



Analysis of Smartphone Usage Habits

By: Zihao Yang, Luke Wittemann, Trevor Kam, Mayank Kumar, and Lingxiao Li

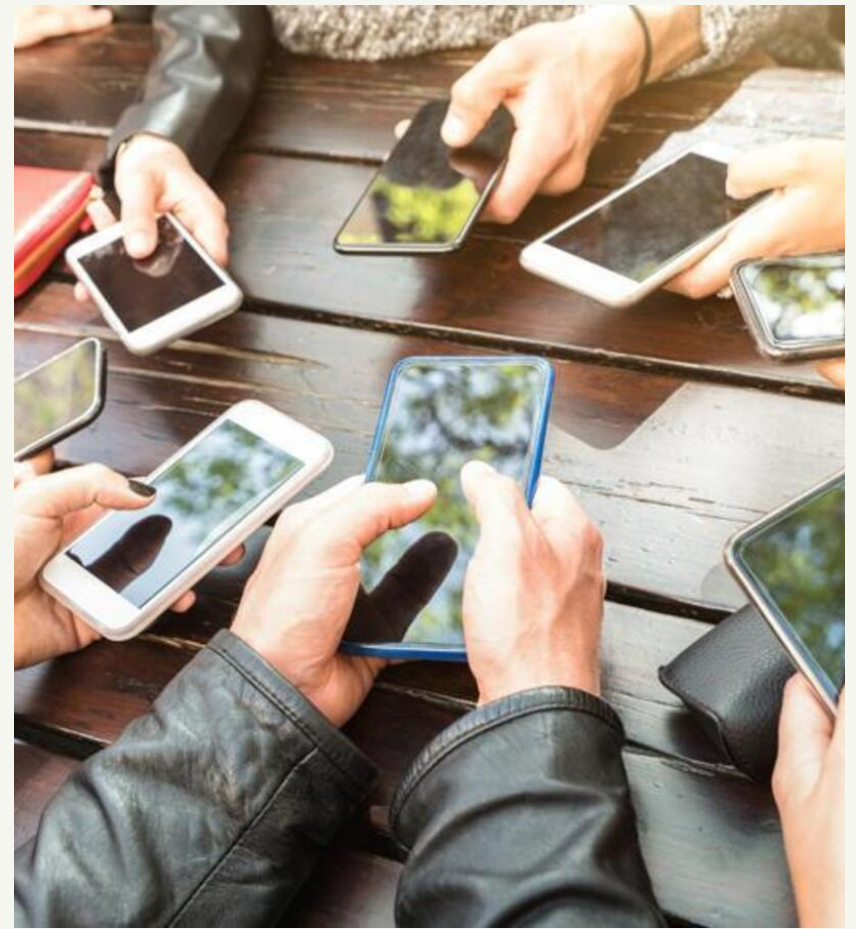
Applications /Background

During the last 20 years, the presence of smartphones have increasingly intruded into our daily lives. How does this affect us and what does our investment of time say about us? By analysing the purported usage of smartphones, we hope to answer these and other questions. These trends could be used in the aid of technological cessation, marketing of new applications, or simply understanding the relationship between human psychology and the usage of these devices.



Dataset and Challenges

For this project, we used a multi-national public survey which contains a plethora of information surrounding usage and demographics of over 10,000 users. Some challenges that had to be overcome to utilize this dataset were the appearance of different languages, different currencies, and coherency of answers to open-ended questions.



Trends of Usage Vs:

