Social Spending: An Empirical Study on Peer Pressure and Player Spending in Games

William Wang and Loutfouz Zaman(✉)

University of Ontario Institute of Technology, 2000 Simcoe Street North,
Oshawa, ON L1H 7K4, Canada
loutfouz.zaman@uoit.ca

Abstract. This study explores the relationship between a player's spending habits and peer pressure with regards to optional purchases in online multiplayer games. We hypothesized that there is a positive correlation between player spending and the number of friends the player has playing the same game. The study was conducted via a survey, collecting the information on spending habits the size of their friend lists other relevant data. We concluded that there could be a positive correlation between player spending and peer pressure in modern Multiplayer Online Battle Arena and team-based First-Person Shooter games, but more research is required, as there were limiting factors to this study. The games used in this study were *League of Legends*, *Defense of the Ancients 2*, *Team Fortress 2*, and *Overwatch*. The findings can potentially be used to design games that encourage more playing with friends and family to increase per player revenue.

Keywords: Computer games · Digital games/online games · Player personality · Characteristics and demographics · Profit · Peer pressure · Per player spending

1 Background

Modern day games have many ways to generate revenue. However, there are very few sources of research to determine how exactly one can increase the effective profitability of their games. The goal of this study was to find if there is a relationship between the level of social engagement of players and the amount of money the players spend on purchasing in-game content.

Multiplayer Online Battle Arena (MOBA) is a genre of games that originated from a subgenre of real-time strategy games in which a player controls a character in one of two teams with the aim of defeating the enemy team, usually through player-vs-player combat.

Frederiksen [5] surveyed players and looked at the reasons why players buy skins in MOBA for the MOBA game *League of Legends*. Frederiksen found that players who play more with real friends bought virtual items more frequently and spent more on virtual items. Frederiksen also found that attention craving has a positive effect on the frequency and the amount of money spent on virtual items in freemium MOBA games. Frederiksen established that this is related to the peer pressure factors this study

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explores as this indicates that players want to express themselves and there may be a larger motivation when the player can express themselves with their friends instead of anonymous individuals.

Although our work explores Frederiksen's [5] third, fourth and eighth hypotheses on a smaller scale, our main focus is finding the correlation between peer pressure and player spending, instead of finding the reasons why players spend money on games in general.

Hsu and Lu [10] conducted a survey on flow experience, social influences and player retention in games where they explore social norms as a factor. Their findings concluded that people play online games due to *critical mass* - a predetermined amount of other people playing the game set by the player. The study also found that social norms and flow experience had an influence on the general acceptance of playing video games. However, this work does not consider social factors in explaining information technology (IT) usage. This study addresses social factors in order to create a more holistic picture of social influences in adoption and retention for games.

Shin and Shin [16] conducted a survey study on pre-existing expectations and their influences on playing games. The study explores the internal influences on why people play and pay for social network games. Our work adopts many elements of the survey design, which is using similar methods to collect data and accounting for the same background variables that may influence the results. Also, in our work, we apply the survey design into gathering data on external influences on why people pay for games.

Musabirov et al. [15] explored player experiences related to cosmetic items in *Defense of the Ancients 2 (DOTA2)* via collecting community discussion data from Reddit.com, a social news and discussion website. Their findings concluded that the e-sports aspects of the game heavily influenced the collecting practices of the players. The main factors found to have the most influence on a player's collecting were rarity of the item, brand recognition, perceived aesthetic value, and authenticity of the item. Authenticity was a factor, because a pro-player's autograph could be added onto a character in game for aesthetic purposes. Our work also investigates *DOTA2* and player collecting, but we look at how much the social factors influence player spending.

Toups et al. [17] explored the collecting behaviours of players in digital games concerning in-game and meta-game collecting. They identified 10 possible factors as to why players would collect anything in a game. They concluded that in-game collections were more valued than meta-game collections, especially in-game collectables that influenced the game's mechanics. Our work explores whether peer influence has any factor on player collecting, a factor that was only briefly considered in this study.

In Guo and Barnes's [7] work on player purchase behaviour in virtual worlds via *Second Life*, additional variables in player purchase behaviours were identified when the players had the ability to communicate with other players. In their case, *Second Life* was a game that had messaging channels for trade and other non-trade channels. Their findings created a theoretical model that included intrinsic, extrinsic, and social influences that predicted player purchase patterns with 45% accuracy. Our work explores how much weight social influence have on an individual's purchase behaviours in online games.

