Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

Grønstad, Mathias

Consumer psychology and purchasing behavior in free-to-play games

Which components of free-to-play games drive purchase intention of virtual goods, and how do they relate to the players' psychological needs?

Master's thesis in Entrepreneurship
Supervisor: Aadland, Torgeir
Co-supervisor: Wang, Alf Inge
June 2021

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Kunnskap for en bedre verden

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Abstract

The majority of mobile games today rely on the freemium model in which games are free to download but monetization typically happens through sales of virtual goods within the game environment. Game designers can create demand for such goods by carefully composing the interplay between the game experience and virtual goods sold therein. However, to do this effectively is not straightforward, and research on the topic of mobile game monetization is scarce. This thesis investigates what makes players buy virtual goods in freemium games and how this relates to the player's psychological needs. The main objective of this thesis was to investigate whether free-to-play games can be used to satisfy a player's psychological needs according to Maslow's hierarchical model and whether players are willing to pay to further fulfill these needs. The thesis also investigated the effect several specific game components had on in-game spending.

A confirmatory factor analysis was done based on non-probability purposive sampling by collecting primary data from online Pokémon GO communities. Pokémon GO was used to study the research questions, and nine of its game features were aggregated into three separate groups, serving as indicators for a three-factor Structural Equation Model. Each of the nine indicators had a corresponding independent variable predicting spending behavior. The hypothesized factors in the specified model were the needs for love & belonging, esteem and self-actualization according to Maslow's hierarchy of needs. Structural Equation Modelling was used with maximum likelihood estimation to do parameter estimations. A pilot study (n = 232) was first conducted, followed by a larger primary study (n = 5149). The model was adequately fitted using RMSEA, CFI, TLI, and SRMR. The results suggest that Maslow's psychological needs can be pursued through freemium games, and that the fulfillment of these can be increased by spending money on virtual items inside the game. Spending had the largest effect on the needs for love & belonging, followed by self-actualization needs and esteem needs. Notably, the opposite effect was seen when reversing the association from the factors to spending, indicating that increasingly meeting Maslow's needs may coincide with a reduction in spending. Several features of Pokémon GO predicted increased spending with moderate to high effects, and spending thus acted as a mediating variable for an increased satisfaction of Maslow's needs. The game features with the largest effect on spending were 'raiding with friends', 'unlocking new content', and 'leveling up'. The former encapsulates multiple needs simultaneously, which may explain why it had the highest effect on spending.

Sammendrag

De fleste mobilspillene i dag bruker Freemium-modellen, hvilket betyr at spillene er gratis å laste ned, og inntjeningen vanligvis skjer gjennom salg av virtuelle varer i spillet. Spilldesignere kan skape en etterspørsel for slike varer ved å komponere samspillet mellom spillopplevelsen og de virtuelle varene solgt deri. Men å gjøre dette er det ikke rett frem, og forskning rundt emnet er begrenset. Denne oppgaven undersøker hva som gjør at folk kjøper virtuelle varer i Freemium-spill og hvordan dette avhenger av spillerens psykologiske behov. Hovedformålet med denne oppgaven var å undersøke om gratis spill kan tilfredsstille spillernes psykologiske Maslows behov, og om spillerne er villige til å betale for å ytterligere tilfredsstille disse behovene. Avhandlingen undersøkte også effekten spesifikke spillkomponenter hadde på betalingsadferd i mobilspill.