Nationality

Employment

Age

Income

Personality

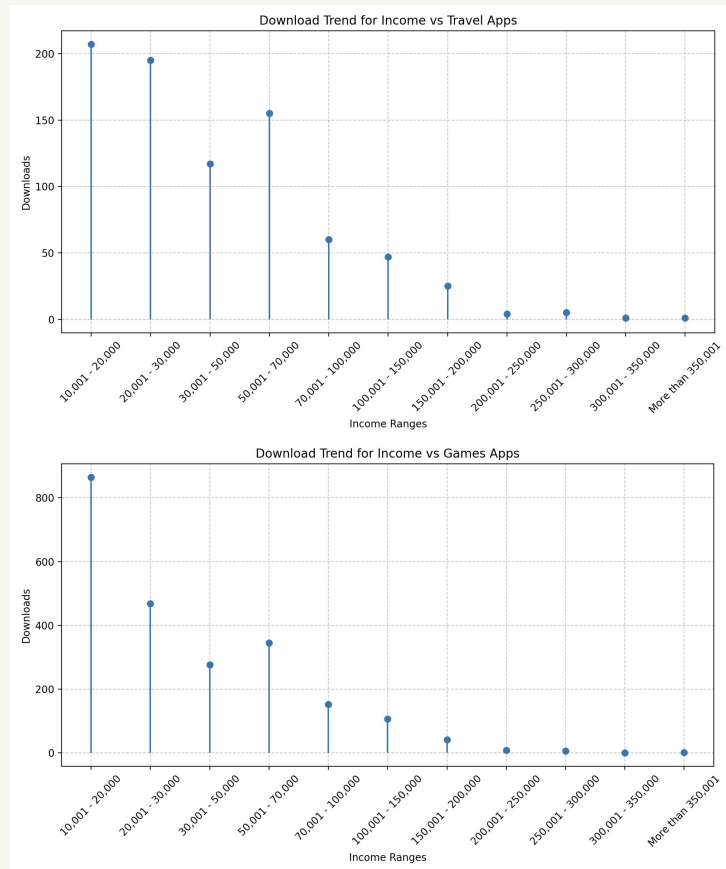
Observed trends of Demographics VS the categories of the apps

Travel & Game app downloads vs. income (USD)

Observations:

Highest downloads in the \$10,001–\$20,000 range

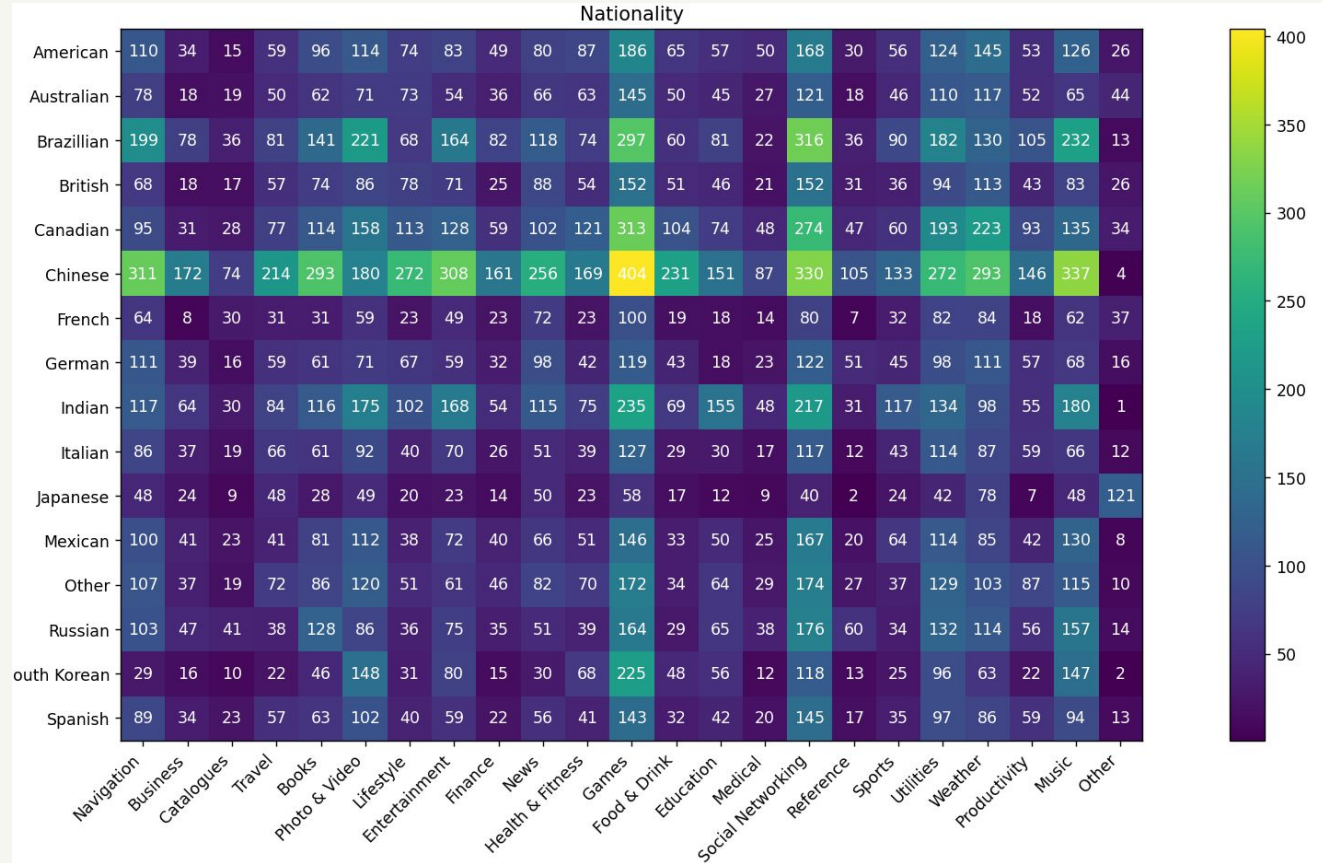
Downloads decline as income increases



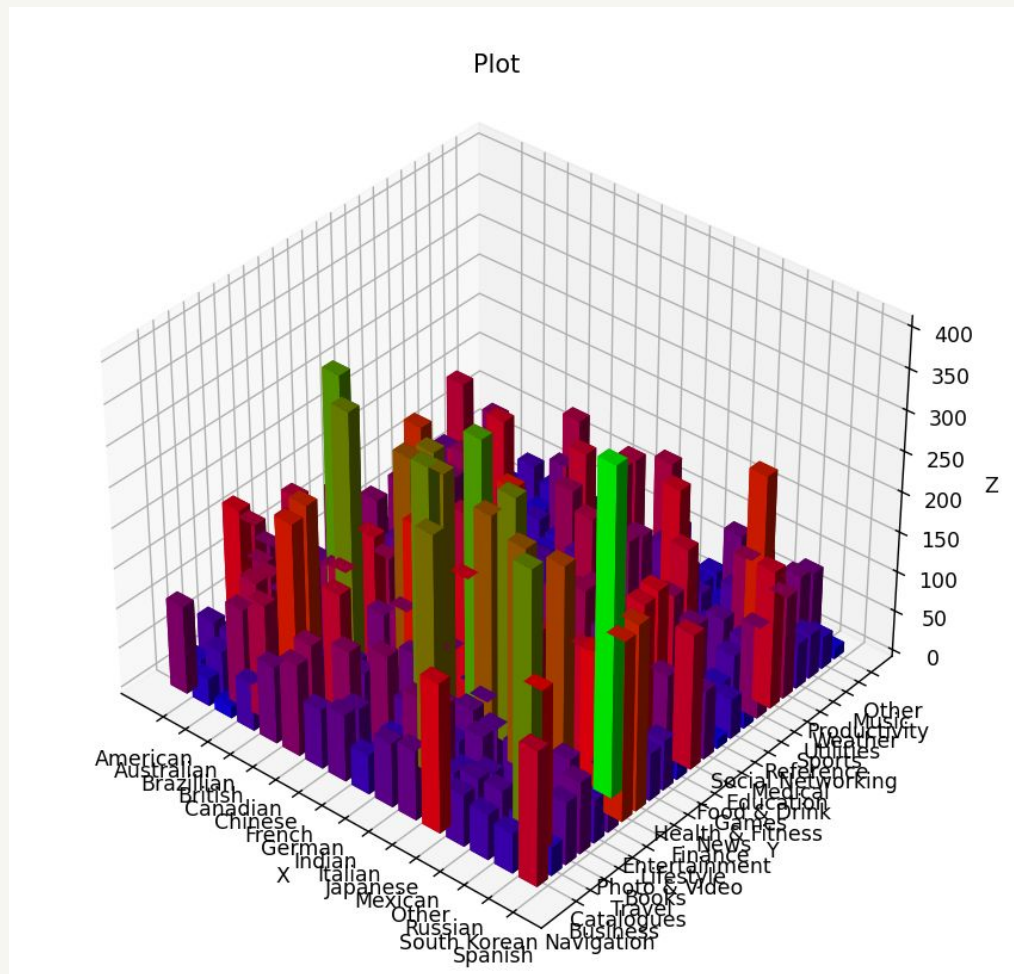
Observed trends of Nationalities VS the categories of the apps

Observations:

- Some apps are universally popular like Games and Social Networking.
- Chinese users have the highest values across all categories.
- South Koreans have a disproportionately high presence in games.
- Indians seem to favour education and productivity apps, suggesting a focus on learning and efficiency.