Guo et al. [6] developed a topic model, Latent Dirichlet Allocation, to take in a multitude of text information, such as discussion threads and documents. The model then produces a list of topics, determined by the frequency of those words appearing in each document. This allows to user to sort the text into topics relating to their research topic. Guo and Barnes [8] also developed a new model to predict player intent on purchasing virtual content with real world money. Their model uses a combination of past models and theories, which include the Technology Acceptance Model, Theory of Planned Behaviour, Theory of Reasoned Action, Web Trust Model, and Unified Theory of Acceptance and Use of Technology. They considered aspects of each model and narrowed down to 10 specific factors that influence player purchase behaviour. However, their work is preliminary and therefore lacks weighting or empirical data to prove the accuracy and reliability of the model. Our work attempts to measure how heavily the "social influence" factor in such models affects purchase behaviours.

Bartle [2] discusses the reasons why, in recent years, has the Massively Multiplayer Online Game (MMOG) genre has seen a steady decline in players. In his work, he mentions that one of the causes is due to a player type imbalance between the four basic player types of *achievers*, *killers*, *socializers*, and *explorers*. Our work focuses on how the industry can add additional social tools to their games to increase the appeal to social gamers (socializers).

Livingston et al. [13] studied why players gave value to their characters in the game *World of Warcraft*. They identified nine different ways in which a player values their characters. Two of those values were *sociability* and *social communication*. Sociability, in this work, is defined as the ability to communicate with other players. Social communication is a value derived from accomplishment and social recognition of those accomplishments. One of the factors we recognized was the ability for players to express their self-images through the game.

Ducheneaut et al. [4] explored how MMOGs were over-estimated in their prevalence in social activities. Using *World of Warcraft*'s longitudinal data, they concluded that MMOGs mostly provided shallow amounts of social engagement, such as finding teammates to complete a mission. However, their finding did reveal an exception to guilds when each of the players' levels are within a small range. This study leads us to believe, and eventually, test how those in a small community, like guilds, may influence a player's purchasing habits, as the player would value the opinions of their guildmates more strongly than the rest of the player population.

Kim et al. [11] investigated the purchase behaviours of members in social networking communities (SNCs). They analysed Cyworld, an SNC, using Customer Value Theory as a base to develop a conceptual framework of customer values in SNCs. The three general dimensions of model consisted of functional, emotional, and social value. Our work over lapses their work in evaluating consumer purchase intent, but in the context of games as opposed to SNCs with a focus in the social values of the players.

Lenhart et al. [12] looked at the gaming habits of teenagers and civic activities. In their work, they state that half of all teenagers who play online games, play with other players they know offline. Our work uses games that have teenagers as their target audience. Therefore, we can use the information from Lenhart to make assumptions on player gaming habits.

Alha et al. [1] studied player opinions of the free-to-play model of video games. They interviewed 14 game professionals to understand the general attitude and ethical problems with the free-to-play model. Overall opinions varied, but the general attitude towards this model was positive. In our study we use games from both the retail and free-to-play models of revenue. If there was a large bias towards one model, then our results may have been skewed and affected our conclusions.

Hamari et al. [9] investigated the reasons why players purchase in-game content. They explored six possible factors that might have been the underlying reasons. Unobstructed Play, Social Interaction, Economical Reasoning were the three factors found to be positively associated with player spending. One of the reasons for the choice of our games is their lack in obstruction of play: the purchased content is purely for aesthetic purposes. Therefore, going by Hamari's model, we can assume social interaction to be the main factor in player purchase behaviours.

Westerlund and Baxter [18] investigated the opinions of professional players of *DOTA2* and *Team Fortress 2* on the cosmetic items available in these games. They interviewed 10 professional players, five from each game, and categorized their comments into four main categories: Aesthetics, Identity, Perception, and Economy. For the majority of the findings, they were consistent with earlier research, namely that the items are obtained for self-expression. In this work, however, two players noted how some of the cosmetic items have high or low contrast to the background environment of the games, which may make the player using the cosmetic item "*distracting and hide other important elements*" or make it harder to pick up on visual cues. However, Westerlund and Baxter investigated the cosmetic items of the two games and did not find an item that fulfilled the criteria. This is an important finding, as many of our participants were surveyed during a gaming event, which implies more competitive players than the average sample. If cosmetic items did have an impact on gameplay, players might have chosen to purchase the cosmetic items for a competitive advantage over their peers.

Yamamoto and McArthur [19] discuss how players value virtual cosmetic items in a marketplace where players can sell or buy these cosmetic items from other players. They used *Counter Strike: Global Offensive* as their study game, which has a key and crate system similar to *Overwatch* and *League of Legends*. Based on their findings, the two main factors that determine an item's value are the supply and demand of the item and the overall design of the cosmetic item. These findings add on to the findings of Kim et al. [11], to create a more holistic model of the factors that influence a player's purchasing patterns, in the context of virtual items.

Minchev and Schmitt [14] interviewed 12 players of *League of Legends* to find why players purchase virtual cosmetic items. Their findings conclude that "personal satisfaction" was the most important factor in purchasing the cosmetic items available in the game. However, Minchev and Schmitt state that social and pragmatic factors are less influential than previously thought.