En bekreftende faktoranalyse ble utført basert på primærdata fra online grupper av Pokémon GO spillere. Pokémon GO ble brukt til å studere forskningsspørsmålene, og ni av spillets funksjoner ble samlet i tre separate grupper, som ble brukt som indikatorer for en trefaktor strukturell ligningsmodell (SEM). Hver av de ni indikatorene hadde også sine respektive uavhengig variabler for å forutsi betalingsadferd i spillet. De foreslåtte faktorene i den angitte modellen var behovene for 'kjærlighet og tilhørighet', 'aktelse' (esteem) og 'selvrealisering' i henhold til Maslows behovshierarki. SEM ble brukt med maksimal sannsynlighetsestimering for å gjøre parameterestimater. En pilotstudie (N = 232) ble først utført, etterfulgt av en større primærstudie (N = 5149). Modellen var tilstrekkelig tilpasset i henhold til testene: RMSEA, CFI, TLI og SRMR. Resultatene antyder at Maslows psykologiske behov kan tilfredsstilles via Freemium-spill, og at tilfredsstillelsen av disse kan økes ved å bruke penger på virtuelle varer i spillet. Kjøp av virtuelle varer hadde den største effekten på behovet for kjærlighet og tilhørighet, etterfulgt av behovet selvrealisering og aktelse. Den motsatte effekten ble observert når assosiasjonene fra betalingsadferd til faktorene ble reversert, noe som indikerer at en økt tilfredsstillelse av Maslows behov kan redusere betalingsvilje. Flere funksjoner i Pokémon GO kunne predikere økt betalingsadferd med moderate til høye effekter, og betalingsadferd fungerte som en indirekte variabel for økt tilfredsstillelse av Maslows behov. Spillfunksjonene med den største effekten på betalingsadferd var "'raiding' med venner", "låse opp nytt spillinnhold", og "å nå høyere nivåer". Den førstnevnte funksjonen kan tilfredsstille flere behov samtidig, noe som kan forklare hvorfor den hadde den høyeste effekten på betalingsadferd.

Abbreviations

AVE	Average Variance Estimate
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
CV	Convergent Validity
DV	Dependent Variable
DVa	Discriminant Validity (DVa)
F2P	Free to Play
GDPR	General Data Protection Regulation
GOF	Goodness-of-Fit
GSEM	Generalized Structural Equation Model
IAA	In-App Advertisement
IAP	In-App Purchase
iOS	iPhone Operating System
IV	Independent Variable
K	Thousands
LV	Latent Variable
MMORPG	Massively Multiplayer Online Role-Playing Games
OS	Operating System
P50	Median
PG	Pokémon GO
RMSEA	Root Mean Squared Error of Approximation
RQ	Research Question
SD	Standard Deviation
SDT	Self-Determination Theory
SEM	Structural Equation Modelling
SRMR	Standardised Root Mean Residual
TLI	Tucker-Lewis Index

Nomenclature

$\boldsymbol{\beta}$	Regression Coefficient
λ	Factor loading
ε	Residual variance
χ^2	Chi-squared

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$Eq.\ 3.2:\quad AVE(\xi_j)\ =\ \frac{\sum_{i=1}^{k}(\lambda_i^2)}{\sum_{i=1}^{k}(\lambda_i^2)+\sum_{i=1}^{k}Var(e_i)}$ 32

$Eq.\ 3.3:\quad CR(\xi_j)\ =\ \frac{\left(\sum_{i=1}^{k}(\lambda_i)\right)^2}{\left(\sum_{i=1}^{k}(\lambda_i)\right)^2+\sum_{i=1}^{k}Var(e_i)}$ 32

1. Introduction

Section 1.1 provides a background to the problem surrounding mobile game monetization. Section 1.2 addresses some of these issues by proposing three research questions.

1.1 Background

The mobile application (app) industry's revenue has grown from virtually zero in 2007, when the first iPhone and the App Store was released, to an expected $189 billion by 2020 (Blair, 2019). Although this remarkable growth has spawned new revenue models, research dedicated to these models is still relatively scarce. In the early days of apps, revenue was generated by premium products, which users had to pay to download. This has changed completely in recent years as the *freemium* model has become increasingly popular, curtailing the ability to charge for apps. Freemium combines the aspects "free" and "premium", meaning the software is free to download, but monetization happens inside the app. The premium model was overtaken by the freemium model as the dominant revenue model during the first half of 2011, and in 2019 over 96% of Android apps were free (AppBrain, 2019).