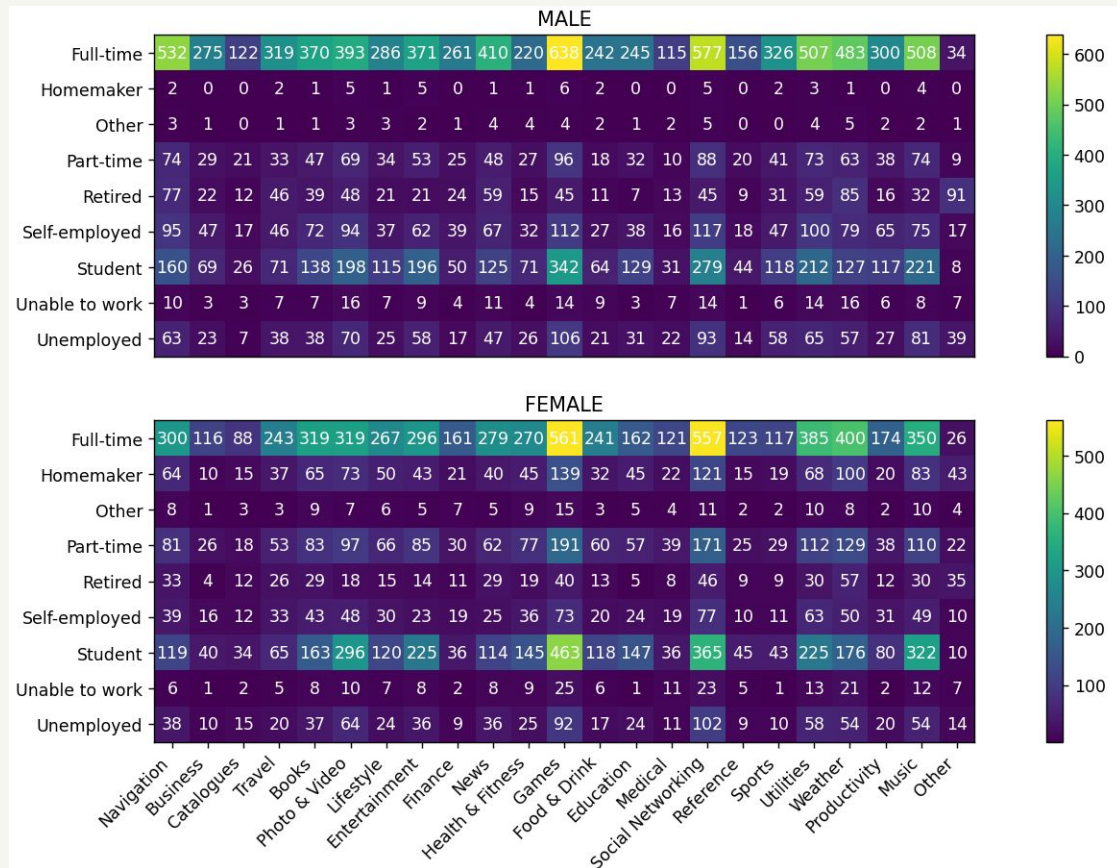


As an aside, fun visualization of the previous graph in 3D



Observed trends of Employment status VS the categories of the apps

- We see that both male and female show in full-time roles show high-usage of apps.
- The next highest usage is seen by students.
- Retired people show high engagement with weather.
- “Other” category : Apps that don’t fit in the other categories, like lottery or flipboard.
- Males show high install rates for apps used for navigation, sports and productivity.
- Females have high usage in categories like F&B, Lifestyle and Social Networking.



