Exploring Gender Disparities in User Behaviour on Tinder

This report is submitted as the fulfilment of the project of Making Society Smart through Computational Social Systems in Semester VII of B.Tech (IT & Mathematical Innovation) at Cluster Innovation Center, University of Delhi

Submitted By

Sai Yash (12050)

Shashi Suman (12054)

Under the Supervision of

Dr. Sachin Kumar

Cluster Innovation Center
University of Delhi, Delhi
India-110007

2023

Certificate of Completion

This is to certify that ***Sai Yash & Shashi Suman*** have successfully completed the project titled '***Exploring Gender Disparities in User Behaviour on Tinder***' at Cluster Innovation Centre under my supervision and guidance in the fulfilment of requirements of the Seventh Semester, Bachelor of Technology (Information Technology and Mathematical Innovation) of University of Delhi, Delhi.

Dr. Sachin Kumar
Assistant Professor
Cluster Innovation Centre
University of Delhi

Acknowledgement

We would like to express our special thanks to our supervisor "**Dr. Sachin Kumar**" who allowed us to work on this research project titled "Exploring Gender Disparities in User Behaviour on Tinder". Without his help, it would have been very difficult to complete this project. We came to know about so many new things and had a good experience. We would also like to express special thanks to "**Kristian Elset Bo"** for providing the dataset of 1209 anonymous tinder profiles. We would also like to show gratitude to our parents for their kind support at home.

Table of Contents

1. Abstract

In the era of digital dating, Tinder has emerged as a prominent platform connecting individuals seeking romantic or social connections. This research project delves into the interesting patterns of user behaviour on Tinder, with a specific focus on identifying and analysing differences in how men and women engage with the application.

Using a comprehensive dataset collected from Tinder's user interactions, this study employs advanced data analysis techniques to investigate the existence of gender disparities in various aspects of the platform. The research explores key dimensions such as profile creation, swiping behaviour, messaging activity, and response rates, shedding light on the underlying dynamics that shape the Tinder experience for both genders.

Our findings reveal interesting insights into the ways men and women navigate the world of online dating. We investigate whether traditional gender norms and societal expectations influence user behaviour, as well as how these disparities may impact the overall success of users in forming connections on the platform. Additionally, we consider the implications of these findings for both individuals and the broader online dating ecosystem.

The outcomes of this research contribute to a better understanding of gender-related patterns in digital dating platforms, offering valuable insights for developers, sociologists, and anyone interested in the evolving landscape of modern relationships. By examining the varying interactions on Tinder, we aim to promote a more informed discussion on the dynamics of online dating and its implications for gender dynamics in the digital age.

2. Introduction

This project's goal is to study and analyse the existence of differences in the behaviour of men and women in the use of the dating app Tinder. As described by *Wikipedia*, "*Tinder is an online dating and geosocial networking application. In Tinder, users "swipe right" to like or "swipe left" to dislike other users' profiles, which include their photos, a short bio, and a list of their interests. Tinder uses a "double opt-in" system where both users must like each other before they can exchange messages*".

The application makes use of a freemium model. Thus, the basic functionalities are free to use, while the advanced functionalities require a fee to be used. Some of the premium features are unlimited likes (100 in the basic version), super likes with messages, discovering who has liked your profile or highlighting your likes to other users. In this way, the app must know how its users use each of the features in order to achieve the best possible business model. Immediately, we can distinguish two groups in the application, men and women (as organised by the application itself). Thus, one of the first questions that arise is whether there are differences in the use of the application between the two groups. This question is especially relevant for a correct segmentation of the market to offer an appropriate set of features to both men and women.

3. Literature Survey

In 2010, Hitsch, Hortaçsu, and Ariely did an important study about how people behave on online dating sites. They looked at things like how people make profiles, what they like, and how they talk to each other. The study helped us understand a lot about how individuals use dating apps by breaking down how people show themselves, what they look for in a partner, and how they communicate. Hitsch and his team's work is special because it gives us a good overall view and adds a lot to what we know about how people act on dating apps in the changing world of online dating.

In 2008, Toma, Hancock, and Ellison explored online dating preferences. They focused on understanding gender differences and how they affect user behaviour. The study looked at the dynamics of choosing partners, emphasizing physical attractiveness and self-presentation. It delved into the criteria people use to evaluate potential partners, offering insights into digital decision-making. The findings contribute to a deeper understanding of factors influencing partner perceptions. The study highlights the importance of self-presentation strategies in online dating dynamics. Overall, it enriches the broader discourse on digital relationships.

In 2006, Gibbs, Ellison, and Heino looked into how society's rules affect online dating. They gave a valuable view from sociology on how digital dating is changing. The study checked out how regular ideas about what men and women should do affect how people act online. The researchers focused on showing how cultural norms, or what society thinks is normal, influence how people behave in online relationships. They wanted to figure out the complicated connection between what society expects and what individuals do in the online dating world. This research helps us understand how cultural factors shape how people behave in digital relationships today.

4. Research Objectives

While doing our analysis following questions were defined to resolve throughout the analysis.

1. Who is more selective? Passes vs Likes by sex
2. Who receives the more attention? Matches by sex
3. Who uses the app the most? App opens by sex
4. Who is most willing to pay for a subscription? Number of times the likes limit is reached per sex
5. Who talks the most? Messaging behaviour by sex
6. What is the minimum, mean and maximum percentage of one message-conversations for every sex? What about the number of ghostings after the initial message?
7. Who uses more Instagram by sex?
8. More used emojis by sex?
9. Daily message frequency of Tinder users
10. Top Countries with number of tinder profiles
11. Top Jobs of Tinder users
12. Top Schools or College of Tinder users
13. Most used hashtags in messages
14. Average word count of messages
15. Average length of messages
16. Word Cloud for Tinder Conversations

5. Data collection & Storage

This section details how the data was collected and how it was cleaned and analysed.

swipestats.io provided the data at no cost for academic purposes. swipestats.io is an anonymous data visualization and comparison web service that seeks to help people understand their Tinder data. For using the service, a person must download its data from the Tinder app and upload it to swipestats to get interesting insights about their behaviour in the app. We would like to express special thanks to "**Kristian Elset Bo"** owner of swipestats.io for providing the dataset of 1209 anonymous tinder profiles.

Linkedin Profile of Kiristian - https://www.linkedin.com/in/kristianeboe/

The dataset consists of JSON & CSV files and not a single description or explanation of the data is given. Thus, the most crucial task of the analysis is to understand the data at hand to be able to get valuable information from it.

Relational DBs are based on the relational model, which organizes data into tables with rows and columns with minimal data repetition. Each row represents a record, and each column represents a field in the record. Nevertheless, the relationships between the tables as well as the column data types need to be defined prior to the use of the database. Some examples of relational databases include MySQL, Oracle, and Microsoft SQL Server.

NoSQL databases, on the other hand, are non-relational databases that are designed to handle large amounts of data that is structured, semi-structured, or unstructured. NoSQL databases are often used for storing large volumes of data that do not fit well into the tabular structure of a traditional relational database. Some examples of NoSQL databases include MongoDB and Apache CouchDB.

Thus, we can state several key differences between relational and NoSQL databases:

- **Data structure**: Relational databases use a tabular structure to store data, while NoSQL databases can use a variety of data structures, such as key-value pairs, documents, and graphs.
- **Query language**: Relational databases use SQL to manipulate and query data, while NoSQL databases may use a variety of query languages, such as MongoDB Query Language.

- **Flexibility:** NoSQL databases are generally more flexible than relational databases, as they can store data in a variety of formats and structures. This makes them well-suited for handling semi-structured and unstructured data.

  In summary, relational databases are good for structured data and support complex queries, while NoSQL databases are better for large volumes of unstructured data. Because of all these reasons, the choice for the task at hand is NoSQL and MongoDB since the data is semi-structured and given in a JSON, not following a tabular structure.

6. Data Description

The following section seeks to describe the data. It should be considered that not a single description or explanation was given. Hence, an analysis should be driven in order to perfectly understand the data at hand, allowing the posterior analysis of the data and the extraction of valuable information. Thus, the data is analysed field by field and each one gets described thanks to the experiments carried out and the actual use of the application to discover the concrete meaning of each one.

The keys found in the dataset are: '_id', '__v', 'appOpens', 'conversations', 'conversationsMeta', 'matches', 'messages', 'messagesReceived', 'messagesSent', 'swipeLikes', 'swipePasses', 'swipes', 'user' and 'userId'.

Description of data found in each key:

'_id' is a unique and anonymous identifier for each instance of the dataset. Moreover, __v is a versionKey that contains information about the internal revision of the document so it's not remarkable for the current analysis

'appOpens' refers to the number of times a user opens the app by date. The information is stored in a dictionary where the key is the date.

'conversations' refers to messages sent by the user considered. The information is stored in a list of dictionaries where every dictionary stores a conversation with a match.

'conversationsMeta' refers to the metadata of the messages sent by the user considered. The information is stored in a dictionary where the following data is found:

- **nrOfConversations:** Total number of conversations held
- **longestConversation:** Length of the longest conversation
- **longestConversationInDays:** Length of the longest conversation considering the days passed since the first and last messages.
- **averageConversationLength:** Average length of the conversations held
- **averageConversationLengthInDays:** Average length of the conversations considering the days passed since the first and last messages.

- **medianConversationLength:** Median length of the conversations held
- **medianConversationLengthInDays:** Median length of the conversation considering the days passed since the first and last messages.
- **nrOfOneMessageConversations:** Total number of conversations consisting of just one message

'matches' refers to the number of total matches a user gets by date. The information is stored in a dictionary where the key is the date.