Monetization of freemium games happens largely by either in-app purchases (IAP) or in-app advertisement (IAA). Whereas IAA entails embedded advertisements inside the app, revenue from IAPs is generated through direct sales of virtual goods, such as coins, materials, accessories, weapons, or other items, which exist solely within the digital environment. Freemium games typically have virtual currencies that users can earn by playing, watching ads, or buying real money. These currencies can then be used to enhance the player's experience by buying certain virtual items or new content. Although the players, in theory, can achieve everything in the game without paying, since they typically can earn virtual currencies by playing, it is often practically impossible due to the sheer amount of time it typically requires. Therefore, games offer to sell players virtual currencies, or virtual items directly, for real money. According to one report (Swrve, 2016), only a tiny fraction of players purchase virtual goods; 1.6% of players make IAPs, and 64.5% of the total revenue is generated from only 0.16% of players. Another study found that 59% of in-app purchases on iPhones come from the top 1% of users, which are more likely to be older men. For example, in the hugely popular game Candy Crush Saga, the average age of purchasers is 40.3 years (Kooti et al., 2017).

Today many developers believe that a hybrid of both IAA and IAP is the most effective monetization structure (Walnut Unlimited, 2019). While revenue from IAA grows in proportion to the size of the user base, the revenue from IAP is more complicated. Most game developers base their monetization strategy on evaluating what works in other games (Walnut Unlimited, 2019), as there is no generally recognized best practice to optimize IAP monetization. To maximize revenue, it is not enough to only increase the user base by developing a great game and marketing it well. Instead, Free-to-Play (F2P) games, which rely on the freemium model, must be designed to entice players to buy virtual goods as frequently as possible inside the app. Game designers manufacture a demand for virtual products by carefully composing the interplay between the gaming-experience and the virtual goods sold therein. However, to do this effectively is not straightforward, and research on the topic is scarce as it is challenging to create datasets across apps that shed light on the effectiveness of different IAPs strategies.

As IAPs make up most of the revenue in F2P games, understanding what may cause purchasing behavior among users ought to be considered imperative for game designers. Due to the sheer size and growth of the mobile gaming market, a deeper understanding of proper monetization of mobile games therefore has important managerial implications as it may help increase market share and profit margins. It is also useful from an academic standpoint, for example in the fields of technology adoption and marketing, which seek to understand consumer behavior on a deeper level.

To the author's best knowledge, there have been three literature reviews related to the topic of purchasing virtual goods, although not focusing on mobile games. The most recent literature review of 29 studies by Syahrizal et al. (2020) investigated why people buy virtual items in video games. They proposed a framework for purchase intention in games by using models from psychology, SOR (Stimulus Organism Response) and from marketing, AIDA (Attention Interest Desire Action,) and a model for playability in video games. The two other studies were a literature review followed by a meta-analysis, both by Hamari and Keronen (2016, 2017), reviewing 34 and 24 studies respectively. They found the value of virtual goods to be context-bound, meaning bound to the virtual environment where it is used. Notably, they looked for *any* reasons why people purchase virtual goods and found the user's attitude towards such purchases to be the dominant factor. Although important, a user's attitude towards purchasing virtual goods is based on personality and is to little extent in the game designer's control. Several studies have looked at personality traits in the context of purchasing virtual goods, e.g., traits such as patience (Ernst, 2018), self-control (Soroush et al., 2015), proneness to bargains (Dinsmore et al., 2017), and intrinsic motivation (Jang et al., 2018). However, since a user's personality is not in the game designer's control, it would instead be more useful from a managerial perspective to investigate how to design games for profit maximization. In their meta-analysis Hamari and Keronen (2017) also revealed some factors affecting IAPs which may be designed for, such as flow state, in-game peer-group size, self-presentation (desire for self-expression), social presence (real human contact in-game), the perceived value of virtual goods, and ease of use (e.g., effortless in user interface). Although several studies have looked at how separate components features of games may predict spending, there is a lack of a broader picture of how to combine these for effective monetization.

