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It’s more than memes: User risk appetite and app enjoyment predict simulated mobile trading app behavior

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17. It's more than memes: User risk appetite and app enjoyment predict simulated mobile trading app behavior

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Abstract

Mobile trading application users have rocked the financial world and are becoming a noteworthy for their ability to contribute to financial uncertainty, often at great risk to their personal wealth. While participation in meme stock culture likely contributes to this risky behavior, other factors such as personal risk appetite and enjoyment could also explain a user's willingness to engage in risky actions on these platforms. In this paper, we describe the results of an experiment whereby participants engaged in a simulated financial trading task designed to mimic the Robinhood trading app. We took a mixed method approach to investigating users' experiences, using time-series machine learning clustering as well as questionnaire measures. We identified distinct clusters of users based on app usage data which reflected degrees of risky behavior and found that these features were associated with a user's perceived risk appetite and the degree to which they enjoyed the simulated technology. Taken together with past evidence that suggests that risk appetite and enjoyment are associated with application use, we posit that these factors play a role in explaining risky behavior on mobile trading platforms, which has implications for financial application design and future research on financial technology applications.

Keywords: Financial Technologies, Hedonic Information Systems, Risk Perception, Time Series Clustering, Simulation

1. Introduction

In January 2021, financial markets were rocked by an unexpected cause. Over the course of two weeks, millions of Reddit users leveraged popular financial trading apps such as Robinhood to propel the stock value of GameStop, a failing company, by more than $1500 (Li, 2021). Though many app users profited from this activity, it also had a negative impact on hedge funds which had bet on the stock failing. Millions of Reddit users also lost money as the stock price subsequently crashed (Brown, n.d.). This activity subsequently caused stock hysteria in various similar assets, ultimately culminating in market volatility and calls for regulation of these apps (Stewart, 2021). Today in 2022, stock markets continue to face increased volatility, and many internet influencers continue to promise gains, which has even prompted action from the Securities Exchange Commission cautioning the public about investing money in meme stocks and related cryptocurrencies which are popularized by social media (Cachero, 2022)

What factors explain this investing behavior? A possible explanation is that users who are most apt to invest in meme stocks and meme cryptocurrencies (hereafter referred to as "meme stocks" for short) are risk takers. Economists have long understood that risk appetite is a personality trait that can predict attitudes towards investments, as well as actual investment behavior such as saving for retirement (Barksy, 1997; Kam & Simas, 2010). This observation has also been observed in the context of information systems (IS) research in the context of cybersecurity notifications (Vance et al., 2014), suggesting that it could generalize in other related contexts. It is thus possible that risk appetite predicts meme stock investing behavior.

Another possible explanation is that people enjoy using the application. Hedonic factors such as enjoyment are known to influence users' satisfaction and propensity to use applications, especially when they involve social media (Agarwal & Karahanna, 2000; Li & Chen, 2012). Users who enjoy the mobile investing experience may be more apt to use the application and be more engaged with interesting and exciting trends. This was posited by both media (Cachero, 2022) and academic sources (Costola, 2022) as a predictive factor in whether people participate in risky activity on mobile investing platforms.

In this paper we describe the results of an exploratory experiment which provides insights into factors that predict risk taking when using trading apps. Inspired by approaches employed by behavioral economics (Geezey & Potters, 1997) and new directions related to experience simulation being undertaken by IS researchers (Labonte-LeMoyne et al., 2017; Beese et al., 2018), we constructed a simulation of a financial trading application to facilitate the analysis of risk taking and enjoyment factors in investing app behavior. Simulation provides some advantages of alternative approaches, such as surveys, when few participants have direct experience with the information technology artifact in question. By providing a shared experience that is similar to the Robinhood application, we can make inferences about factors that influence behavior which may generalize to the actual technology. Simulation applications also allow us to analyze actual use behaviors in way that we would not otherwise be able to without access to the application itself. The approach that we take to our research methods leverages machine learning clustering of the behavioral data, designed to answer a recent call among IS researchers for new approaches to computationally intensive research (Berente et al., 2019; Miranda et al., 2022). We also conducted standard linear regression of the survey to complement the machine learning findings and help interpret the results. We have articulated our research question as follows:

RQ1 – Does risk appetite predict risky trading app behavior?

RQ2 – Does platform enjoyment predict risky trading app behavior?