2 Research Hypothesis

In this work, we explore the following research hypotheses:

- **H1**: Players' in-game spending is positively correlated with the size of the group the player regularly plays with.
- **H2**: Player's in-game spending is positively correlated to the number of friends, related to the player, playing the same game.

3 Methodology

We collected the data using an online survey. The survey was completed by the students at the University of Ontario Institute of Technology (UOIT). The questionnaire was designed around the following games:

- *Overwatch* by Blizzard Entertainment Inc.
- *Team Fortress 2* by Valve Corporation.
- *League of Legends* by Riot Games
- *Defense of the Ancients 2* by Valve Corporation.

We chose these games due to the similarities in their mechanics, and play styles to their "twin" game, pairing *Overwatch* with *Team Fortress 2 (TF2)* and *League of Legends (LoL)* with *DOTA2*. *Overwatch* and *TF2* are both first person shooter (FPS) games with a focus on team-oriented play and different classes of characters. *LoL* and *DOTA2* are the leading games in the MOBA genre by player count and both are currently investing into the competitive e-sports scene.

In the survey, the participants were asked questions about their gender, occupation and education status, the relationships to the people they play with, number of friends on their friend lists, time spent playing the game in question in relation to player spending, total time invested playing the game, and time invested in the game in the past month. All these measurements were recorded on a Likert scale. Age, average player group size and average number of people the player plays a game session with were measured using a ratio scale.

In the first iteration of the survey participants were asked to rate *closeness* to their groups on a Likert scale of 1 to 5, 1 being "not close at all" and 5 being "very close relationship". However, pilot testing revealed that it was confusing to most participants and therefore we changed the question's format to multiple choice.

Participants were encouraged, but were not required, to consult their purchase history of the respective game to get the most accurate information about their spending. At the time of the study, this was achieved via "privacy.riotgames.com" for *LoL*, "battle.net" account history for *Overwatch*, and the available Steam client for *DOTA2* and *TF2*.

Data was collected via social media, at large gaming events, during undergraduate lectures, and word of mouth.

Participants were also asked for their yearly income, in order to control for disposable income as an influence on the findings.

The calculations based on the data collection are as follows:

- Average player's spending per month vs. average group size
- Average player's spending per month vs. player's friend list size

From the data and calculations, we were able to determine whether there is any correlation between player's spending with per session average group size or player's friends list size. The detailed findings are revealing in the conclusions section.

4 Survey Design

1. Participants were initially asked about their enrollment at the University of Ontario Institute of Technology: part-time, full-time, or not affiliated with the university. Unaffiliated participants were directed to the end of the survey. Their data was not collected.
2. Participants were then asked if they played the game and if they did, how often they played the game per week. Answer options were as follows (in hours):
   a. N/A – I don't play the game
   b. Less than 3
   c. 3–6
   d. 6–9
   e. 9+
3. Participants then were asked if the following applied to them, with regards to the game:
   a. I enjoy playing the game.
   b. I can connect emotionally with other games in this game.
   c. I have made friends through this game.
   d. I regularly invite people I met online to a game with me.
   e. I regularly invite In-Real-Life (IRL) friends to a game with me.
   f. I regularly invite family members to play a game with me.
4. Participants were then asked for their average group size when playing the game, with possible answers being restricted to the game's possible sizes.
5. Participants were then asked about their monthly spending in Canadian Dollars on the respective game using an ordinal scale:
   a. 0
   b. 1–5
   c. 6–10
   d. 11–19
   e. 20–50
   f. 51 or more
6. The final question was asked about the size of the friend's list using the following increments to differentiate between the degree of social ability between players. This question was designed to be in ordinal measurement increments that are easily memorable for participants that were not willing to log into their accounts to check for exact numbers. The options were the following:
   a. Less than 10
   b. 10–50

c. 51–100
d. 100+

Questions 2–6 were asked individually for *Overwatch, Team Fortress 2, League of Legends,* and *DOTA2,* thus extending the survey to 20 questions at this point.

21. Age (recorded on a ratio scale)
22. Gender (Male, Female, Transgender – Female to Male, Transgender – Male to Female, Gender Variant/Non-conforming, other)
23. Program faculty (all participants at this point would have been students)
24. Occupation status (unemployed, part-time, or full-time)
25. Yearly income in CAD, with increments as follows:
    e. 0
    f. <10 000
    g. 10,001–30,000
    h. 30,001–70,000
    i. 70,000+

5 Variables

The independent variables were the average size of the group the player plays with (H1) and the number of friends one has on their friend's list for the game (H2). The dependent variable across both hypotheses was the average player spending measured in dollars. Control variables were: The games, group sizes (independent for hypothesis 1), cost of accessing the game, gender, age, participant's availability to spend time on games, frequency of play, and place of residence.

