This also includes monitoring customer feedback on all properties to ensure that users are not misled by inaccurate or fake posts.
   - Encouraging hosts to post high quality photos or upload 3D virtual tours of their properties might instill more trust in the information provided on the platform.
3. **Offering a superior experience:**
   - We advise Airbnb to enforce stricter rules for property hosts. If they are caught not following the safety protocols in their properties, posting false information and fake photos, blocking CCTV cameras or attempting to scam customers, they will be immediately banned from the platform.
   - If property hosts are looking to post a listing on Airbnb, they should be

encouraged to set up CCTV cameras outside their property for the protection of their guests. If this is not feasible for any reason, another solution should be found to assure customer security at the property.

- Additionally, we recommend that Airbnb give greater importance to protecting customer information by strengthening their cyber security department and investing money into establishing encrypted channels that will reduce scamming attempts

5.1 Action Plan

Action Plan 1:

Airbnb must resolve customer complaints consistently so that consumers trust the platform and are willing to make new reservations. It also shows that the company values the opinions of their customers and will do what they can to improve their user experience.

Action Plan 2:

To enhance perception and assure long-term growth, revamp the consumer outreach approach. Collaborate with credit card providers, launch marketing initiatives and efficiently use social media and other digital platforms to advertise and set up reward point systems, discounts, and promotions for customers.

Action Plan 3:

Airbnb should take measures to improve their online and mobile platforms to offer the greatest user experience. Check property listings to verify that there are not any duplicates, fake posts or inaccurate property descriptions, and offer virtual tours to build customer confidence in the property.

6. Appendix

6.1 Research Tools & Data Collection Forms

Final Survey Questions & Codebooks:
https://docs.google.com/document/d/13n_JjZKMVhTKiFtPu0QvlkiQnm8taN4Sv-Oqjq1rBnc/edit

Data Analysis Plan:
https://www.canva.com/design/DAFVAADoljw/lpnzO2gYG5BQ5gGALH7V7Q/view?utm_content=DAFVAADoljw&utm_campaign=designshare&utm_medium=link2&utm_source=sharebutton

Survey Questionnaire:
https://usfca.qualtrics.com/jfe/form/SV_3r5M3BP3jzI2j1s

Survey Responses - csv file (raw data set provided by Qualtrics):
https://drive.google.com/file/d/1qsB5gOE2_f0XYMQKX6O_AadbhSd0W1NR/view?usp=share_link

Respondent Demographics (graphs & pie charts):
https://drive.google.com/file/d/1CBdskbn6v4S2FVRrUCen37g1clEH-FCH/view?usp=share_link

Visualization reports from Tableau:
https://docs.google.com/presentation/d/17N9QKzX8vtkcaNuS0McpRfig9q8ofDYW/edit?usp=share_link&ouid=100844832202915871393&rtpof=true&sd=true

Data Analyze - RStudio code:
Category 1: Consumer Insights
https://drive.google.com/file/d/1YVlViZI9oEgrUKRSTsbe8EsXDZWm2XWz/view?usp=share_link

[1] library(ggplot2)
[2] library(afex)
[3] library(emmeans)

[4] library(dplyr)
[5] library(car)
[6] library(corrplot)
[7] ci.df = read.csv('C:\\R\\Consumer Insights.csv', header = T)
[8] str(ci.df)
[9] table(ci.df$ci_booking)
[10] table(ci.df$ci_purpose)
[11] table(ci.df$ci_decision)
[12] table(ci.df$ci_overnight)
[13] table(ci.df$ci_photogenuity)
[14] table(ci.df$ci_postdescription)
[15] corrplot(cor(ci.df[,c(8,9:13)]),method = 'ellipse', type = 'upper')
[16] modelci <- lm(ci_booking ~ ci_purpose + ci_decision + ci_overnight + ci_photogenuity + ci_postdescription, data = ci.df)
[17] summary (modelci)
[18] ci.aov <- aov(ci_booking ~ ci_purpose + ci_decision + ci_overnight + ci_photogenuity + ci_postdescription, data = ci.df)
[19] summary(ci.aov)

Category 2: App Interface
https://drive.google.com/file/d/1hGtxOY_OVfCqPMNk8TK6FHsLHfcK0nHM/view?usp=share_link