RQ3 – Do clusters of user data will exhibit differences in trading behavior?

The remainder of this paper is structured as follows. We begin by discussing the theoretical framework, complete with the research questions that we seek to pursue. We then describe the methodology, detailing the psychometric, behavioral and machine learning analysis approaches to the research question. The results are provided along with a discussion about the theoretical and methodological contributions of this work. We ultimately conclude by discussing ways to improve this approach, with attention to future research directions.

2. Theoretical Framework

2.1 Risk appetite & Enjoyment

Risk appetite and enjoyment are social factors that have been studied in social sciences broadly, and in IS research specifically. For example, researchers have explored factors that contribute to collective social behaviors on social media such as those exhibited on Reddit (TsaI & Bagozzi, 2014). There are also well-established theories that investigate the role that enjoyment plays in information technology use such as cognitive absorption (Agarwal & Karahanna, 2000), as well as the role that risk perception may play in driving risky and impulsive IT behavior (Vance et al., 2014). More recently, e-commerce researchers have applied similar techniques to the assessments of the effects of gamification on online shopping behavior, finding that they influence online shopping trends (Garcia-Jurado et al, 2021). These social scientific approaches can offer considerable insight into the latent causes of risky behavior, though offer relatively little insight into specific design factors that influence it in the context meme stocks traded on popular platforms such as Robinhood, which are purported to influence the behavior (Li, 2021).

The meme stock phenomenon can be conceptualized in light of a mobile trading information technology artifact. Mobile applications have been extensively studied in the literature, perhaps most influentially from the perspective of a hedonic/utilitarian dichotomy (Wakefield & Whitten, 2006). In this conceptualization, hedonic applications (e.g. social media) are primarily designed to promote user enjoyment, while utilitarian applications (e.g. trading apps) are primarily designed to promote practical or business needs (Wakefield & Whitten, 2006; Sledgianowski & Kulviwat, 2009; Li & Chen, 2012). Mobile trading applications blur this dichotomy, as the affordance of the application seems to be practical gain, while the antecedents of use may be hedonic influenced by factors such as enjoyment.

While there are many factors that could influence risky trading, we were led to investigate two: *risk appetite* and *enjoyment*. Risk appetite has been previously investigated by IS researchers often in the context of cybersecurity notifications, finding that it predicts disregard for cybersecurity warnings (Vance et al., 2014) and plays a role in the wider context of protection motivation theory, which explains a users' motivation to protect their computer assets (Haag et al., 2021). Building on the work of Vance et al. (2014) as well as Kam & Simas (2010), we explore the ways that risk appetite influences a users' interest in taking risky decisions over less risky ones.

By contrast, enjoyment is often explored in the context of hedonic IS, especially in the context of social media (Li & Chen, 2012; Turel & Serenko, 2012). Enjoyment is often associated with positive impacts on IS use, such as through increased engagement with a system or the experience of cognitive absorption (Agarwal & Karahanna, 2000), though it has also been found to predict negative aspects of social media (Turel & Serenko, 2012). In the case of the study described by Turel & Serenko (2012), enjoyment of social media was found to play a role in forming bad habits and dependence on the information technology; we can similarly conceptualize a way that enjoyment influences risky trading behavior.

2.2 Machine learning approaches to IS research

Even from its earliest days, the IS discipline has drawn from mixed methods approaches, ranging from qualitative to quantitative; the discipline is now drawing from increasingly computationally intense methods to advance theory (Miranda et al., 2022). While machine learning is certainly not new and has been applied to IS research in the past, many of these applications have not advanced IS theory (Berente et al., 2019). More recently however, IS researchers are employing such methods to make advancements in the application of grounded theory and the advancement of theories of information technology use (Miranda et al., 2015; Tidhar & Eisenhardt, 2019; Vaast et al., 2017). Machine learning can contribute to IS theory not just by providing descriptive analysis, but also exploratory analysis into factors that could explain IT use behaivour by leveraging large amounts of data that cannot be easily analyzed using conventional techniques (Miranda et al., 2022).