6 Results

In total, there were 104 responses. Of the 104 responses, 85 were considered valid. Responses were discarded if they met any of the following criteria:

- The participant was not a student at UOIT.
- The participants did not play any of the surveyed games. This also included the possibility of all their answers being the first option, which indicated that the participant just wanted to complete the survey as soon as possible, instead of providing meaningful data.
- All the answers were the last option, which again indicated that the participant just wanted to complete as soon as possible, instead of providing meaningful data.
- The participants took less than 30 s to complete the survey. During the pilot study, we determined that it took 1–4 min to complete the survey on average.

The largest group of participants, 53 of 104 of the totals and 36 of 85 valid participants, were surveyed during LANWAR - a gaming event that took place at UOIT. The event occurred during November 25–27, 2016.

Bonferroni correction was applied to each scenario to counteract the problem of multiple comparisons when testing for correlations between Friend List size and Player Spending. In all the surveyed games the analyzed data was not normally distributed. This violates one of the assumptions for the standard one-way ANOVA test. As a result, we used an Independent-Samples Kruskal-Wallis Test to determine if there was any statistical significance between the variables. The data was analyzed to determine the effect of Friend List size on Player Spending, and Group Size on Player Spending.

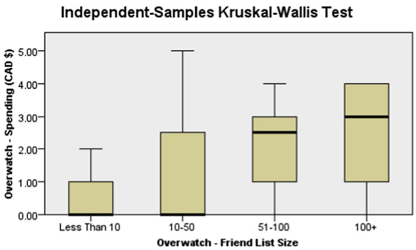
6.1 Overwatch

The sample size for this data was 66. The Kruskal-Wallis Test revealed a significant effect of Friend List Size: $H(3) = 10.896$, $p < 0.05$. See Fig. 1.

A Dunn's post-hoc test revealed that the 100+ group was different from the group of 10 people or less ($p < 0.05$). See Fig. 2.

The Kruskal-Wallis test for the Average Group Size indicated a significant difference: $H(3) = 10.843$, $p < 0.05$. See Fig. 3.

(a)



(b)

Fig. 1. Spending vs. Friend List Size in *Overwatch*.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-5.498	6.586	-.835	.404	1.000
Less Than 10-51-100	-17.041	8.045	-2.118	.034	.205
Less Than 10-100+	-19.285	7.047	-2.737	.006	.037
10-50-51-100	-11.543	6.816	-1.693	.090	.542
10-50-100+	-13.787	5.603	-2.461	.014	.083
51-100-100+	-2.244	7.262	-.309	.757	1.000

Fig. 2. Spending vs. Friend List Size in Overwatch- post-hoc test results.

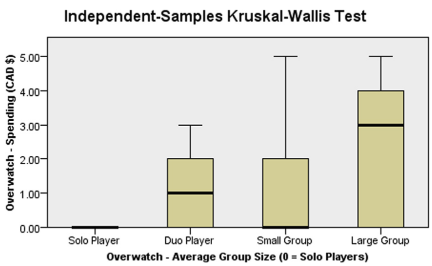


Fig. 3. Spending vs. Average Group Size in *Overwatch.*

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Solo Player-Small Group	-13.500	13.494	-1.000	.317	1.000
Solo Player-Duo Player	-15.000	14.763	-1.016	.310	1.000
Solo Player-Large Group	-27.250	13.447	-2.026	.043	.256
Small Group-Duo Player	1.500	7.810	.192	.848	1.000
Small Group-Large Group	-13.750	4.884	-2.815	.005	.029
Duo Player-Large Group	-12.250	7.729	-1.585	.113	.678

Fig. 4. Spending vs. Average Group Size in *Overwatch* - post-hoc test results.

A Dunn's post-hoc test revealed a significant difference between the players who play in small groups and those that play in large groups, $p < 0.05$. See Fig. 4.

6.2 Team Fortress 2

The sample size for this data set is 42. The Kruskal-Wallis Test on the effect of Friend List Size revealed a significant difference: $H(3) = 12.340$, $p < 0.01$. Figure 5.

A Dunn's post-hoc test revealed that the sample groups of those who had less than 10 people on their friend lists were different from those who had between 51–100 ($p < 0.01$) and those who had more than 100 ($p < 0.05$). See Fig. 6.

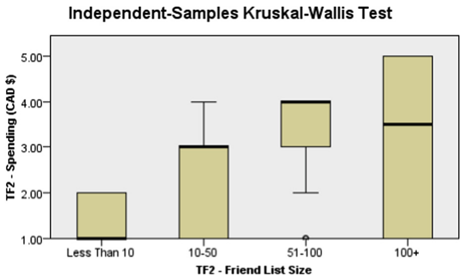


Fig. 5. Spending vs. Friend List Size in *TF2*.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-6.833	5.565	-1.228	.219	1.000
Less Than 10-100+	-15.133	5.424	-2.790	.005	.032
Less Than 10-51-100	-15.798	5.044	-3.132	.002	.010
10-50-100+	-8.300	5.424	-1.530	.126	.756
10-50-51-100	-8.964	5.044	-1.777	.076	.453
100+-51-100	.664	4.888	.136	.892	1.000

Fig. 6. Spending vs. Friend List Size in *TF2* - post-hoc test results.