[1] library(ggplot2)
[2] library(afex)
[3] library(emmeans)
[4] library(dplyr)
[5] library(car)
[6] library(corrplot)
[7] app.df = read.csv('C:\\R\\apps.csv', header = T)
[8] str(app.df)
[9] table(app.df$app_search)
[10] table(app.df$app_booking)
[11] table(app.df$app_reviews)
[12] table(app.df$app_hostcommunicate)
[13] table(app.df$app_sortfeature)
[14] table(app.df$app_selfcheck)
[15] table(app.df$app_glitch)

[16] table(app.df$app_thirdparty)
[17] corrplot(cor(app.df[,c(9,8:15)]),method = 'ellipse', type = 'upper')
[18] modelapp <- lm(app_booking ~ app_reviews + app_hostcommunicate + app_sortfeature + app_selfcheck + app_glitch + app_thirdparty, data = app.df)
[19] summary (modelapp)
[20] app.aov <- aov(app_booking ~ app_reviews + app_hostcommunicate + app_sortfeature + app_selfcheck + app_glitch + app_thirdparty, data = app.df)
[21] summary(app.aov)

Category 3: Price
https://drive.google.com/file/d/1ReCzG4v21KB0jci2Bt2BL8QP4pTIK--x/view?usp=share_link

[1] library(ggplot2)
[2] library(afex)
[3] library(emmeans)
[4] library(dplyr)
[5] library(car)
[6] library(corrplot)
[7] price.df = read.csv('C:\\R\\Price.csv', header = T)
[8] str(price.df)
[9] table(price.df$price_base)
[10] table(price.df$price_frequency)
[11] table(price.df$price_superhost)
[12] table(price.df$price_fee)
[13] table(price.df$price_negotiation)
[14] table(price.df$price_hike)
[15] table(price.df$price_bestdeals)
[16] corrplot(cor(price.df[,c(14,9:14)]),method = 'ellipse', type = 'upper')
[17] modelprice <- lm(price_bestdeals ~ price_base + price_frequency + price_superhost + price_fee + price_negotiation + price_hike, data = price.df)
[18] summary (modelprice)
[19] pi.aov <- aov(price_bestdeals ~ price_base + price_frequency + price_superhost + price_fee + price_negotiation + price_hike, data = price.df)
[20] summary(pi.aov)

Category 4: Promotion
https://drive.google.com/file/d/1cMeUtKB9EFQzlNBWufyZG6BjCv59MVGm/v

iew?usp=share_link

[1] library(ggplot2)
[2] library(afex)
[3] library(emmeans)
[4] library(dplyr)
[5] library(car)
[6] library(corrplot)
[7] promo.df= read.csv("C:\\R\\promo.csv",header=T)
[8] str(promo.df)
[9] table(promo.df$promo_channel)
[10] table(promo.df$promo_creditcard)
[11] table(promo.df$promo_monthlypromo)
[12] table(promo.df$promo_amenities)
[13] table(promo.df$promo_flexibility)
[14] table(promo.df$promo_rewards)
[15] str(promo.df)
[16] corrplot(cor(promo.df[, c(5,6:11)]),method='ellipse',type = 'upper')
[17] modelpromo<-
lm(promo_discount~promo_channel+promo_creditcard+promo_monthlypromo+
promo_amenities+promo_flexibility+promo_rewards,data = promo.df)
[18] summary(modelpromo)
[19] promo.aov <- aov(promo_discount
~promo_channel+promo_creditcard+promo_monthlypromo+promo_amenities+p
romo_flexibility+promo_rewards , data = promo.df)
[20] summary(promo.aov)

Category 5: Safety/Security
https://drive.google.com/file/d/1-
B2g5f9fITVf44vr5j94S9SNFYrRdCpH/view?usp=share_link

[1] library(ggplot2)
[2] library(afex)
[3] library(emmeans)
[4] libary(dplyr)
[5] library(car)
[6] library(corrplot)
[7] ss.df = read.csv('C:\\R\\Safety and Security.csv', header = T)

[8] str(ss.df)
[9] table(ss.df$ss_security)
[10] table(ss.df$ss_cleanliness)
[11] table(ss.df$ss_protocols)
[12] table(ss.df$ss_scam)
[13] corrplot(cor(ss.df[,c(8,9:11)]),method = 'ellipse', type = 'upper')
[14] modelss <- lm(ss_security ~ ss_protocols + ss_scam + ss_cleanliness, data = ss.df)
[15] summary (modelss)
[16] ss.aov <- aov(ss_security ~ ss_protocols + ss_scam + ss_cleanliness, data = ss.df)
[17] summary(ss.aov)