In the context of trading apps, machine learning analysis can similarly yield insights into risk behavior that might not be captured by conventional technique such as interviews or surveys. By observing use data that is collected from actions generated by a computer application, we can observe organic behaviors that mimic real use behavior, similarly to how a researcher may do observations in grounded theory approaches to social science (Berente et al., 2019; Miranda et al., 2022). In an ideal world, we would gather data directly from a mobile trading application such as Robinhood, which would contain transactions that reflect actual users' behavior. Instead, as academics not associated with the popular trading platforms, we build on past IS research which leverages behavioral data gathered from simulations in order to make inferences (Labonte-LeMoyne et al., 2017; Beese et al., 2018). By applying machine learning clustering, we may discover clusters of behavior that reflect patterns of IT use, which can in turn be corroborated with an alternative method, such as questionnaires.

3. Methodology

3.1 Application Description

The first step for our study was to develop a web application which can simulate a mobile trading app where people can buy and sell stock. We used the Python programming language to create the web app, specifically the Plotly Dash library (Plotly, n.d.) for building interactive dashboards and SQLAlchemy (SQLAlchemy, n.d.) for managing database operations. The application was hosted on Heroku the cloud platform. The simulation leveraged stock market indices, equities and cryptocurrency data and a central display. Asset prices were updated every second during the simulation, with one second simulating a single trading day. The interface leveraged buttons to ease the purchase and selling of the virtual assets. The application was called "Nottingham" to demonstrate that the purpose of the simulation was to reflect the Robinhood trading application.

In Figure 1, we illustrate two interfaces from the application. Users landed on the welcome screen and when they click the 'Participate' button, took them to a Consent procedure, followed by a pre-session survey which asked questions related to risk appetite. The second screen demonstrates the main simulation page where there were two tabs: 'Instructions' and 'Invest'. Former gives information about the assets available in the simulation and the available actions they can perform. The later has sub-tabs of all the assets and those assets are based on their volatility and the reward one can get after investing on them.

The assets were always based on historical stock or cryptocurrency data, though the names of the actual assets were not known to the users and the specific assets and time periods that they were presented were generated randomly every time user starts a new session. Assets were limited to five options and were placed in order of volatility: government bonds (lowest volatility, lowest reward), a major stock index fund, a single bank stock, a meme stock (e.g. Gamestop, Blackberry), and a cryptocurrency (e.g. Bitcoin, Litecoin; most volatile, highest reward). Users could see the status of each asset by touching the related tabs. The graph updated every 1500 ms and the simulation consisted of four rounds, each corresponding to 46 to 47 days of real data. To help manage cognitive load and quick decision making, users were given a quick buy option where there were several buttons with the number of stocks they want to buy. Apart from this there was a 'Sell' button where one can sell any number of stock they want to sell from the asset and another is 'Sell All' button through which one can sell all their asset from their portfolio. After all the rounds complete, the user was prompted with a post-session survey regarding the enjoyment they had using the simulation. The submission of survey takes them to debriefing page where the top-3 performers on the simulation were displayed along with their portfolio data.

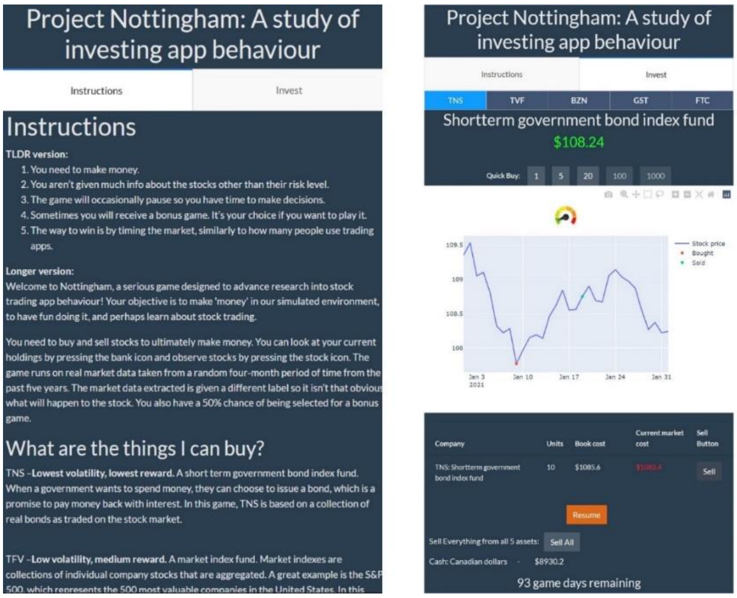

Figure 1: Sample screens of the web app, designed for mobile. Left: Instructions Right: Stock Simulation