The Kruskal-Wallis Test on effect of the Average Group Size revealed a significant difference: $H(3) = 10.843$, $p < 0.01$. Figure 7.

A Dunn's post-hoc test revealed that the sample groups of players who play in small groups were different from those who play in large groups ($p < 0.05$). See Fig. 8.

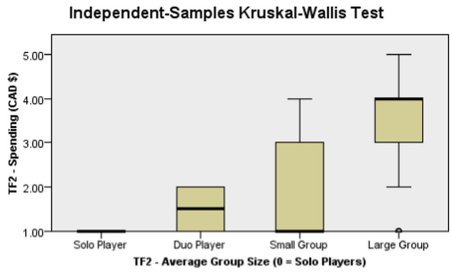


Fig. 7. Spending vs. Average Group Size in *TF2*

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Solo Player-Duo Player	-4.750	11.805	-.402	.687	1.000
Solo Player-Small Group	-6.812	8.854	-.769	.442	1.000
Solo Player-Large Group	-20.386	8.718	-2.338	.019	.116
Duo Player-Small Group	-2.062	8.854	-.233	.816	1.000
Duo Player-Large Group	-15.636	8.718	-1.793	.073	.437
Small Group-Large Group	-13.574	3.879	-3.500	.000	.003

Fig. 8. Spending vs. Average Group Size in *Overwatch* - post-hoc test results.

6.3 Pairing Overwatch and Team Fortress 2

The sample size for this combined data set was 108. The Kruskal-Wallis Test on the effect of Friend List Size revealed a significant difference: H(3) = 22.615, $p < 0.001$. See Fig. 9.

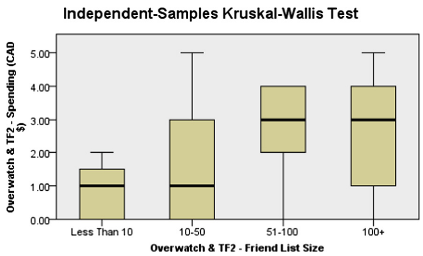


Fig. 9. Spending vs. Friend List Size in *Overwatch+TF2*.

A Dunn's post-hoc test reveals the following significant differences:

- Less than 10 Friends/100+ Friends: $p < 0.01$
- Less than 10 Friends/51–100 Friends: $p < 0.001$
- 10–50 Friends/100+ Friends: $p < 0.05$
- 10–50 Friends/51–100 Friends: $p < 0.01$

For more details see Fig. 10.

The Kruskal-Wallis Test on the effect of the Group Size indicated a significant difference: H(3) = 23.754, $p < 0.001$. See Fig. 11.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-8.417	8.557	-.984	.325	1.000
Less Than 10-100+	-31.786	8.983	-3.539	.000	.002
Less Than 10-51-100	-34.104	9.289	-3.671	.000	.001
10-50-100+	-23.369	7.731	-3.023	.003	.015
10-50-51-100	-25.688	8.085	-3.177	.001	.009
100+-51-100	2.318	8.535	.272	.786	1.000

Fig. 10. Spending vs. Friend List Size in Overwatch+*TF2* - post-hoc test results.

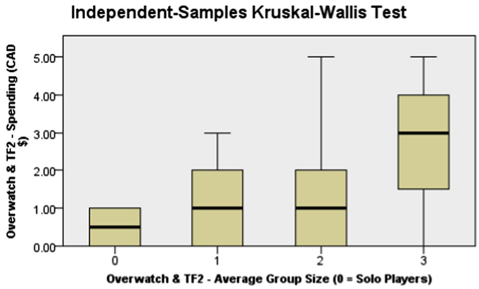


Fig. 11. Spending vs. Average Group Size in Overwatch+*TF2.*

A Dunn's post-hoc test revealed that the sample groups of players who play alone were different from those who play in large groups ($p < 0.05$). The test also revealed a significant difference between small and large groups ($p < 0.001$). See Fig. 12.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Solo Player-Duo Player	-13.556	18.438	-.735	.462	1.000
Solo Player-Small Group	-15.953	16.039	-.995	.320	1.000
Solo Player-Large Group	-42.615	15.920	-2.677	.007	.045
Duo Player-Small Group	-2.398	11.247	-.213	.831	1.000
Duo Player-Large Group	-29.060	11.077	-2.623	.009	.052
Small Group-Large Group	-26.662	6.324	-4.216	.000	.000

Fig. 12. Spending vs. Average Group Size in Overwatch+*TF2* - post-hoc test results.