1.2 Research Questions

This thesis aims to expand on the knowledge of the previous literature, with a particular focus on sales of virtual goods in the context of mobile games and how this may relate to the psychological needs of players. The thesis first presents a literature review of relevant research done thus far, which identifies factors predicting revenue generation in mobile games. In addition, the review presents an overview of independent variables correlating with IAPs, revenue, and retention, which are again all related measures for a game's commercial success. Secondly, this thesis will investigate the factors influencing players' purchase of virtual goods. To explore this topic, Pokémon GO (PG) is investigated and is a relevant choice as it is one of the most commercially successful freemium mobile games ever made. Moreover, large online communities around the game have been created, making it possible to gather relevant survey data for quantitative analysis.

The focus of this study is analyzing in-app purchasing behavior, and using Maslow's hierarchy of needs as a theoretical foundation (Maslow, A.H., 1970), previously used as a psychological model in consumer behavior theory. The study will investigate whether games can be used as vehicles to fulfill some of these needs and whether players are willing to pay to get further fulfillment of these needs. To the author's best knowledge, no study to date has attempted this. To that end, this thesis proposes three research questions (RQs):

- RQ1: Which components of freemium games drive purchase intention of virtual goods?
- RQ2: Can specific game features contribute to fulfilling a player's need for love & belonging, esteem, and self-actualization as per Maslow's hierarchy of needs?
- RQ3: Can spending money on in-app purchases increase the fulfillment of the above-mentioned needs?

RQ1 will be investigated in the available literature which will be presented in Section 2.3. The results from the first research question will be analyzed in the context of Maslow's hierarchy of needs to propose a multivariate analysis model for answering the second and third research questions. The thesis starts with a presentation of Maslow's hierarchy of needs and is followed by a section applying the theory in video games and discussing how players can meet their psychological needs through such games. The thesis continues to answer the first research question with a literature review on why people purchase virtual goods in video games. The findings will then be categorized and aggregated according to how they fit into Maslow's hierarchy. These aggregated results will then be used to form a set of hypotheses around the research questions. The hypotheses will be tested in the context of the popular mobile game PG, and a multivariate research model is proposed to answer RQ2 and RQ3. A survey is designed to fit the research model and then shared in large online communities with active PG players. The data is then imported to the statistical software package Stata to test the multivariate model.

The study results suggest that Maslow's psychological needs can be met through in games, and that the fulfillment of these needs can be increased by spending money on virtual items inside the game. Notably, effect was reversed when reversing the association from the psychological needs to spending, indicating that increasingly meeting Maslow's needs may coincide with a reduction in spending. Several features of PG predicted increased spending with moderate to high effects. The feature with the largest effect on spending was 'raiding with friends', followed by 'unlocking new content', and 'leveling up'. The former encapsulates multiple needs simultaneously, which may explain why it had the highest effect on spending.

2. Theory

This section presents Maslow's hierarchy of needs and how these needs can be met through video games. The section continues with a literature review on why people purchase virtual goods in video games, and the findings will be grouped according to how they fit into Maslow's hierarchy. Lastly, these aggregated results will be used to form a set of hypotheses around the research questions.

2.1 Maslow's Hierarchy of Needs

Psychology professor Abraham Maslow strived to understand human motivation and developed the theory called Maslow's hierarchy of needs (Maslow, 1970). It has become one of the most recognized theories for human motivation and has been used in consumer psychology (Schütte and Ciarlante, 1998; Kotler, 2012; Ward and Lasen, 2009). The model attempts to describe human motivation by segmenting it into five different needs which motivate action. Motivation is one of the key psychological processes which fundamentally influence consumer responses and can result in purchase decisions. Once a need becomes sufficiently intense as to drive action, it becomes a motive.