Personality Vs App Downloading

Data set: Q15 Which type of apps do you download? (please select all that apply)

1. Navigation
2. Business
3. Catalogues
4.
22. Music
23. Other

Output:

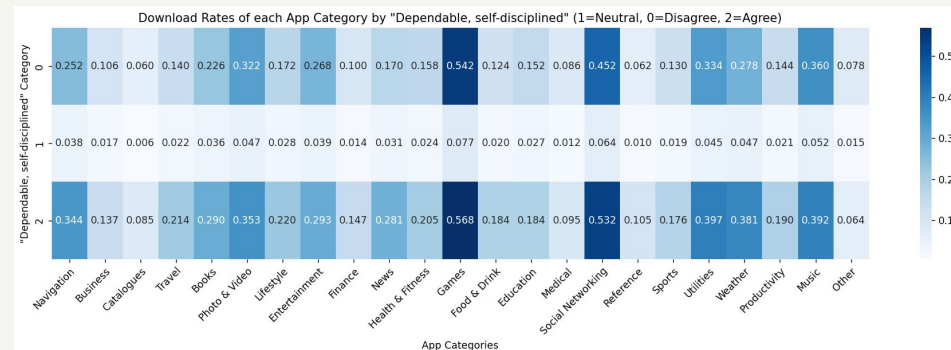
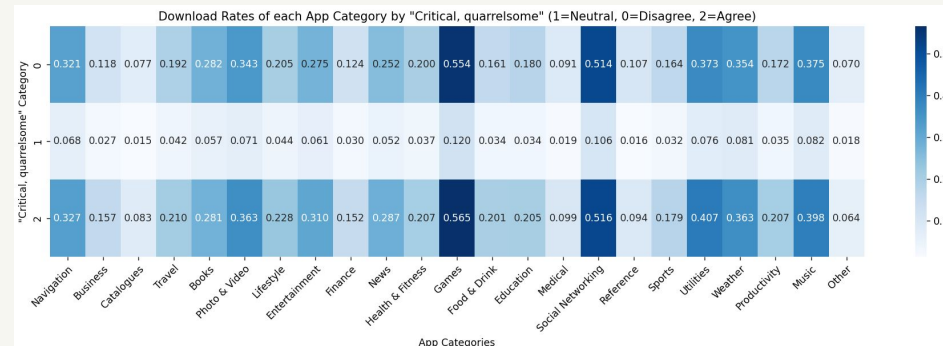
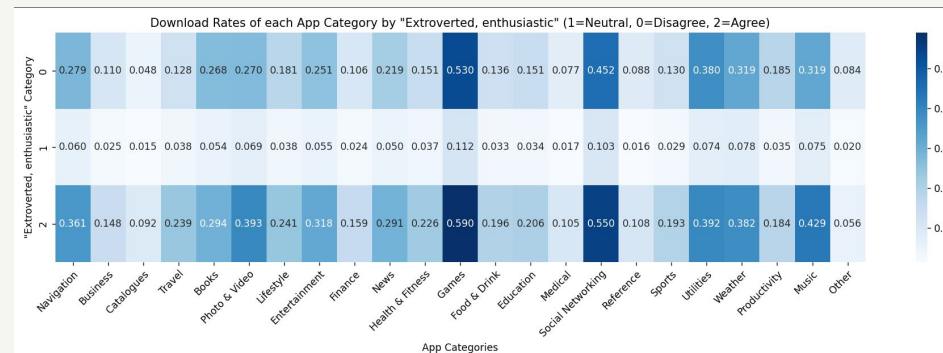
1—(downloaded corresponding category of app)

Blank— either not downloaded or ignore it

Q30 personality may influence the types of apps you like. 1 = Disagree strongly 2 = Disagree moderately 3 = Disagree a little 4 = Neither agree nor disagree 5 = Agree a little 6 = Agree moderately 7 = Agree strongly see myself as:

- _____ Extraverted, enthusiastic (1)
- _____ Dependable, self-disciplined (3)
- _____ Sympathetic, warm (7)
- _____ Disorganized, careless (8)
- _____ Calm, emotionally stable (9)
- _____ Conventional, uncreative (10)

Observation



interpretation: The heatmap suggests that **“Games”** category shows **higher download rates among extroverted (Agree) respondents and introverted (disagree) respondents**. And not only for one personality traits among all other personality traits characteristic. Games downloading rate is always number 1 downloading and **social networking** is number 2 most popular app downloading.