'messages' refers to the number of total messages a user sends or receives by date. The information is stored in a dictionary where the keys are 'sent' and 'received'. In a similar way, each key refers to a dictionary where the key is the date and the value of the number of messages.

'messagesReceived', 'messagesSent' and 'messages' contain the same information and thus, 'messagesReceived', 'messagesSent' can be deleted since it is redundant information.

'swipes' refers to the number of total swipes a user performs. The information is stored in a dictionary where the keys are 'likes' and 'passes', each one referring to the swipes for people the user likes and for people the user doesn't like respectively. Similarly, each key refers to a dictionary where the key is the date and the value of the number of swipes.

'swipeLikes', 'swipePasses' and 'swipes' contain the same information and thus, 'swipeLikes', 'swipePasses' can be deleted since it is redundant information.

'user' refers to the personal data of the user considered. The information is stored in a dictionary where the following data is found:

- **birthdate**
- **ageFilterMin:** Minimum age parameter for profiles displayed to the user.
- **ageFilterMax:** Maximum age parameter for profiles displayed to the user.
- **createDate:** Profile creation date
- **education:** Whether the profile has or has not high school or college education.
- **gender:** M and F as possible values
- **interestedIn:** Gender the profile is interested in. M, F or M and F.

- **genderFilter:** Gender parameter for profiles displayed to the user.
- **instagram:** Whether the profile links to an Instagram profile or not
- **spotify:** Whether the profile links to a Spotify profile or not 8
- **jobs:** Dictionary with job information containing: companyDisplayed (whether the company is displayed or not), titleDisplayed (whether the job title is displayed or not) and title.
- **educationLevel:** Whether the profile has or has not high school or college education.
- **schools:** Dictionary with school information containing: displayed (whether the school name is displayed or not), and name.

'_id' and **'userId'** store the same information. Thus, 'userId' can be deleted since it is redundant information.

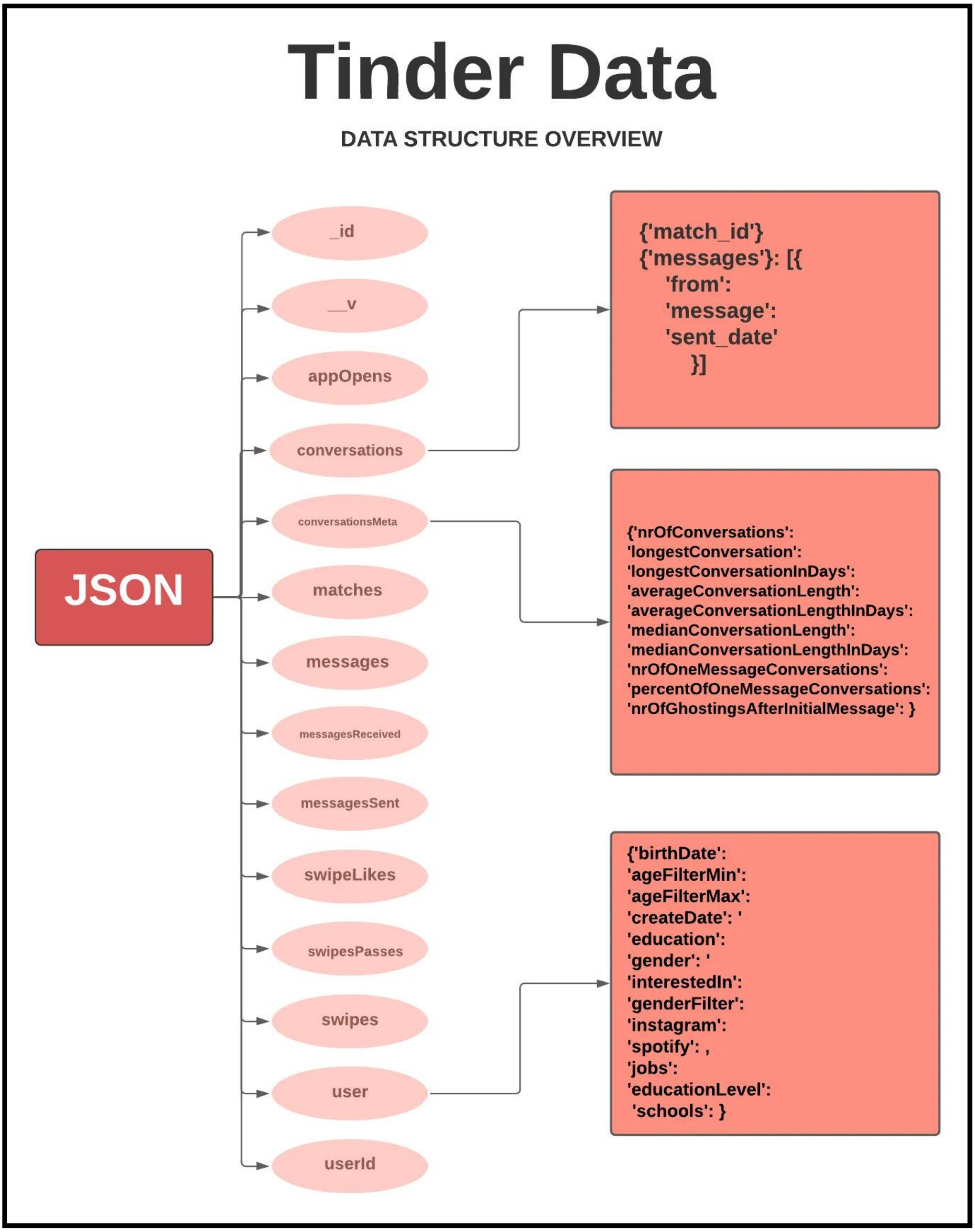

Fig 1 : *Flowchart of Tinder Data*

7. Exploratory Data Analysis

The exploratory data analysis phase is critical to get to know the data the project is working with. Hence, statistics and visualization of the most relevant features are created to get a general sense of the data. Some of the statistics and visualizations include mean, median, standard deviation, minimum, maximum and boxplots. Moreover, these techniques are also going to be used for outlier detection.

On the other hand, the question of missing values has as goal the identification of how missing values are indicated in the dataset and thus, how MongoDB is treating them. The vast majority of missing values are empty chains of text ('') and Mongo's null value is not used in the dataset.

The boxplots generated are shown below:

In *figure 2,* the boxplot depicts the distribution of minimum age parameters for profiles displayed on the Tinder app. The box spans from 18 to 19, indicating that the interquartile range captures the majority of the data. The median age is positioned at 19, showcasing the central tendency of the distribution. Whiskers extend from the box to encompass the entire range, reaching a maximum age of 46. The data's standard deviation of 3.34 suggests moderate variability around the mean age of 20.47, providing a concise visualization of the age filter parameters.

In *figure 3,* the boxplot visualizes the distribution of maximum age parameters for profiles displayed on the Tinder app. The box spans from 18 to 30, capturing the interquartile range where the majority of the data lies. The median age, positioned at 30, serves as the central tendency of the dataset. Whiskers extend from the box to encompass the entire range, reaching a maximum age of 100. The standard deviation of 9.13 indicates a considerable degree of variability around the mean age of 31.96, providing a succinct representation of the age filter parameters.