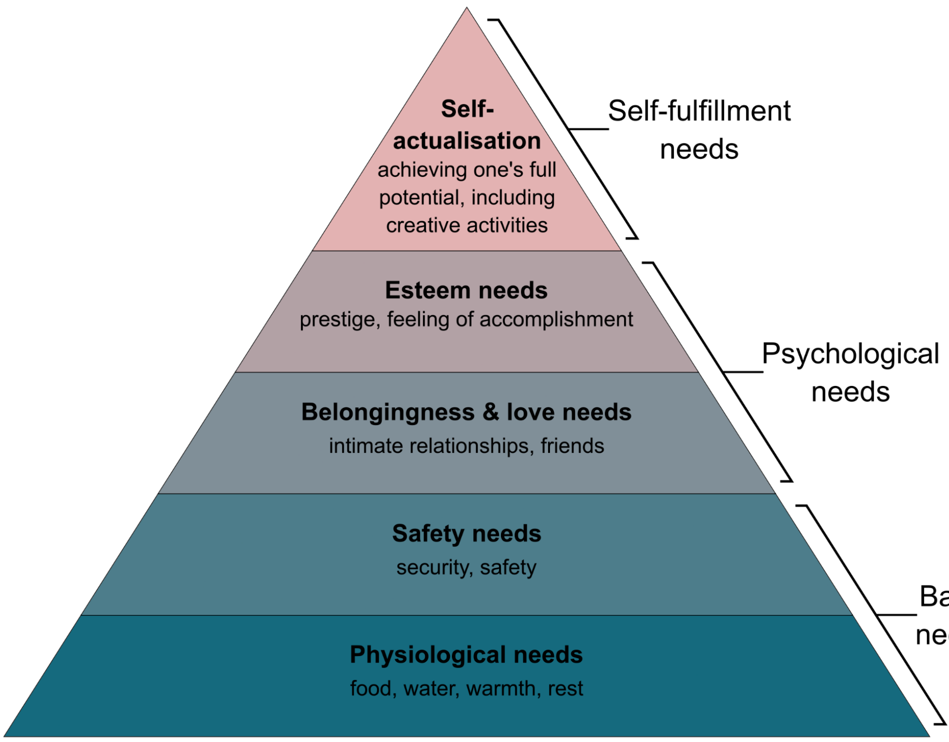

Figure 2.1: Maslow's Hierarchy of Needs by Androidmarsexpress, licensed under CC BY-SA 4.0.

The lowest needs are physiological or biogenic needs, meaning those which are prerequisites for survival. Above that, there are safety needs that are also needed for survival or avoiding harm. Once we have fulfilled these basic needs, we move to more psychological or psychogenic ones like the need for belongingness and love. As social animals, humans crave connection with others, and in fact, a lack thereof can be detrimental to our health. The next psychological need is the esteem need which relates to how we are viewed by others in terms of respect and status. Fulfilling esteem needs makes us feel significant, important, and admired by others. On top of the hierarchy, we find needs for self-actualization, which are about achieving our potential and/or pursuing creative endeavors and mastery.

According to Maslow's theory, the needs are met stepwise, meaning in order to meet a higher level need, the needs of a lower level must first be met. In fact, each need has been found to statistically predict the need immediately above it (Taormina and Gao, 2013). Naturally, the survival needs must come first since without survival; we cannot fulfill any other need. Only when the most urgently pressing need is met, the need above it becomes prominent. On a societal level, we observe that when people's income increases, they tend to spend a proportionally higher amount of their income on activities higher in Maslow's pyramid and less on the lower needs (Ward and Lasen, 2009).

Although the needs are separated in distinct stratified segments, there is overlap between them because the needs are generally never completely satisfied (Schütte and Ciarlante, 1998), but the lowest level unsatisfied need typically generates the strongest impetus for an individual's behavior. Figure 2.2 illustrates that the different needs overlap and have different intensities. The needs may be felt simultaneously rather than sequentially, although we tend to prioritize lower-level needs if they are unsatisfied (Maslow, 1943).