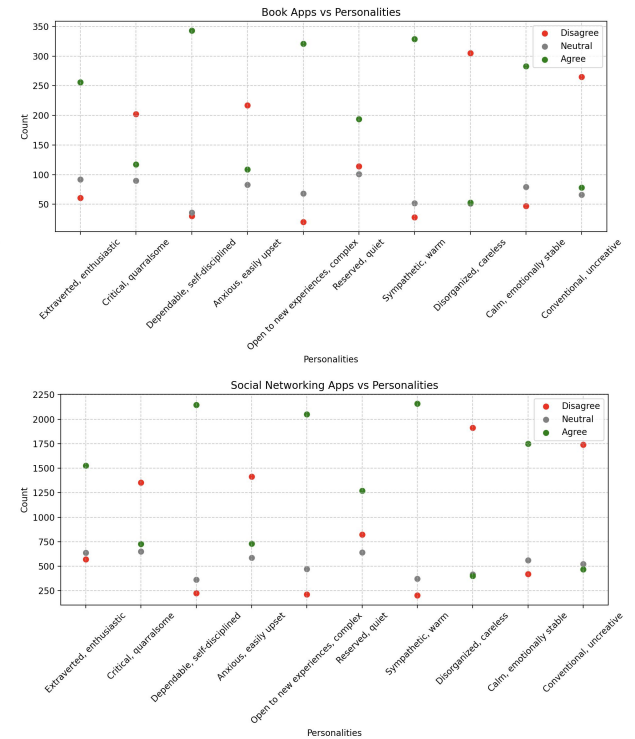
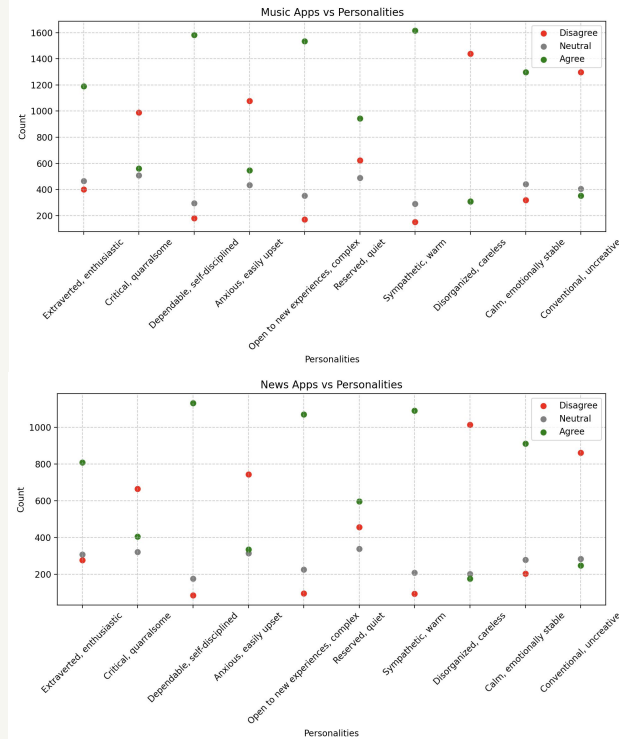
Interesting Finding

Those who identify as “Dependable, self-disciplined” appear more inclined toward productivity or business apps. This trend aligns with a structured, goal-oriented personality that values tools to enhance efficiency.

Respondents who rate themselves high on “Open to new experiences, complex” tend to show higher download rates for travel or education apps. This suggests that an adventurous or curious personality may drive interest in apps that offer exploration or learning opportunities.

Where The Survey Might Fail?

- Response counts varied significantly, which helped identify trends across apps.
- Despite these trends, individual app responses were often similar.
- Possible reasons for this pattern:
 - Personality traits may have positive or negative connotations, affecting responses
 - The way responses were categorized in a binary format may have influenced the results
- How to fix this:
 - Including only positive traits in the survey could reduce this effect





Thank You

Methodology

Data Cleaning and Transformation

- **Handling Missing Values:**
 - **Q15 Data:** Missing values are replaced with 0. This approach assumes that a missing response in the context of app downloads indicates no downloads or a baseline measure.

Custom Recoding Function:

A function (`recode_q30`) is defined to transform the original personality responses into categorical values:

- **Neutral (Value 4):** Mapped to 1.
- **Disagreement (Values 1, 2, 3):** Mapped to 0.
- **Agreement (Values 5, 6, 7):** Mapped to 2.
- **Non-responses or other values:** Mapped to -1.