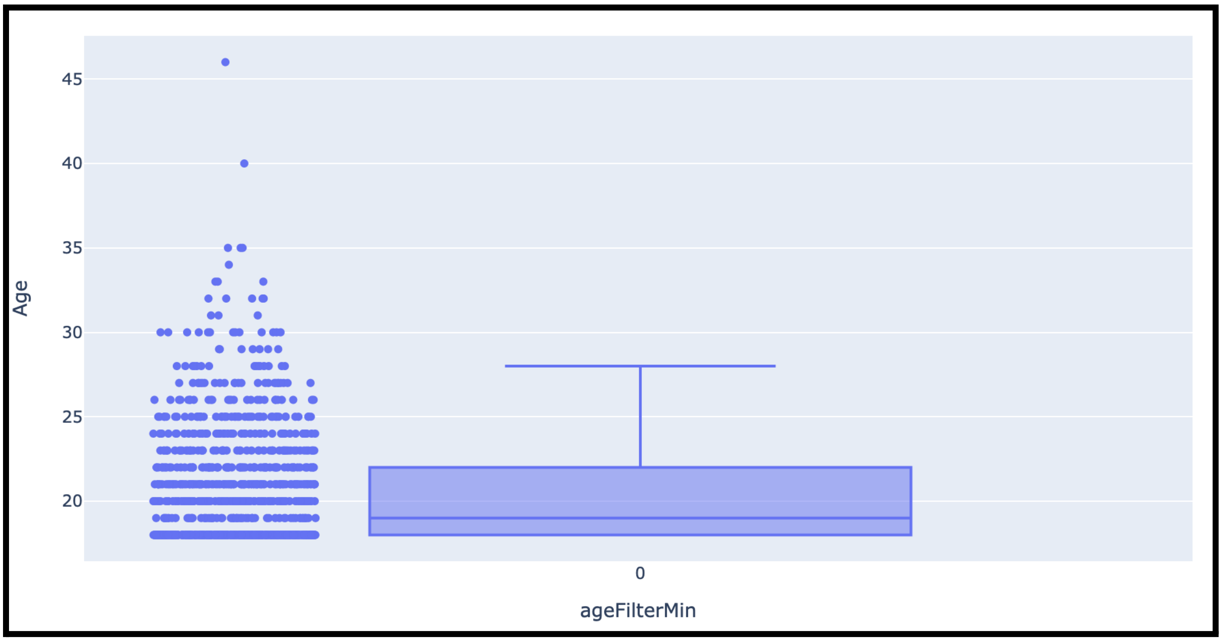

Fig 2 : *Age filter Min boxplot*

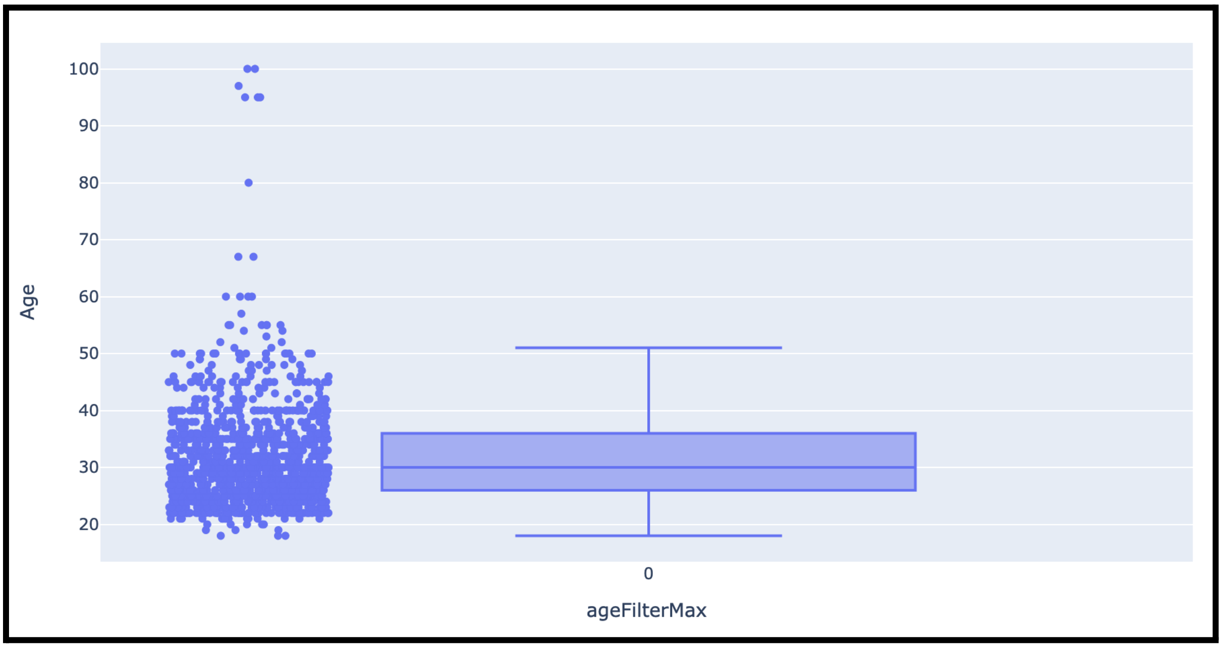

Fig 3 : *Age filter Max boxplot*

In *figure 4,* the boxplot represents the distribution of ages for users on Tinder. The box extends from 18 to 24, encapsulating the interquartile range where the majority of user ages lie. The median age, situated at 24, serves as the central point of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum age of 52. The standard deviation of 5.43 indicates a moderate degree of variability around the mean age of 24.81, offering a concise visualization of the age distribution among Tinder users.

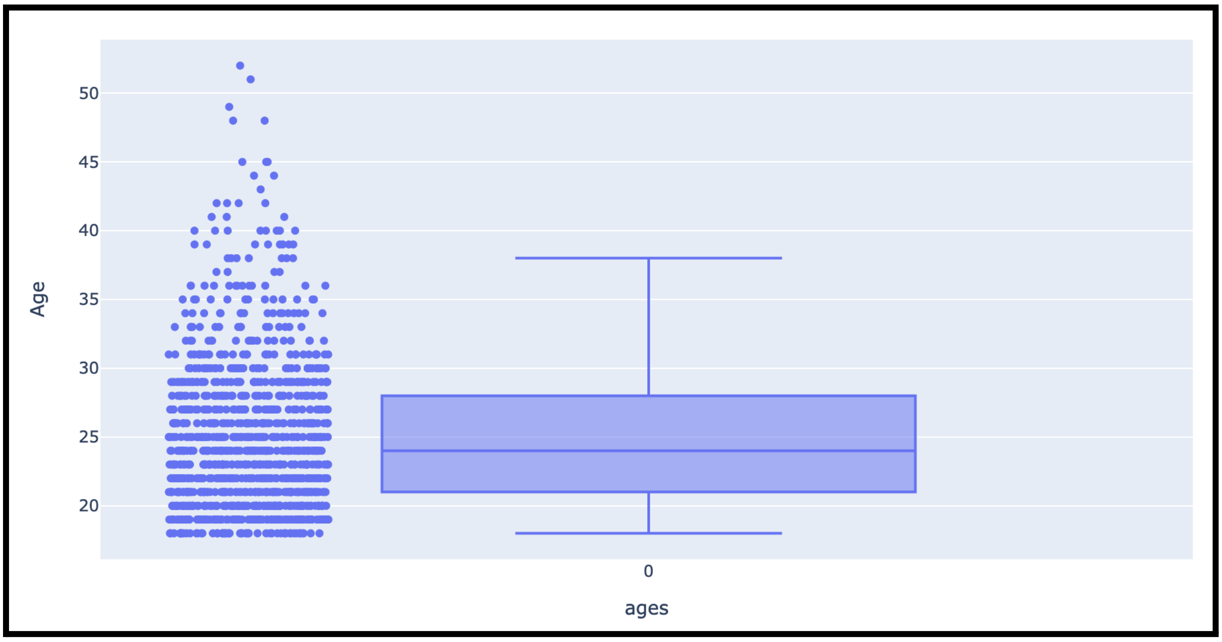

Fig 4 : *Age boxplot*

In *figure 5,* The boxplot illustrates the distribution of the number of passes (profiles rejected) by users on Tinder. The box extends from 0 to approximately 60.56, capturing the interquartile range where the majority of the data lies. The median number of passes is 60.56, indicating the central tendency of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum of 331.8. The standard deviation of 72.70 suggests a considerable degree of variability around the mean number of passes, which is 85.28. This boxplot provides a concise visualization of user behaviour in rejecting profiles on Tinder.

In *figure 6,* The boxplot visualizes the distribution of the number of likes (profiles liked) by users on Tinder. The box extends from 0 to approximately 29.5, capturing the interquartile range where the majority of the data lies. The median number of likes is 29.5, serving as the central point of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum of approximately 133.73. The standard deviation of 29.64 indicates a notable degree of variability around the mean number of likes, which is 36.74. This boxplot succinctly represents user engagement in liking profiles on Tinder.