3.2 Survey Development

There has been well-established theories that investigate the role that enjoyment or cognitive absorption plays in information technology use (Agarwal & Karahanna, 2000) as well as the role that risk perception may play in driving risky and impulsive IT behavior Vance et al. (2014). We thus incorporated two surveys in our web simulation i.e. the user profile survey in the beginning and the session survey at the end. The profile survey consists of 9 questions which included 7 previously validated questions about general risk appetite from (Barksy et al., 1997), as well as control variables: age and demographics. The session survey concerned the enjoyment that participants experienced and consisted of 11 questions based on a well-known enjoyment measure known to be associated with technology use (Agarwal & Karahanna, 2000).

3.3 Participants and Procedure

All procedures were reviewed and approved by our university's research ethics board and was found to adhere to the Canadian Tri-Council Policy Statement 2 on Ethical Conduct for Research Involving Humans. We took several approaches to recruit participants for our study such as email, social media, and paid panel. We contacted students via our lab and faculty mailing lists and offered them to enter for a chance to win a random draw of $50 CAD gift voucher as well as a competitive award for the best three performers. We also used the Prolific platform to find volunteers, who were paid £2 for their time and were compensated whether or not they finished the activity. Though 214 consented to participate and conducted at least more than a minute of interaction with the app, due to technical difficulties, only 147 completed the entire simulation and answered all of the questionnaire items.

When the participant clicked the link to the application, they were presented with a consent screen, and consent was given by agreeing to get to the pre-session survey. Participants then completed the risk questionnaire and completed the stock trading simulation, which consisted of four rounds consisting of 46-47 seconds during which participants could buy and sell simulated assets, which were arranged in order of volatility. The simulation was paused in between each round and resumed by the participant at will which gives them chance to analyze their portfolio and take actions based on it for their future investments.

3.4 Data Description

The data that were collected from the application was comprised of 4 different tables: ‘Userinfo’, ‘Sesioninfo’, ‘Postsurveydata’ and ‘Playbehavior’. The first had information about the user’s age and gender along with the survey about their risk-taking decisions. The second one consisted of the data about the session played such as start-time of the session, number of times user played the session, amount left in their account, portfolio value including all the assets they invested on, and profit/loss. The third one contained information about the survey on enjoyment of the simulation they played and the last one contained the data of transactions they did on the simulation such as buy/sell with company name, on which simulation day they did transaction, number of stocks bought, market value of single stock and total value of the stocks purchased.

We calculated and extracted the relevant features that would be useful for our Machine Learning models from tables ‘Sessioninfo’ and ‘Playbehavior’. Those features are summarized in Table 1. As our application had 3 pauses on 31st, 62nd and 93rd simulation day, we had a total of 4 rounds. We thus refined the data into 5 different tables as Round 1 - data between game day 1 to 31, `Round 2' - data between game day 32 to 62, `Round 3' - data between game day 63 to 93, `Round 4' - data between game day 94 to 124 and 'Total Rounds' of the mentioned features where the last table ‘Total Rounds’ contains the summation of all four rounds of extracted data.

3.5 Data Mining Approach

We took an unsupervised learning approach to data mining, so that we did not have to presuppose anything about the data as we conducted exploratory analysis. The algorithm that we've selected for our experiment is Time Series K-Means, which was implemented using the tslearn Python library (Tavenard et al., 2020). We selected this approach because the simulation had four rounds in and we treated each round data as time series to monitor how they performed. Using the data described in Table 1, we generated two clusters, to identify high risk-taking and lower risk-taking simulation users based on the behavioral data.