6.4 League of Legends

The sample size for this combined data set was 71. The Kruskal-Wallis Test on the effect of Friend List Size indicated a significant difference: $H(3) = 14.669$, $p < 0.05$. See Fig. 13.

A Dunn's post-hoc test reveals that the sample groups of those who had less than 10 people on their friend lists were different than those who had between 51–100 ($p < 0.01$) and those who had more than 100 ($p < 0.05$). See Fig. 14.

The Kruskal-Wallis Test on the effect of the average Group Size indicated no significant difference between the average player's Group Size and Player Spending.

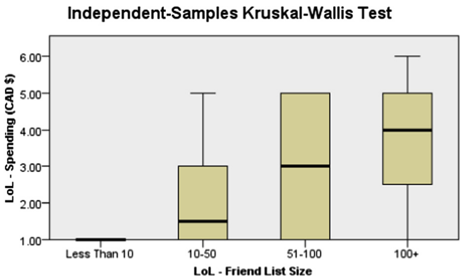


Fig. 13. Spending vs. Friend List Size in *LoL*.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-14.375	9.676	-1.486	.137	.824
Less Than 10-51-100	-24.441	9.845	-2.483	.013	.078
Less Than 10-100+	-30.185	9.421	-3.204	.001	.008
10-50-51-100	-10.066	6.384	-1.577	.115	.689
10-50-100+	-15.810	5.709	-2.769	.006	.034
51-100-100+	-5.744	5.991	-.959	.338	1.000

Fig. 14. Spending vs. Friend List Size in *LoL* - post-hoc test results.

However, it should be noted that the sample size for solo players (Group Size of 0) only consists of two participants and the sample size for duo players (Group Size of 1) only consists of three participants. Therefore, a definite conclusion cannot be reached with regards to correlating group size and player spending in *League of Legends*.

6.5 DOTA2

The sample size for this combined data set was 45. A Kruskal-Wallis Test on the effect of Friend List Size revealed a significant difference: H(3) = 27.774, $p < 0.001$. See Fig. 15.

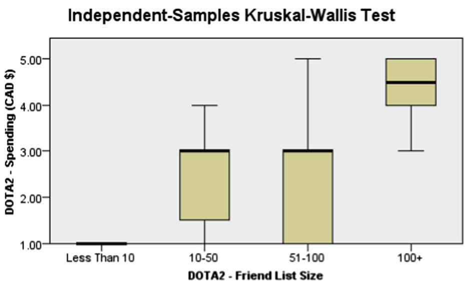


Fig. 15. Spending vs. Friend Size in *DOTA2*.

A Dunn's post-hoc test revealed that the sample groups of those who had less than 10 people on their friend lists were different from to those who had more than 100 people on their friend lists ($p < 0.001$). The test also reveals significant difference between the 10–50 group and 100+ group ($p < 0.05$), and a difference between 51–100 group and the 100+ group ($p < 0.005$). Figure 16.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-11.000	6.196	-1.775	.076	.455
Less Than 10-51-100	-11.750	5.492	-2.139	.032	.194
Less Than 10-100+	-27.536	5.492	-5.014	.000	.000
10-50-51-100	-.750	5.492	-.137	.891	1.000
10-50-100+	-16.536	5.492	-3.011	.003	.016
51-100-100+	-15.786	4.684	-3.370	.001	.005

Fig. 16. Spending vs. Friend List Size in *DOTA2* - post-hoc test results.

The Kruskal-Wallis Test on the effect of the Average Group Size indicated a significant difference: $H_3 = 10.843$, $p < 0.01$. See Fig. 17.

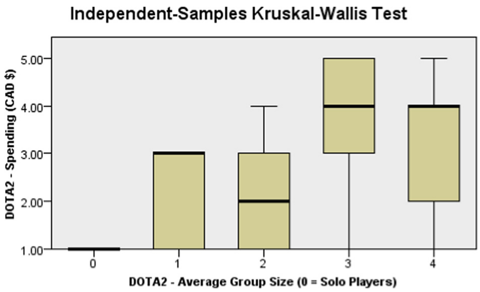


Fig. 17. Spending vs. Average Group Size in *DOTA2*.

A Dunn's post-hoc test with adjusted significances revealed no significant correlation between player's Average Group Size and Player Spending.

However, it should be noted that the sample size for solo players (Group Size of 0) only consists of three participants. Therefore, a definite conclusion cannot be reached with regards to correlating group size and player spending in DOTA2.

6.6 Pairing League of Legends and DOTA2

The sample size for this combined data set was 113 The Kruskal-Wallis Test on the effect of Friend List Size of indicated a significant difference: $H_3 = 36.919$, $p < 0.001$. See Fig. 18.