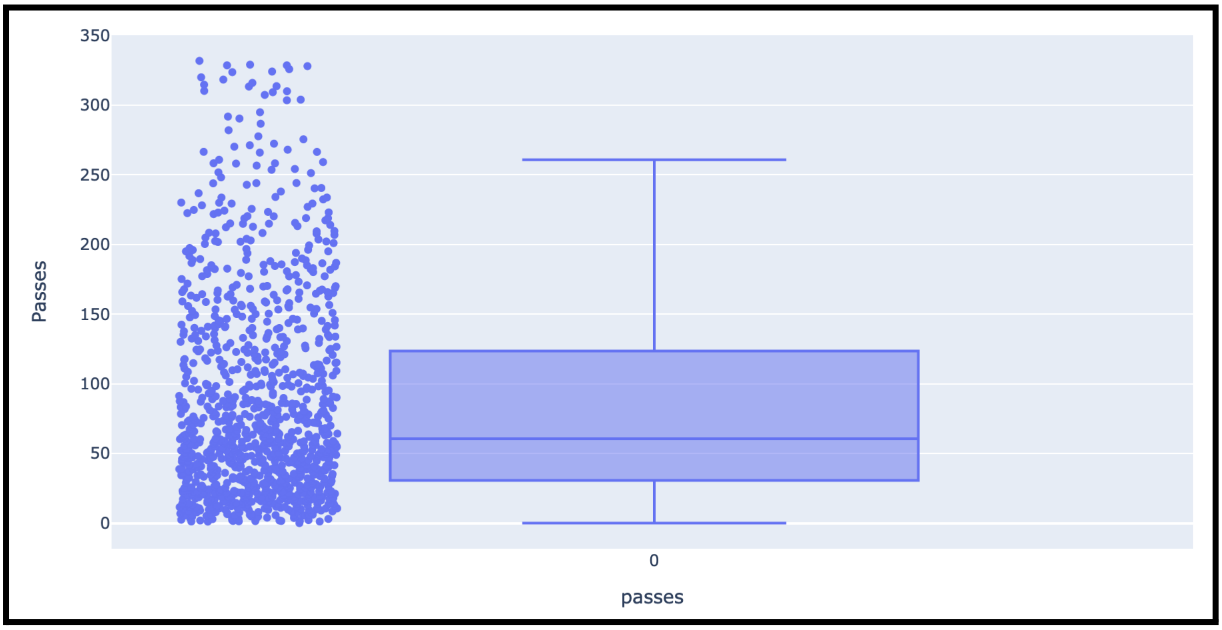

Fig 5 : *Swipe Passes Boxplot*

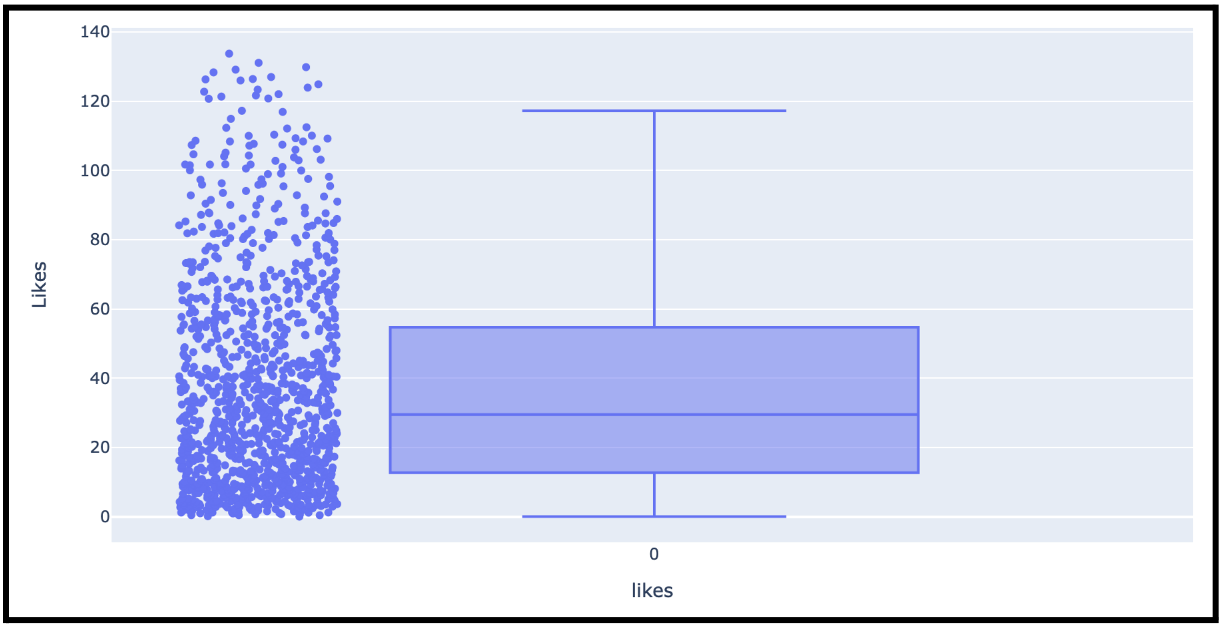

Fig 6 : *Likes boxplot*

In *figure 7,* The boxplot illustrates the distribution of daily matches made by users on Tinder. The box extends from 0 to approximately 0.77, capturing the interquartile range where the majority of the data lies. The median number of matches is 0.77, serving as the central point of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum of approximately 4.14. The standard deviation of 0.93 indicates a moderate degree of variability around the mean number of matches, which is 1.03. This boxplot provides a concise visualization of the frequency of matches per day for Tinder users.

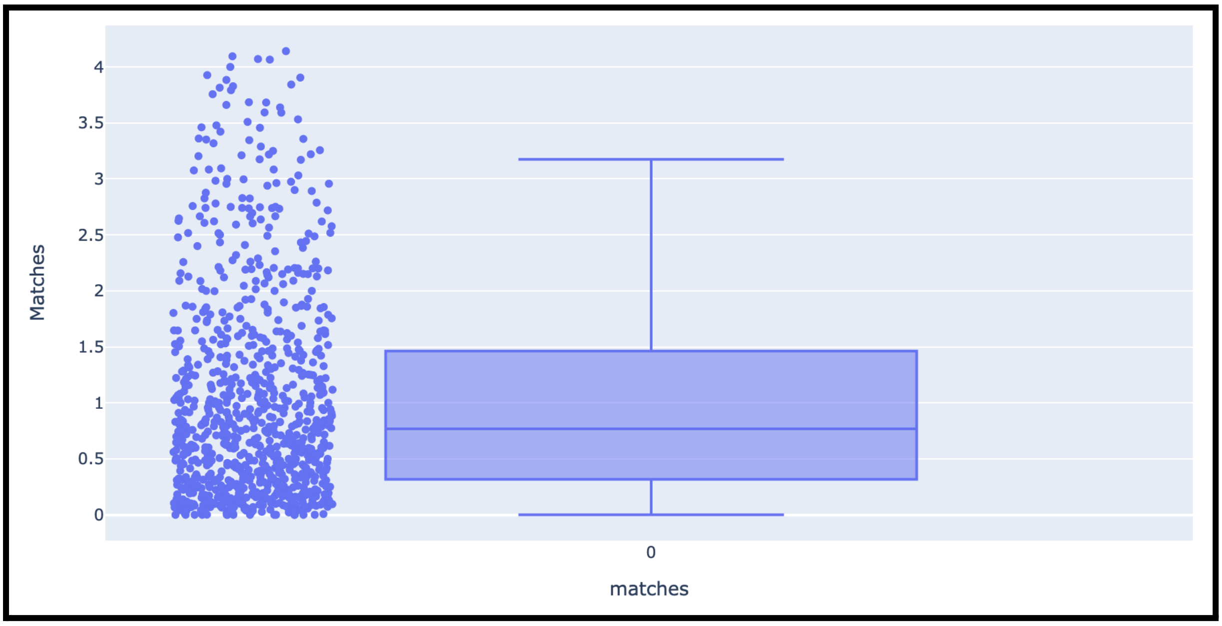

Fig 7 : *Matches boxplot*

In *figure 8,* The boxplot represents the distribution of the total number of conversations made by users on Tinder. The box extends from 0 to approximately 54, capturing the interquartile range where the majority of the data lies. The median number of conversations is 54, serving as the central point of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum of 535. The standard deviation of 122.30 indicates a considerable degree of variability around the mean number of conversations, which is 104.25

.

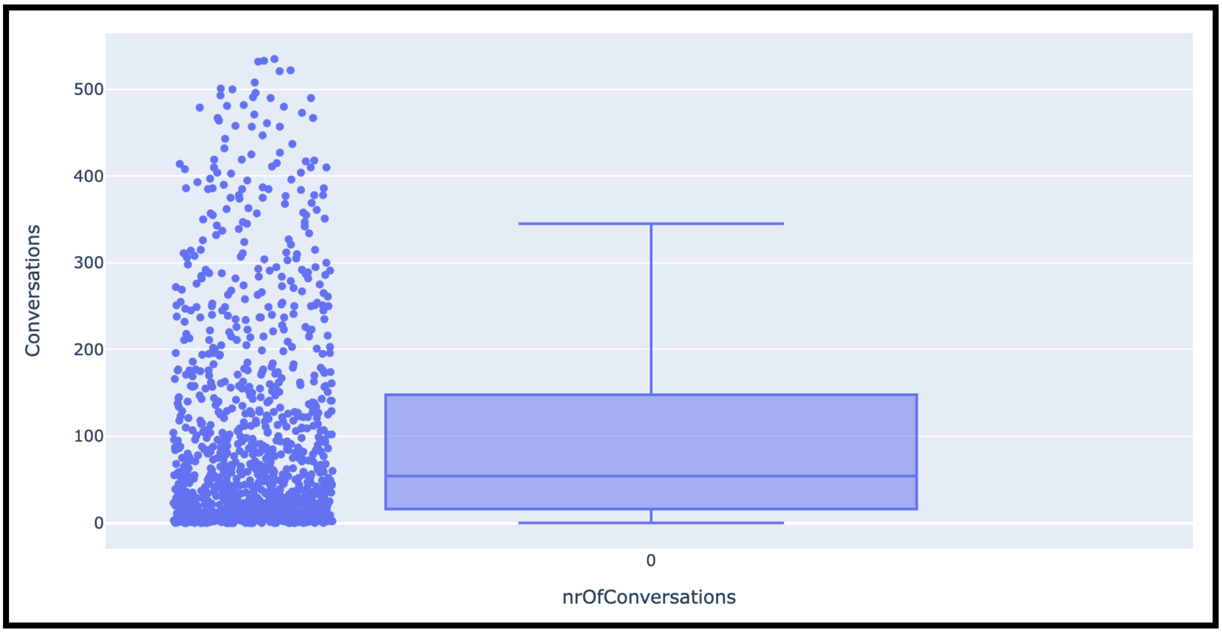

Fig 8 : *No of conversations boxplot*

In *figure 9,* The boxplot illustrates the distribution of the average number of conversations held by users per day on Tinder. The box extends from 0 to approximately 5.98, capturing the interquartile range where the majority of the data lies. The median average conversation length is 5.98, serving as the central point of the dataset. Whiskers extend from the box to cover the entire range, reaching a maximum of approximately 21.31. The standard deviation of 4.83 indicates a moderate degree of variability around the mean average conversation length, which is 7.04.