Feature	**Description**
TRANSACTIONS_PER_MINUTE	Number of transactions users made per minute
STOCKS_PER_MINUTE	Total number of assets bought per minute (e.g. stocks or cryptocurrency)
COSTBUY_PER_MINUTE	Total amount of assets bought per minute
BOUGHT	Total number of assets bought in a single session
NUMBER_OF_TRANSACTIONS	Total number of transactions made in a session
BUY_VALUE	Total value of assets bought in a session
MIN_BUY_AMOUNT	Minimum value of assets bought in a session
MAX_BUY_AMOUNT	Maximum value of assets bought in a session
RISK_METER	Most frequently bought asset of the five assets
TNS_AVGTIME	Average time taken between buy and sell of lowest volatility, lowest reward asset
TFV_AVGTIME	Average time taken between buy and sell of low volatility, low reward asset
BZN_AVGTIME	Average time taken between buy and sell of moderate volatility, moderate reward asset
GST_AVGTIME	Average time taken between buy and sell of high volatility, high reward asset
FLIPCOIN_AVGTIME	Average time taken between buy and sell of highest volatility, highest reward asset
PROFIT/LOSS	Profit or loss at the end of the simulation
RISE_BUY	Number of times a user bought assets when it increased versus previous day
FALL_BUY	Number of times a user bought assets when it decreased versus previous day

Table 2: Extracted features used in machine learning analysis

3.6 Survey Data Analysis

In addition, we analyzed the survey data using a separate linear regression approach, in an effort to evaluate the validity of the clustering algorithm. We investigated the risk appetite and enjoyment survey instruments using Chronbach's alpha and all items demonstrated an alpha of at least 0.7, so were aggregated. We ran simple ordinary least squares linear regression models on extracted features from the simulation and the survey data to predict the risk appetite and enjoyment, to establish a link between the play behavior and the established survey-based measures.

4. Results

4.1 Clustering

Figure 2 demonstrates the results of our clustering approach. The time series k-means identified two distinct clusters: one "low risk" cluster which contained 143 participants which exhibited lower risk activities and one "high risk" cluster of 71 participants which largely exhibited higher risk activities. The clusters are illustrated based on their average values from seven of the indicators previously mentioned in Table 1. Six of these indicators are illustrated below. In Figure 3, we filtered out the unique sessions of users and then took the ones who played full session and it is clear that most of the people around 40% of the users that we've analyzed were 'Low Risk' takers and made profit whereas only 16% of the users that were detected as 'High Risk' takers but made loss on simulation.