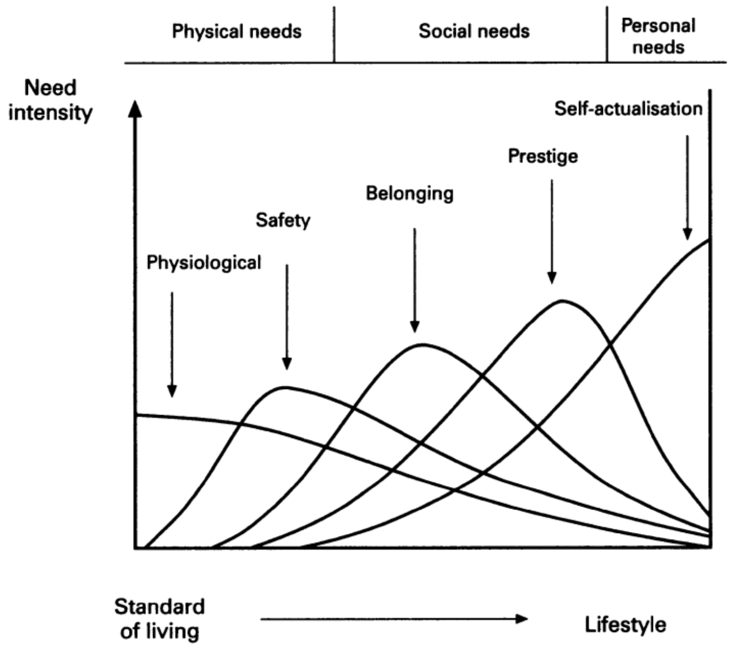

Figure 2.2: Maslow's Hierarchy of Needs with overlap. Illustration from Schütte and Ciarlante (1998)

2.2 Meeting Psychological Needs Through Video Games

One of the central premises of this thesis is that video games can, to some extent, satisfy some player's Maslow needs. In this context, the proposed needs would be limited to connectedness, esteem, and self-actualization since we assume the physiological- and safety needs are prerequisites for people to engage in hedonistic activities like games. For example, a person is unlikely to play a video game for fun if he/she is in danger; neither are games typically built to satisfy biogenic needs. In this thesis, therefore, only the needs for belongingness & love, esteem, and self-actualization are considered relevant in the context of games. For simplicity, we assume that the self-fulfillment needs are also psychological needs, as depicted in Figure 2.3, which is a modification of Figure 2.1. From hereon, referring to psychological needs entails the top three needs in Maslow's hierarchy.

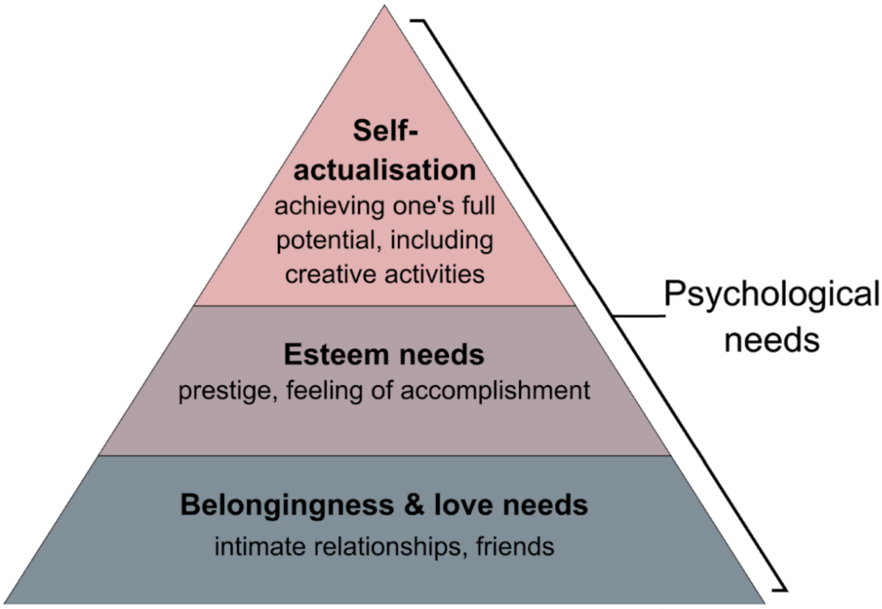

Figure 2.3: Modified "Maslow's Hierarchy of Needs"
by Androidmarsexpress, licensed under CC BY-SA 4.0.