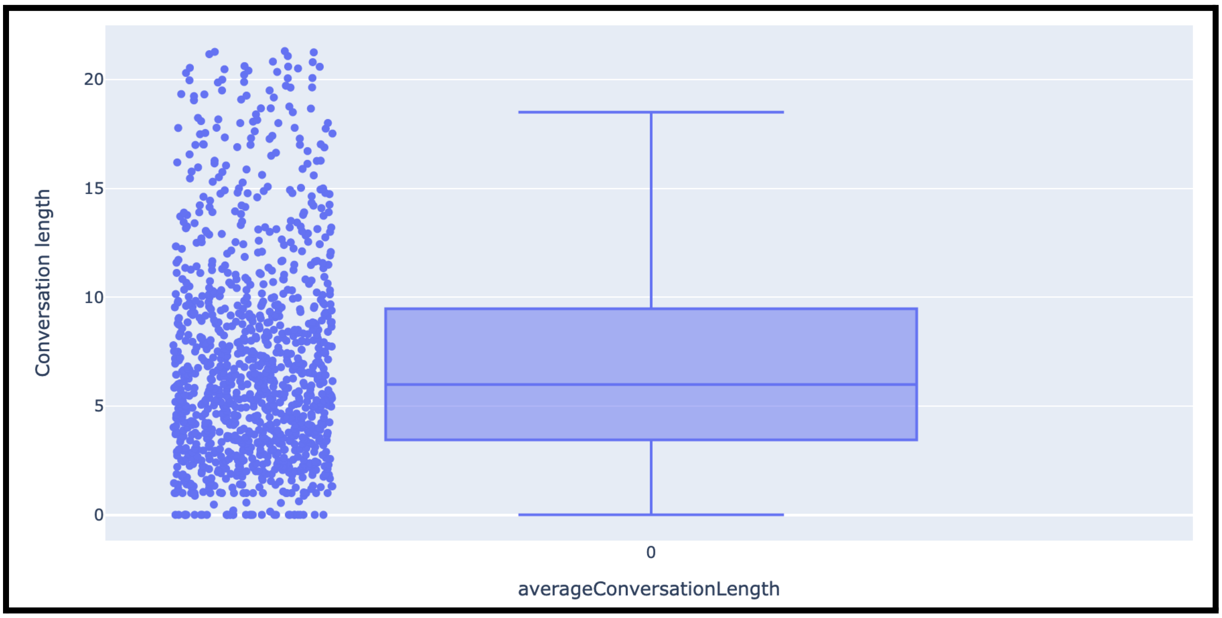

Fig 9 : *Average conversations length boxplot*

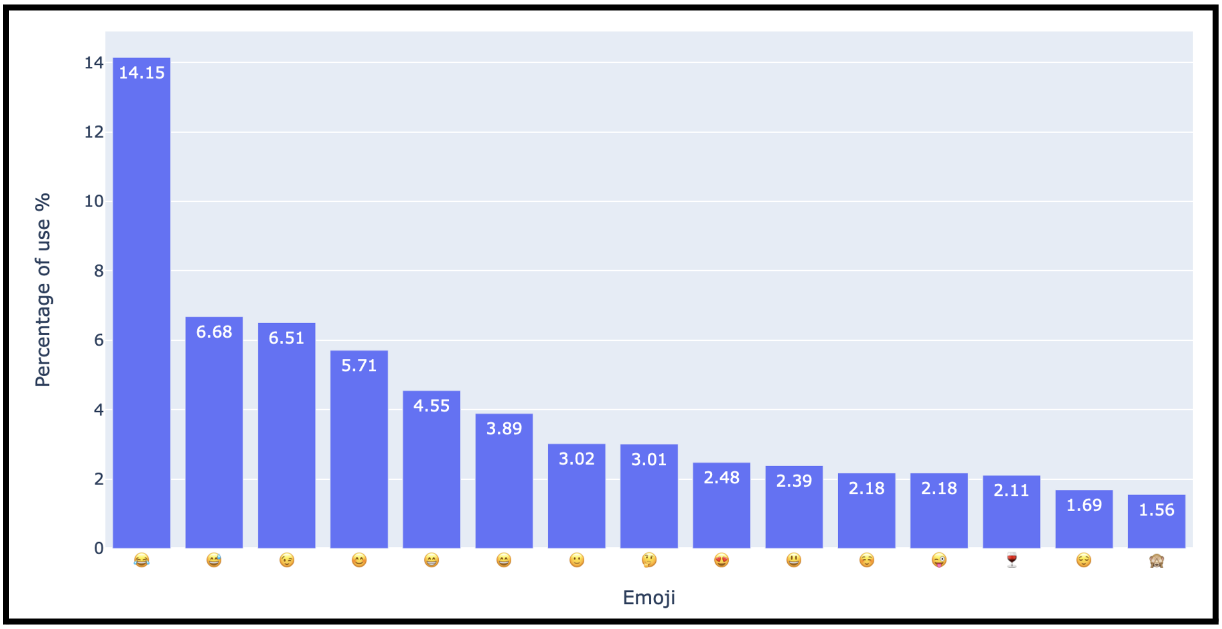

Fig 10 : *Top 15 most used emojis for men*

Figure 10 shows top 15 most used emojis for men during conversation on Tinder. While for women the top 15 most used emojis are shown in figure 11.

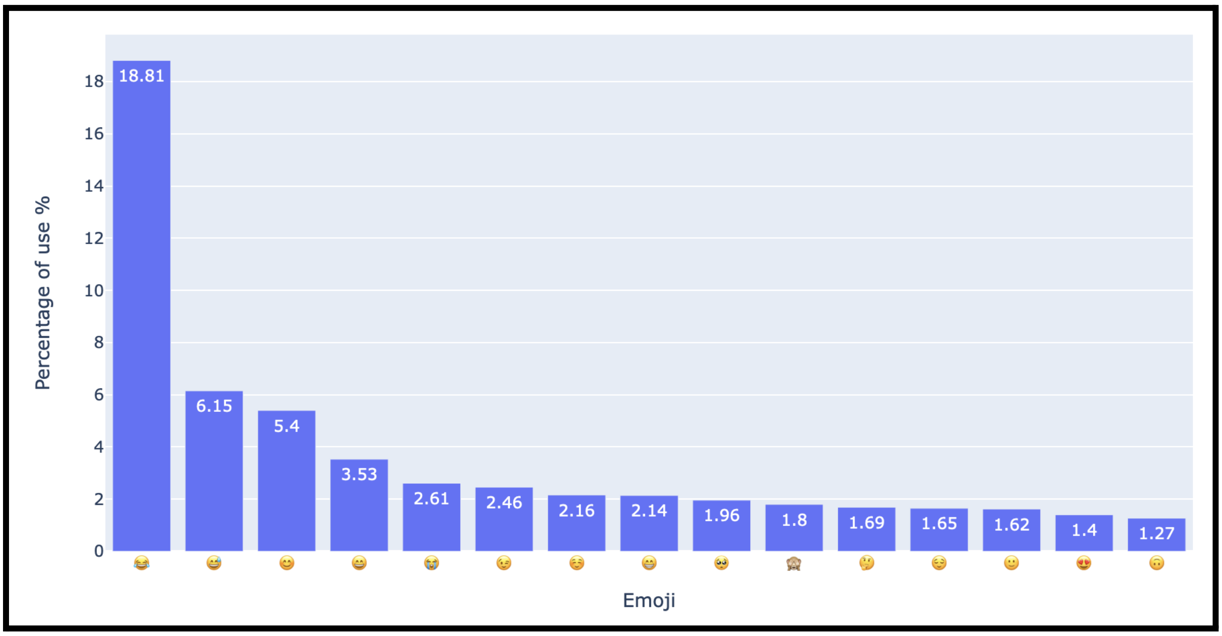

Fig 11 : *Top 15 most used emojis for women*

Table 1 : Data Analysis based on generated Boxplot

S.No	BoxPlot	Mean	Max	Min	std	Median
1	Age Filter Min Boxplot	20.47	46	18	3.34	19
2	Age Filter Max Boxplot	31.96	100	18	9.13	30
3	Age Boxplot	24.80	52	18	5.42	24
4	Swipe Passes Boxplot	85.28	331.8	0	72.70	60.55
5	Likes Boxplot	36.74	133.73	0	29.63	29.5
6	Matches Boxplot	1.03	4.14	0	0.92	0.76
7	No of Conversations Boxplot	104.25	535	0	122.30	54.0
8	Avg conversations length boxplot	7.04	21.30	0	4.83	5.98

8. Data Analysis

In this section, several questions relating to the main issue to be addressed in this project are answered. Thus, thanks to the data extracted, it will be possible to answer the question: How do men and women use dating apps, and are there differences between the two?

- **Who receives more attention? Matches by sex**

  On Tinder, a match occurs when two people have given each other a like. The aim of this question is to find out whether there is a significant difference between the number of matches men and women receive on the app.

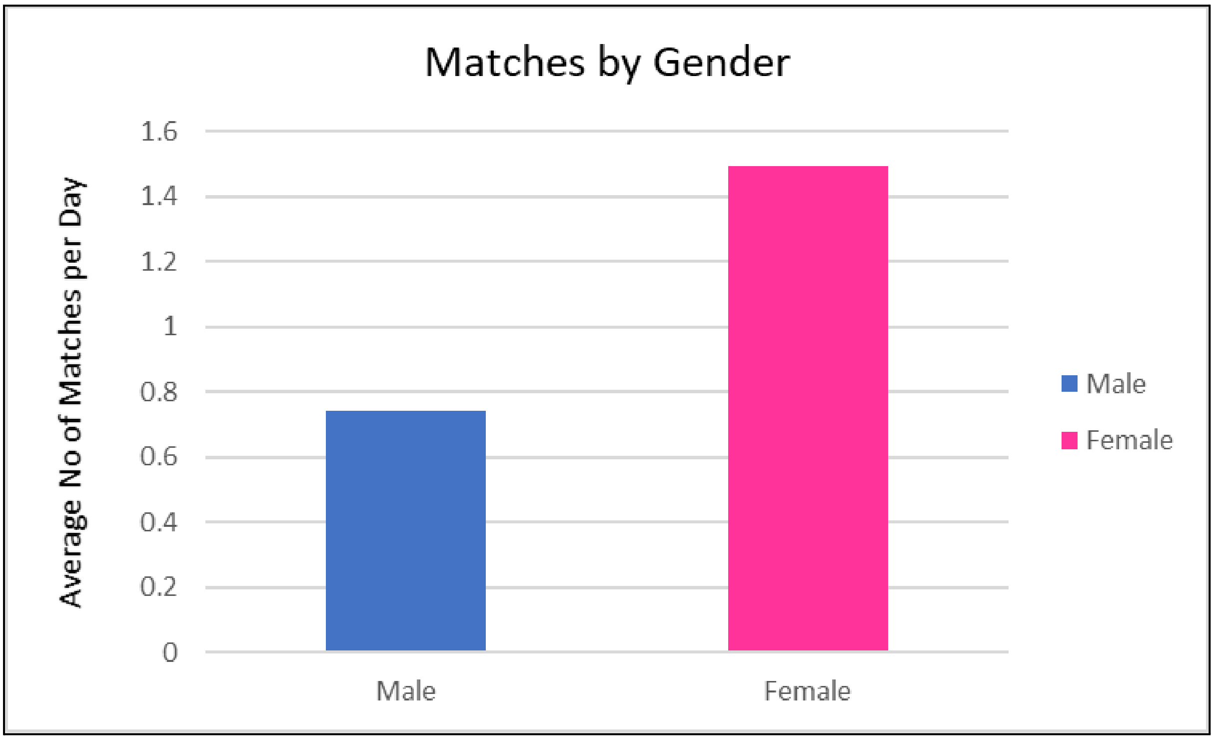

Fig 12: Matches by gender

- **Who is more selective? Passes vs Likes by sex**

  On Tinder, users can swipe left on a profile to ignore it (pass) or swipe right to like it (like). The aim of this question was to find out whether there is a significant behavioural difference between men and women on the app in terms of the average number of swipes and likes per day.