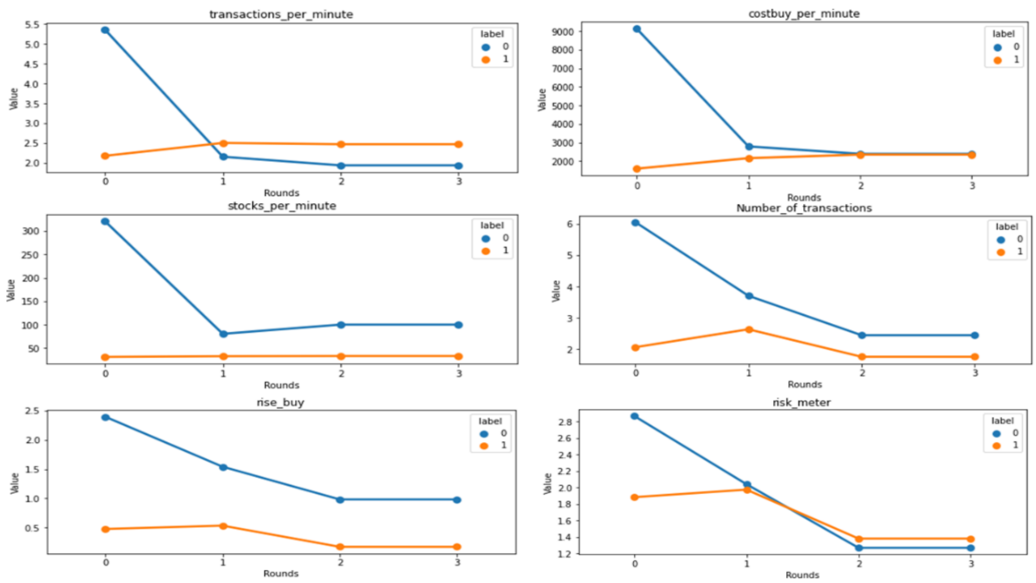

Figure 2: Comparison of the Time Series K Means clusters

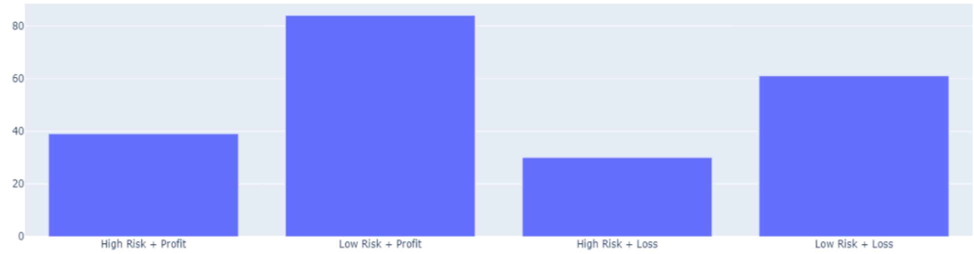

Figure 3: Type of Risk takers and Profit/Loss

4.2 Survey Analysis

Figure 4 provides a correlation table of the various survey instruments and behavioral features measured. We analyzed the seven of the features that most differentiated the clusters using the risk and enjoyment survey data using linear regression. Figure 4 provides a correlation table of the various features. Seven of these features (risk_meter, counts, max_buy_amount, buy_value, costbuy_per_minute, number_of_transactions, and avg_buysell_time) were found to be significantly correlated with both the enjoyment and risk surveys.

5. Discussion

5.1 Implications

To get the insights about the users risk taking decisions, we used 'TimeSeriesKMeans' algorithm to distinguish the clusters which helped in identifying their behavior. There were total 69 sessions in 'Cluster 1' while 145 sessions identified in 'Cluster 0'. The clusters that we obtained clearly reflected two distinct behaviors: Cluster 0 which can be described as high risk taking, and Cluster 1 which can be described as low risk taking. While high risk-taking players tended to purchase a large number of risky assets at the outset of the simulation, they continued to trade throughout the session, and tended to maximize on rising asset prices. By contrast, low risk-taking players purchased fewer, less risky assets early on and traded less frequently, as illustrated by Figure 2. Though all players tended to interact with the application less as the simulation proceeded, the differences between the two clusters are clearly defined. The reason we selected 2 clusters for the algorithm is less data and increasing the clusters resulted in highly imbalanced clusters and uninterpretable b their features compared to 2 clusters.

Importantly, we can be confident that these clusters reflect more than just engagement with the application because we observed significant relationships between behaviors and the surveys. We observed associations between the seven behavioral features that were identified by the clustering algorithm and both the risk and enjoyment survey measures. The measures were also closely associated, suggesting that there was a strong relationship between a user's risk appetite, how much they enjoyed the simulation, and their risk-taking behvior, as described in Tables 2 and 3.