To the author's best knowledge, no study to date has examined the link between purchasing behavior and Maslow's needs in video games, although some have used it as a framework to predict consumer purchase motivation in other contexts (Cui et al., 2021). Moreover, some studies have looked at why people play games through the lens of models for human motivation. Motivation is at the core of making games engaging and fun (Hoden, 2020), and motivation to continue playing a game translates to higher retention rates, which again is a determining factor for purchase intention in games. Retention rate, or loyalty, is a measure of how often a player comes back to the game over a certain period of time. Games are often engaging and fun when they can induce a psychological state of intense focus, where the player sinks into the activity to the point that nothing is more important. This is a state often referred to as Flow, which was first coined by Csikszentmihalyi (1990), and has later been recognized as an important aspect of games in regards to monetization and retention (Alhirz and Sajeev, 2015; Liu and Shiue, 2014; Kao and Chiang, 2015; Su et al., 2016; Hamari and Keronen, 2017; Putra et al. 2019).

Motivation to continue playing social mobile games can also be explained by using Maslow's hierarchy of needs as proposed by Himeno and Tano (2019). Their model could accurately predict the motivation of players to continue playing if their Maslow's needs were being met by playing the game. The study measured players' social needs by the "need of playing with others" and found that social factors in games could accurately predict whether a player would continue playing over time. Esteem needs were reflected in the "need of being more prominent in the game, and being praised". Getting praise from other players in the game made them more likely to continue playing over time. The model also looked at self-actualization needs by the “need of attaining the highest state that the user can aim for within the game”, albeit prediction results on this need were not reported. Other studies have also looked at the importance of social aspects of games and player motivation. Neys et al. (2014) studied why people play video games by applying self-determination theory (SDT). SDT is one of the most widely recognized models for human motivation and has gained more popularity in later years. It is a more recent model which shares many similarities to Maslow’s hierarchy of needs. SDT revolves around three main motivators, which are autonomy, connectedness, and competence. Competence refers to a sense of progression or achievement, which can be either skill-based or not (Hodent, 2020). For example, the player can master game dynamics or improve reaction time and mental capabilities which make them more skilled at a specific game. They can also become more powerful in the game by leveling up their game character, which does not necessarily mean that their skills in playing the game have improved. The second component, autonomy, is about the player’s self-expression in the game by, for example, customization of their game character. The third component, relatedness, refers to meaningful relationships with other people. In their study, Neys et al. (2014) found that both casual- and heavy gamers were motivated to play due to a sense of connectedness through the game, further supporting the importance of the social aspects of games. Alhirz and Sajeev (2015) also found that community and involvement in the game Pokémon GO were associated with continuation of play.

Self-actualization has also been recognized as an important need in games; Richard Bartle, an artificial intelligence and game researcher, who is famous for coining the four player types; achievers, explorers, socializers, and killers (Bartle, 1996) noted that “self-actualization is there at the top of Maslow’s Hierarchy of Needs, and it’s what many games deliver”. Also, Eyal (2015) points out that “rewards of the self are a defining component in video games, as players seek to master the skill needed to pursue their quest. Leveling up, unlocking special powers, and other game mechanics fulfill a player’s desire for competency by showing progression and completion”. Alhirz and Sajeev (2015) found that achievements in the game Pokémon GO were associated with enjoyment which mediated continuation of play. A currently ongoing project by Sharma et al. (2021) is studying a Battle of Royale game through Maslow’s hierarchy of needs. It is an online multiplayer video game with ‘components of survival, exploration, competitiveness, and winning by eliminating all opponents’. Qualitative data from their study indicate that self-actualization needs can be met by winning the games, and love/belongingness and esteem needs can get fulfilled through the game’s social and competitive nature. Esteem needs can also be met by building up a ‘career in gaming’ while also getting acknowledged by other players and achieving a good rank.