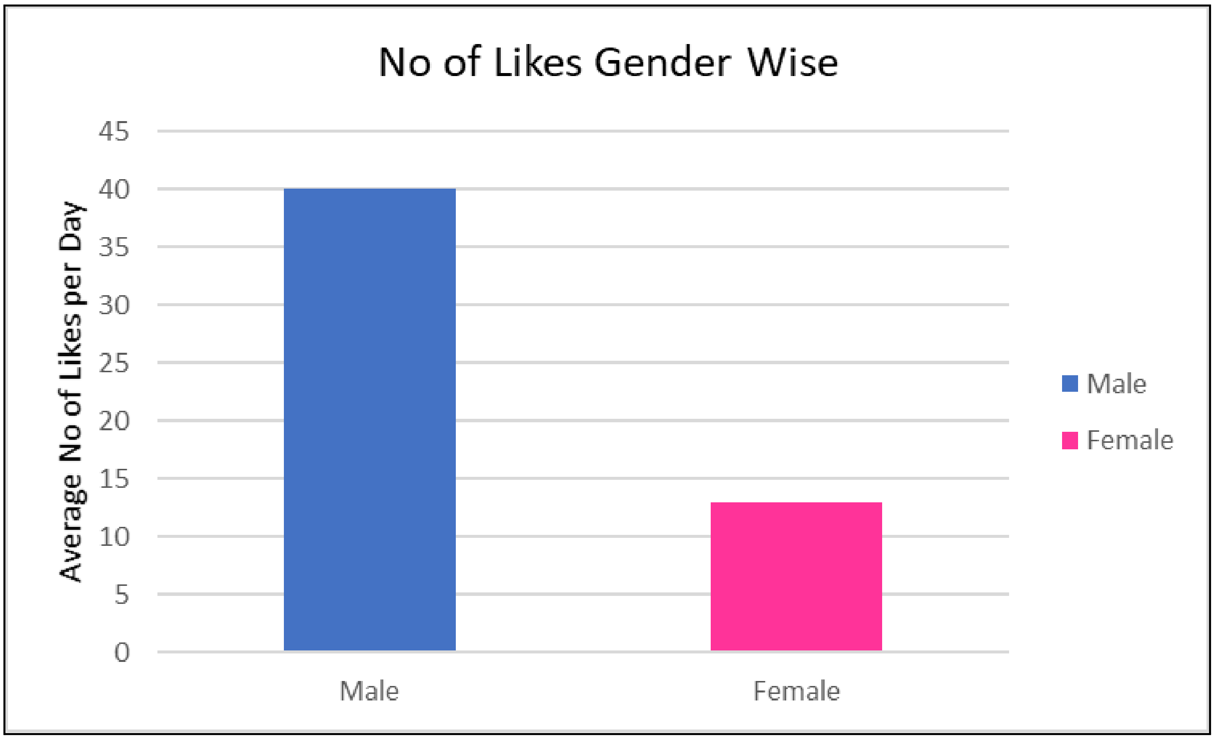

Fig 13: No of likes gender wise

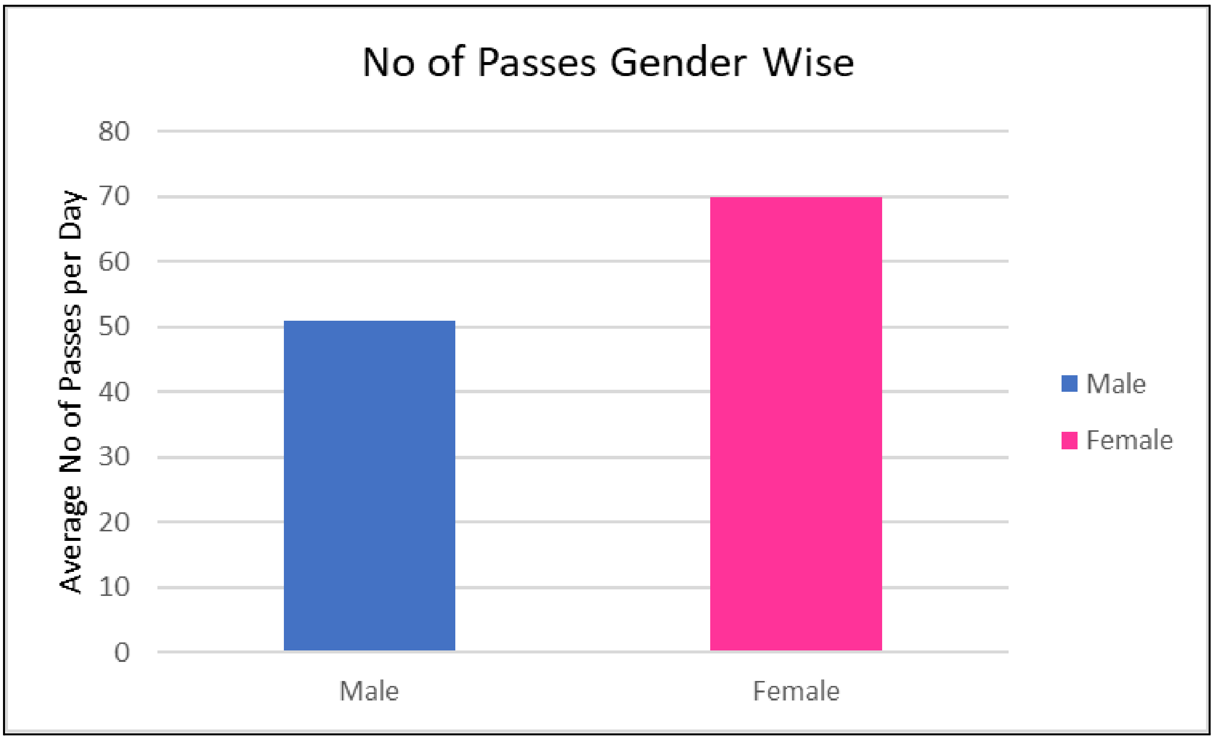

Fig 14: No of Passes gender wise

- **Who uses the app the most? App opens by sex**

The purpose of this question is to find out which sex logs on more times a day to the application than the other.

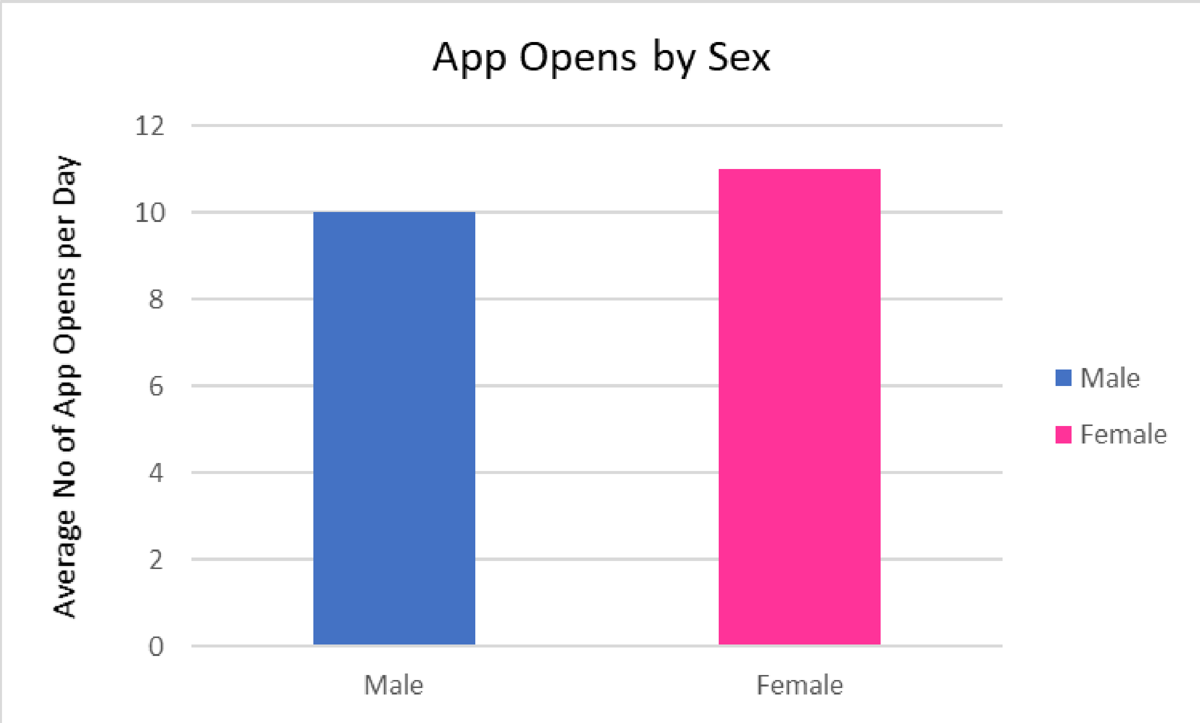

Fig 15: App Opens by gender

- **Who is most willing to pay for a subscription? Number of times the likes limit is reached per sex**