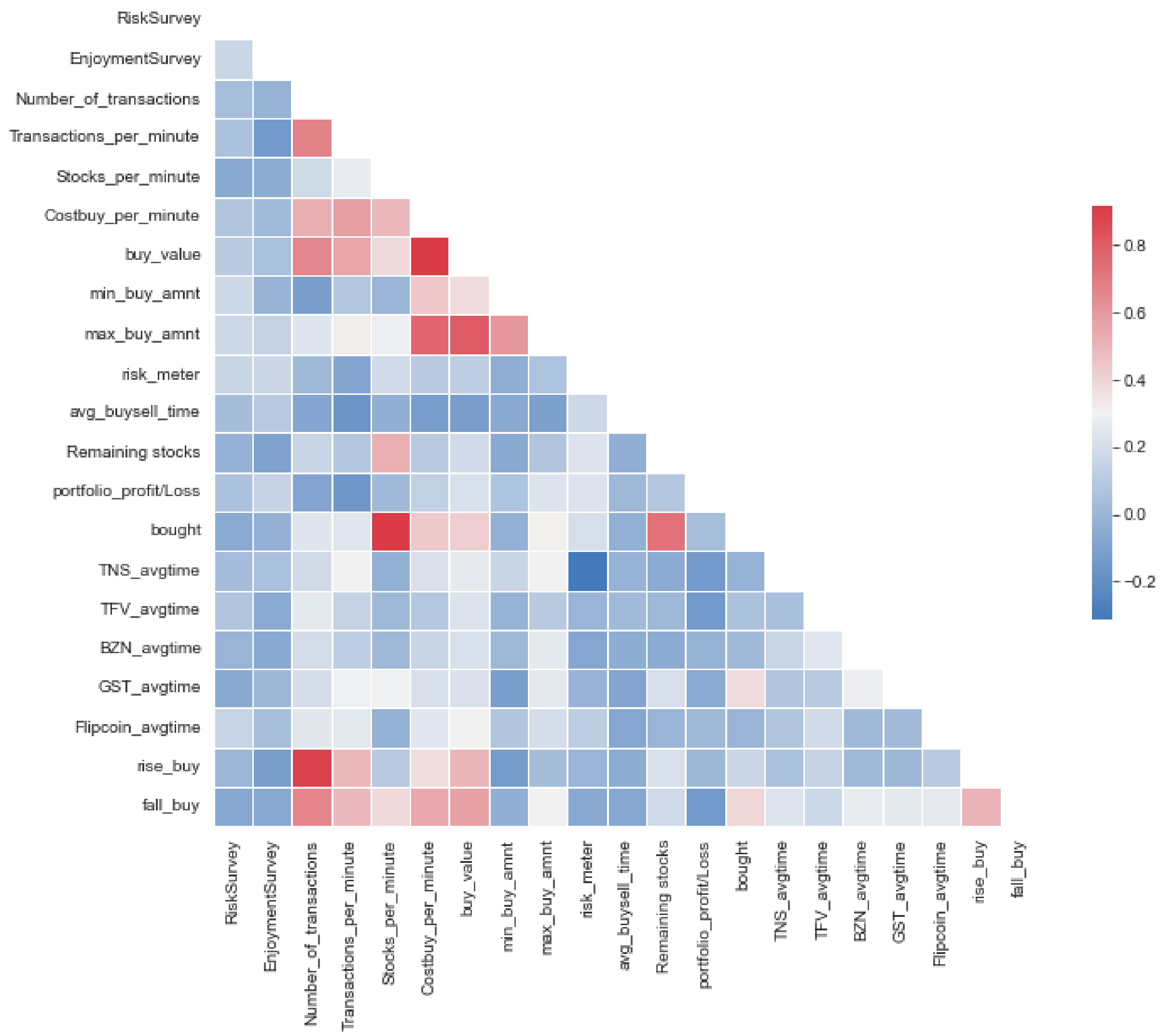

Figure 4: Correlation table of the various measured features

These findings have interesting theoretical contributions. They suggest that social factors such as risk appetite and enjoyment had influence on risk taking behavior of users on stock trading simulation, which could generalize to the meme stock phenomenon. User enjoyment has is known to be key factor in predicting hedonic information system use (Wakefield & Whitten, 2006; Sledgianowski & Kulviwat, 2009) and risk appetite is known to influence decision making (Vance et al. 2014). We are led to assert that these findings generalize to the case of investing applications.

Finally, there are also practical implications. Investing applications such as Robinhood incorporate design features which encourage users to take risky decisions and reinforce hedonic affordances. For example, Robinhood features a referral program and a rewards system that mimic features of mobile games and social media. Depending on their goal, application designers or other stakeholders can limit or encourage features that either identify risk-taking, encourage enjoyment, or limit these things. Future work could refine these findings to assess specific features that either encourage or limit the risk or hedonic factors.

5.2 Limitations

Our findings are limited by challenges with recruitment and data quality. While 214 participants consented to participate, many of the participants were recruited from Prolific, which is a platform of convenience, who were extrinsically motivated by payment. In addition, much of our data was incomplete, as only 147 participants completed the full task and answered both the pre and post survey. The results described in this paper can be considered complete, though an uncomprehensive analysis.

Secondly, there are theoretical challenges with drawing conclusions from a simulation task. While the task was designed to mimic the Robinhood trading application, participants in the study may not be similarly motivated as individuals who actually use the real-life trading application. Future work can overcome this limitation by collecting opinions from people who use the Robinhood application in addition to drawing inferences from the behavioral task. Alternatively, future work can improve on the generalizability of these findings by grounding future experimental work in a well-developed theory, such as the theory of planned behavior (Ajzen, 1991).

6. Conclusion

In this paper we explored possible factors that motivate individuals to engage in risky trading behavior when using mobile trading platforms. The approach that we took was to create a simulation of a mobile trading platform, through which we identified clusters of risky behavior, and that perceived risk appetite and reported enjoyment predicted people's engagement with risky behavior. We are ultimately led to conclude that while memes and hype can explain some of the engagement with these apps, people's risk appetites and experienced enjoyment during the application use predict risky behavior.

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