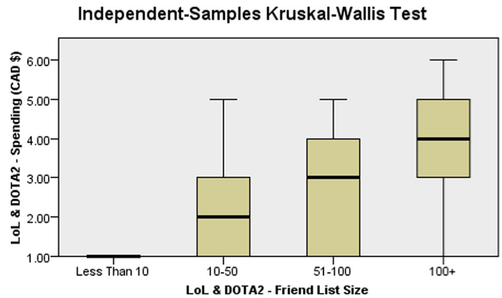


Fig. 18. Spending vs. Friend List Size in *LoL+DOTA2*.

The Dunn's post-hoc test revealed significant differences as follows, after adjustments. See Fig. 19.

- Less than 10 Friends/51–100 Friends: $p < 0.005$
- Less than 10 Friends/100+ Friends: $p < 0.001$
- 10–50 Friends/100+ Friends: $p < 0.001$
- 51–100 Friends/100+ Friends: $p < 0.05$

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Less Than 10-10-50	-25.143	10.620	-2.368	.018	.107
Less Than 10-51-100	-35.919	10.455	-3.436	.001	.004
Less Than 10-100+	-56.268	10.072	-5.587	.000	.000
10-50-51-100	-10.776	8.250	-1.306	.191	1.000
10-50-100+	-31.125	7.757	-4.012	.000	.000
51-100-100+	-20.349	7.531	-2.702	.007	.041

Fig. 19. Spending vs. Friend List Size in *LoL+DOTA2* - post-hoc test results.

The Kruskal-Wallis Test on the effect of Average Group Size revealed a significant difference: $H(3) = 11.298$, $p < 0.05$. See Fig. 20.

A Dunn's post-hoc test with adjusted significances failed to reveal any significant difference between Average Group Size and Player Spending.

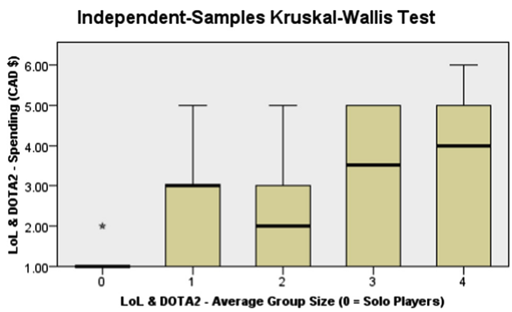


Fig. 20. Spending vs. Average Group Size in *LoL+DOTA2*.

However, as mentioned before, it should be noted that the sample size for solo players (Group Size of 0) only consists of two participants and the sample size for duo players (Group Size of 1) only consists of three participants for *League of Legends*. The sample size for solo players (Group Size of 0) only consists of three participants for *DOTA2*. Therefore, a definite conclusion cannot be reached with regards to correlating group size and player spending in *League of Legends* and *DOTA2*.

7 Discussion

For *Overwatch* we found a significant difference between "Less than 10 friends" and "100+ friends" groups, which suggests a positive relationship between a player's friend list size and their spending. Although the results for the test do indicate a correlation, the correlation shown in the test is weak and may require more data to avoid a false positive.

The results for the test on the average group size in *Overwatch* also indicates a relationship between the size of each player's group sessions and their spending, except for the small group sizes (3–4 players per group). These results appear in the support of our hypotheses.

The results for *TF2* were also in support of H1, where we found a difference between two groups. These differences were between the smallest and the top largest groups.

As originally expected, the limited pool of participants gave us a large margin of error when it came to the higher extremes in player spending. This is especially prevalent in *TF2* and *Overwatch* when studied individually.

When data for those two games were combined the results were stronger. For the friend list size, a significant difference was found between the two smallest groups and the two largest groups. For the average group size, we found differences between the solo and large groups and small group and large group. This also supports our hypotheses.

For *LoL* we found a significant difference between "Less than 10 friends" and "100 + friends" and between "10–50 friends" to "100+ friends". This supports our first hypothesis. It is worth mentioning that for this game there was a larger amount of data that we were able to collect, likely due to the larger player base.

However, there was not enough data points in each group to perform proper tests for H2 for *LoL*, namely the "solo" and "duo" groups, which only had one and two data points respectively.

For *DOTA2* we found a significant difference each time every other group was compared to the "100+ friends" group. Due to a small sample size, however, this could be a false positive.

The was a lack of data points for each group to perform proper tests for H2 for *DOTA2*.

When we combined the data points for *LoL* and *DOTA2* the post hoc test revealed four significant differences (out of six) for the first hypothesis, indicating that the more friends the players have, the more money they spend.

However, after combining the data from *LoL* and *DOTA2* for group sizes, there is still a lack of data to perform tests, as we still did not have enough data for “solo” and “duo” groups. This could be since the majority of our participant data was collected at a gaming event that involved tournament play. As a result, most of the participants were likely from teams, rather than single or partnered players.