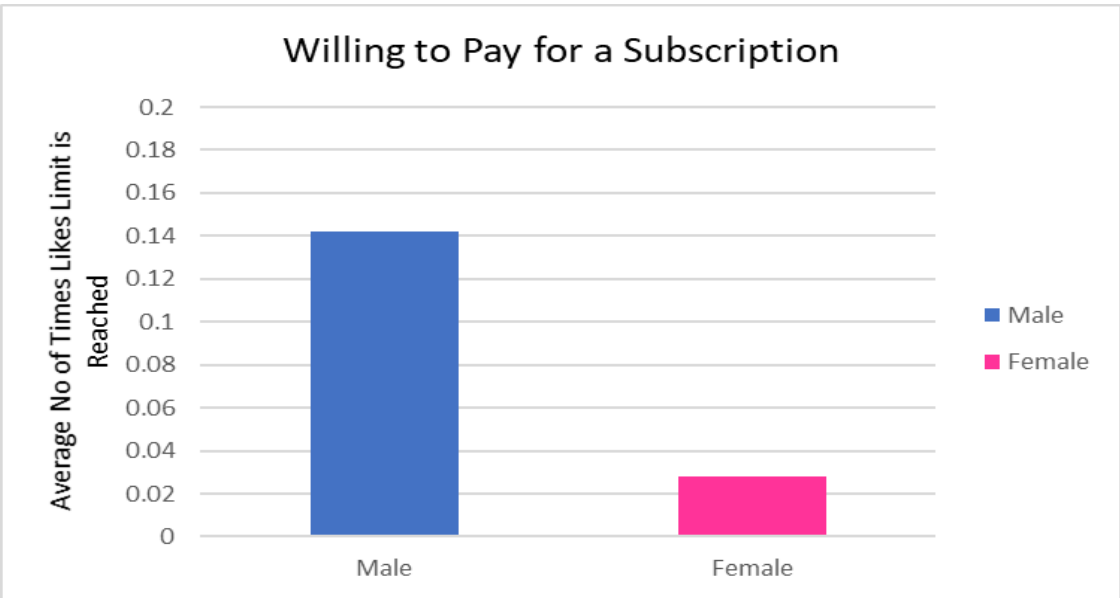

Fig 16: Users willing to pay for a subscription

On Tinder, non-premium users can only give a maximum of 100 likes per day. This question aims to find out whether there are differences between the number of times men and women reach this limit.

- **Who talks the most?Messaging behaviour by sex**

Once two people are matched on Tinder they can start talking. Therefore, it is interesting to know if there is any difference in the length of the conversations held by one and the other.

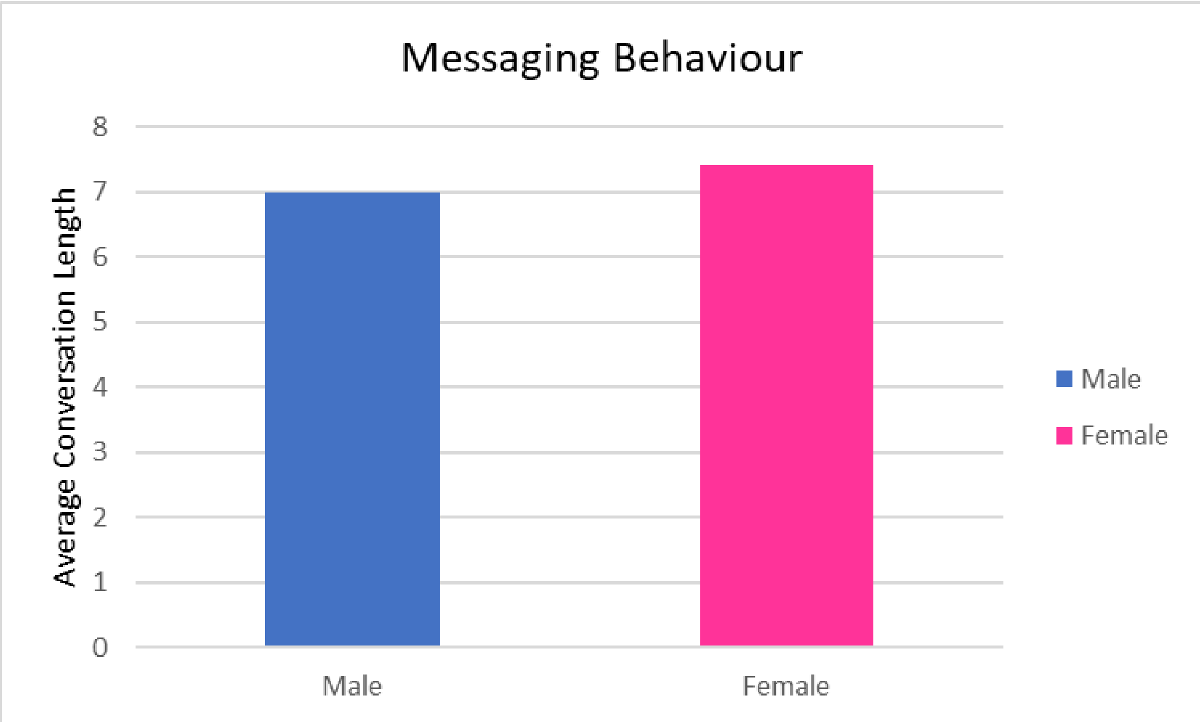

Fig 17: Messaging Behaviour

- **What is the minimum, mean and maximum percentage of one message-conversations for every sex? What about the number of ghostings after the initial message?**

Initially, the percentage of conversations consisting of a single message is analysed in order to find out the degree of satisfaction with the matches achieved. On the other hand, ghosting is analysed. Ghosting occurs when, after a match is made, the other person sends a message to the user and the user decides not to reply to the message. Thus, this metric is related to how selective the user is, since, even after having made a match, the first interaction has not been appropriate and the user decides not to reply to the message.

Table 2 : Percentage of One Message Conversations

Sex	Avg	Min	Max
M	30.73%	0%	74.12%
F	30.73%	0%	62.86%

- **Who uses more Instagram by Sex?**

On Tinder, users can link their profiles to Instagram so that other users can view their photos or even communicate with them outside of the app.

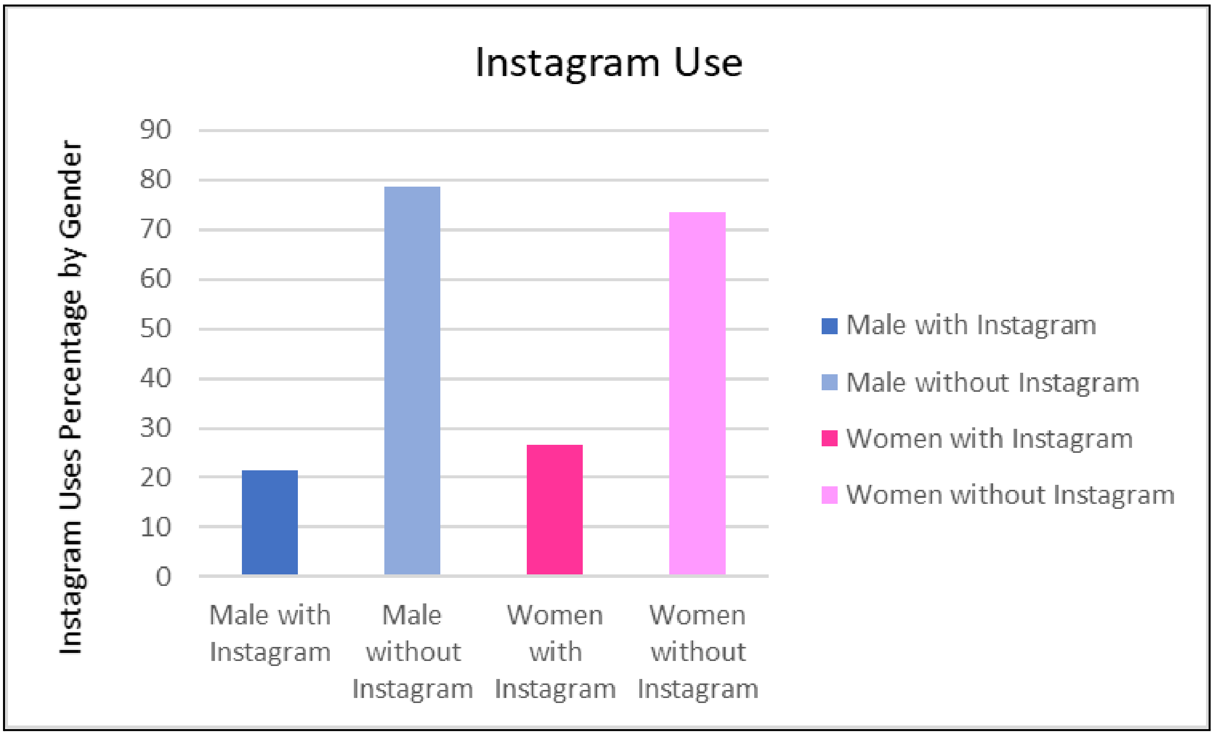

Fig 18: Users using Instagram

Table 3 : Top 30 Countries with number of tinder profiles

Country	Count
CA	27
England	20
Germany	19
United Kingdom	18
France	17
California	17
Finland	15
Deutschland	14
Sweden	12
New York	12

Country	Count
Suomi	12
NY	12
ON	10
Washington	10
Netherlands	9
Denmark	9
Italia	8
Texas	8
Ireland	8
Canada	7

Country	Count
Brasil	7
Belgium	7
Australia	6
WA	6
Polska	6
Scotland	6
Belgium	6
Switzerland	6
Austria	6
Norway	6

Table 4 : Top 30 jobs of Tinder users

Job	Count
Software Engineer	33
Engineer	8
Software Developer	7
Student	7
PhD Student	5
Consultant	4
Barista	4
Research Assistant	3
Accountant	3
Mechanical Engineer	3

Job	Count
Writer	3
Software engineer	3
Civil Engineer	3
Web Developer	3
Business Owner	2
Trader	2
Unknown job	2
Programista	2
Sales	2
Developer	2

Job	Count
Owner	2
Data Scientist	2
Android Developer	2
Machine Learning Engineer	2
Manager	2
Entrepreneur	2
software developer	2
Grad Student	2
Analyst	2
Project Manager	2

Table 5 : Top 15 schools or college of Tinder users

School	**Count**
University of Illinois at Urbana-Champaign	5
The University of York	5
New York University	5
University of Toronto	4
Tampereen yliopisto	3
Rensselaer Polytechnic Institute	3
Kungliga Tekniska Hogskolan	3
California State University, Fullerton	3
Rutgers University-New Brunswick	3
University of New South Wales	3
Mississippi State University	3
York University	3
UniversitÃ commerciale Luigi Bocconi	3
Tampereen teknillinen yliopisto	3
Villanova University	3

Table 6 : Top 10 Most used hashtags in messages

Hashtag	Count
bfmaterial	17
metoo	9
np	7
SoundCloud	7
winning	7
nohomo	7
imgrc	6
adulting	6
firstworldproblems	5
goals	3

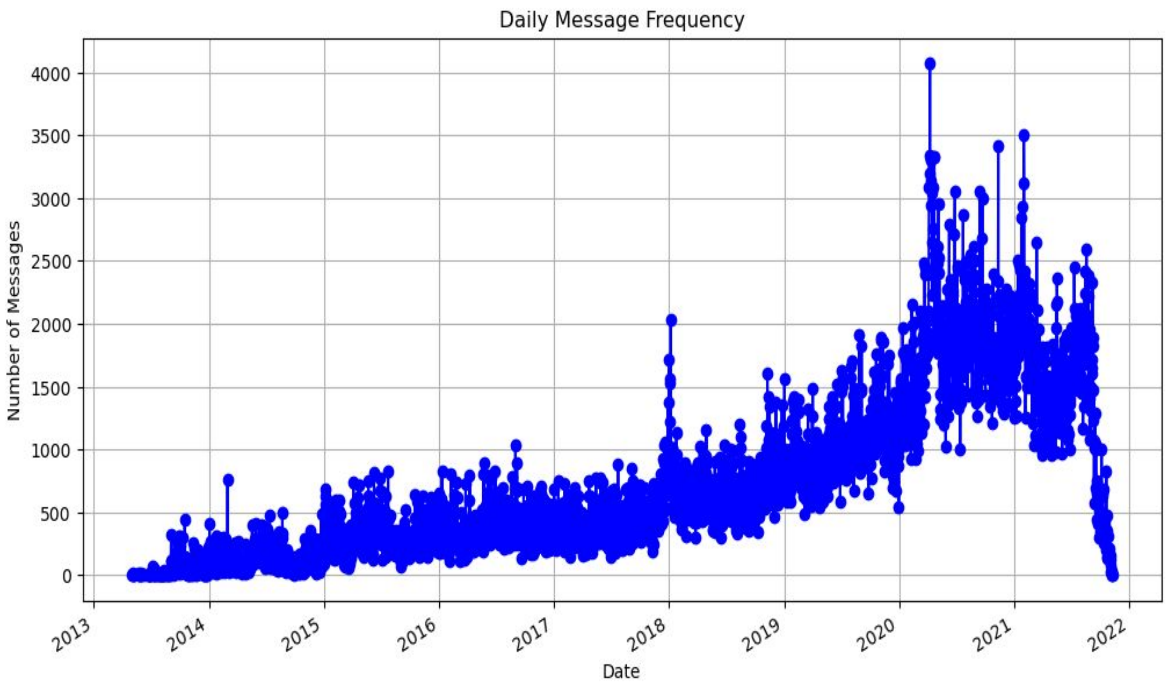

Fig 19 : Daily message frequency of Tinder users from 2013-2022

- Average word count of messages: 11093

- Average length of messages: 53617

Fig 20 : Word Cloud for Tinder Conversations

9. Results & Discussions

Throughout this study, the differences between the two predominant groups on Tinder, men, and women, have been analysed. To do so, data provided by swipestats.io from real users has been used, and an important descriptive and cleaning task has been carried out on the data, as it did not have any type of explanation and it contained redundancies in certain fields. In this way, the data exploration process has been carried out on each of the fields that made up the dataset.

Among the insights discovered, the following stand out:

- Men give many more likes than women (x3.1 times).
- Women ignore many more profiles than men (x1.4 times).
- Women get many more matches than men (x2 times).
- There is no significant difference between the number of times men and women log on to the application per day. - Men reach the daily likes limit many more times than women (x5.1 times).
- There is no significant difference in the length of conversations between men and women.
- Men tend to have a higher number of worse conversations as their percentage of single-message conversations is much higher than that of women (x1.4 times).
- Women do much more ghosting than men (x2.7 times).
- Women tend to link their Instagram profiles slightly more than men (26.67% women vs 21.45% men).

There are no major differences between the emojis used by men and women, with the two preferred emojis being the same for both sexes. The emojis used by men but not by women (in the Top 15 most common) are 😃,😜 , 🍷 . The emojis used by women but not by men (in the Top 15 most common) are 😭, 🥺, 🙃.

Therefore, it can be deduced that there are significant differences between men's and women's use of Tinder. ***The data obtained support the hypothesis that women have a more selective pattern of dating behaviour than men.*** This information is drawn from the fact that there are no significant differences in terms of the number of times the application is used per day, but there are significant differences in the ratio of profiles that are valid for a possible date (like + match + long enough conversation) between men and women.

Thus, ***the assessment of the project is highly positive***, given that the proposed objectives have been met satisfactorily. A clear question has been defined, the necessary data have been obtained, appropriate management, exploration and cleaning have been proposed and a complete analysis has been carried out, which has provided valuable answers to the questions defined. Thus, **the extracted information is highly relevant for making business decisions concerning the freemium model used in the app.**

10. Future Works

One more analysis can also be done that would be the prediction of the matches of profiles. How the profiles should look like and what should be the description and other factors of the profile should look like for having good chances of matching. The profiles can be categorized into three categories- less chances of right swipe, average chances of right swipe and good chances of right swipe.

11. Conclusions

We studied how people behave on Tinder and looked closely at the differences between men and women on the app. We used a big set of data from real users and analyzed it in a smart way. Our research found important information that helps us understand how gender plays a role in online dating.

We discovered some important differences between how men and women use Tinder. Men are more likely to give likes more freely, while women tend to be more choosy and often ignore profiles. Surprisingly, even with these distinctions, women end up with more matches, showing that being selective plays a big part in their success on the app.

Both genders use it regularly, showing a shared interest in online dating. However, we found significant differences in how they navigate the platform, especially in terms of daily likes and one-message conversations.

We also looked into ghosting, and our research showed that women tend to do this more often. Connecting Instagram profiles, a small detail, highlights how people present themselves on the app, with women being a bit more likely to link their social media.

Looking at emoji use added more layers to our understanding. We found similarities and differences between men and women in how they express themselves digitally. These details provide insights into the subtle aspects of online conversations, supporting the idea that women generally take a more selective approach to dating on Tinder, seen in how they assess profiles for potential dates.

Basically, our project met its goals. We looked closely at how people act on Tinder, backed by strong data analysis. The information we found is important for decision-making, especially regarding how the app makes money. By sparking more informed discussions about online dating, our research helps us understand modern relationships in the digital age better. Our findings are useful for both users and developers, adding to the ongoing conversation about how online relationships are changing.

12. References

M. (2019, July 21). *A match made in heaven: Tinder and Statistics — Insights from an unique Dataset of swiping*. Data-Dive. Retrieved November 9, 2023, from https://data-dive.com/tinder-statistics-insights-from-unique-dataset/

(n.d.). *Visualize your Tinder data*. Swipestats. https://www.swipestats.io/

LOPES, M. R., & VOGEL, C. GENDER DIFFERENCES IN ONLINE DATING EXPERIENCES. *IT HAPPENED ON TINDER 31*, 31-47. http://www.tara.tcd.ie/bitstream/handle/2262/91343/Lopes-Vogel-IHoT-2019.pdf

(n.d.). *Tinder Insights: Analyze your Tinder Stats (2023 Edition)*. Roast. Retrieved November 9, 2023, from https://roast.dating/blog/tinder-insights-review

Tiffany, K. (2019, March 18). *The Tinder algorithm, explained.* Vox. Retrieved November 8, 2023, from https://www.vox.com/2019/2/7/18210998/tinder-algorithm-swiping-tips-dating-app-science