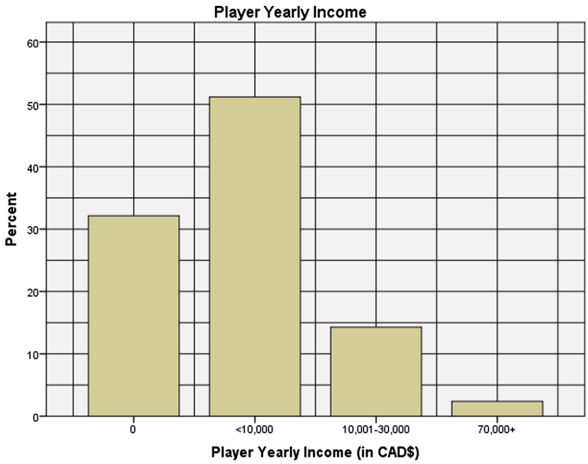


Fig. 21. Overall player income.

Although player income was suspected to be a large factor, most participants reported less than $10,000 per year from employment (Fig. 21). Interestingly, a large percentage of participants still paid for content that did not affect their gameplay. Only seven of the valid participants were part-time students, therefore there is insufficient enough data to determine being under part-time study is a factor in the results. Other variables that we were unable to determine as factors, due to lack of data, were program of study and employment status.

One last variable that was controlled for was gender. The results of the study indicated that gender identity was not a significant factor in affecting player spending in this study, as the average difference between females and males was less than 5%.

8 Limitations

The limitations of the study are as follows:

- Geography: All the surveyed participants were students at the University of Ontario Institute of Technology. Seven were part-time students. Therefore, most participants are from Ontario, Canada.
- Age: Most particiapants were between the ages of 18 and 23.
- Employment Status: 39 unemployed, 37 part-time employed and seven full-time employed.

- The surveyed participants mostly consisted of enthusiast gamers, because one of the paths to distribute the survey was at LANWAR, a local gaming event where students bring their computers onto the campus to play over a 48-h period.
- All the measurement scales were ordinal aside from "age" and player's average "group size".

9 Conclusion

We can conclude that within the limitations of this study, there is a positive relationship between a player's friend list size and their monthly spending in the game. In every tested game with adequate sample sizes, and in the combined cases, we found at least one case of significant differences between a player's friend list size and the player's average spending per month. However, we cannot conclude a definite cause-and-effect relationship between the two variables. For instance, a player could have a large friend list simply due to high overall play time with the game, therefore giving the player more time to accumulate more friends and become more invested into the game, which may result in a positive relationship between play time and player spending. Thus, we believe more research is required to reach a generalized description for the public as a whole.

Although there are cases with no significant differences, as noted before, those cases also have very few samples in the small group sizes. Therefore, we determined those results were inconclusive.

Two cases that should be noted are the *DOTA2* standalone and combined tests for group size. After Bonferroni corrections were applied to compensate for multiple comparisons, there was no significant difference in spending between group sizes. This could be due to low sample sizes of DOTA2's data influencing the overall results, resulting in a false negative.

Player income, with regards to the sample group, does not seem to have an influence in player spending throughout all the games tested. The explanation for this could be that the majority of participants reported less than $10,000 as their yearly employment income. This indicates that they are almost certainly receiving money from other sources, such as loans and/or family support. In most scenarios, this means that players are willing to spend money that they did not earn to purchase in-game content. Therefore, we can conclude that player spending is not directly influenced by their employment income.

To summarize, there is a possible positive relationship between a player's friend list size and their spending between all four games studied, with regards to the population of gaming students at UOIT. There could also exist a possible positive relationship between a player's average group size, the average number of people the player plays a game session with, with regards to *Overwatch* and *Team Fortress 2* for the population of gaming students at UOIT. However, we cannot determine if this is the case for *League of Legends* and *DOTA2*, due to insufficient data.

The results of this study could have an implication that implementing social features into the games can help game developers to increase their revenue.

10 Future Work

In the future we plan to expand the study to include more genres of games to come to a broader conclusion. Additionally, we plan to expand the survey to include the general gaming public, instead of being restricted to just the student population at UOIT. Future work could also involve interventional studies to minimize observer interference and reliance on self-reporting via in-game metrics.

To expand on data collection, Cummings and Sibona [3] argue that crowdsourcing surveys may be a viable alternative to collecting survey data. The data collected via this method eliminates the issue with most of the generalizability issues we found in our study. However, the quality of the data may be compromised if there is still an insufficient number of samples to find a reliable average.

Guo et al. [6] developed a topic model, *Latent Dirichlet Allocation*, to take in a multitude of text information, such as discussion threads and documents. The model then produces a list of topics, determined by the frequency of those words appearing in each document. This allows to user to sort the text into topics relating to their research topic. When our work is expanded to include collecting large quantities of data, we can use this model to assist in sorting out the relevant information.

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