The social elements of video games are undoubtedly important, and games are becoming increasingly more interactive through multiplayer features. People may seek to meet their needs for belongingness and love through social game-mechanics in games and virtual worlds. For example, massively multiplayer online role-playing games (MMORPG), like World of Warcraft, are especially rich in such features as guilds, chats, cooperation, and communities. There are even stories of players meeting their future spouses through the game. Mobile games also have an increasing tendency for incorporating more social features, and they have a positive effect on both revenue and give benefits to the player. For example, Pokémon GO (PG), which is one of the highest-grossing mobile games in history, exceeding $1 billion USD in revenue in 2020, has been shown to provide significant social and health benefits to players. A recent literature review of 59 articles on PG by Wang (2021) found the game to increase social motivation, reduce social anxiety, increase social interaction, and improve and strengthen social relationships. These social benefits were seen among friends, families, as well as between generations and strangers.

Many social games also cater to the player's esteem needs as they offer ways for the player to get recognition, status, and feel importance and respect from other players. Customization of one's game character is a pertinent feature in such games, as it allows players self-presentation, and to show off their achievements to others. The game Fortnite had revenue of $2.4 billion in 2018 from sales of "skins". These are virtual items with no utility other than a changed appearance of the game character. Although these skins offer no functional advantage in the game, they are a way for players to show off to each other and to display their achievements for every other player to see. Leaderboard mechanics have similar effects as they are mechanics which display different player's status to peers which allows them to gain respect and status by pursuing excellence and being better than other players.

Some games may, to some players, be vehicles for self-actualization by allowing players to fully realize their potential in the context of the virtual environment. This could mean developing one's talents and abilities and pursuing goals within the game environment. To pursue self-actualization through a game, the player would likely require some degree of self-identification with the game character, and through it, seek achievements and fulfill their potential. This is not all too common in mobile games, which often are simple, but it is more often seen in MMORPG or virtual worlds where players spend large amounts of time and may self-identify with their game character or avatar.

2.3 Literature Review

The literature review was part of the subject "TIØ4530 - Specialization Project", also written by the author, but has been modified to fit the purpose of this thesis. This section describes the phases of the literature review, which answer the first research question (RQ1). The first step of the review consisted of exploratory searches on Google Scholar for industry reports and papers to identify common terminology used. This iterative approach resulted in a collection of search terms and keywords, which was used in formal searches on the Scopus database. Several inclusion criteria were developed to evaluate which studies to include in the review (see Figure 2.4). The result of the review was 39 articles after 215 had been discarded for failing to meet the inclusion criteria. Cross-citations among past review papers were used to expand the literature base to a total of 43 articles. The articles were coded on dependent and independent variables as well as their contexts. Studies that could relate to Maslow's needs were then grouped thematically to create a coherent narrative for their summarization in sections 2.3.4.1 and 2.3.4.2.

2.3.1 Search

The initial exploratory searches were performed on Google Scholar to identify commonly used terminology and keywords in relevant articles. Search terms containing phrases like "in-app purchase", "in-game purchase" and "virtual item purchase" were initially used, and the first two page results were scanned for title, abstract, and keyword sections to find relevant articles and new search terms to be included in the future search iterations. This iterative approach resulted in a search string that was executed on the Scopus database in November 2020. Scopus was used as the main literature source as it includes the AIS, ACM, IEEE, and ScienceDirect libraries and is a relevant archive for studies on buying behavior of virtual goods. The search string consisted of three parts: 1) the action of purchasing, 2) the type of purchase, and 3) the context of the purchase. This string covers the literature focusing on purchases of virtual goods in the context of freemium games, often being mobile apps.

The search was intended to target meta-data such as titles, keywords, and abstracts instead of the entire text and yielded 117 hits on Scopus. Some alternative terms were also included, making the total to 253 papers. The final search string was executed using the following Boolean operators:

TITLE-ABS-KEY (buy OR purchase AND virtual AND goods OR item OR asset AND free-to-play OR game)*
OR
TITLE-ABS-KEY ((feature OR design) AND (revenue OR sales) AND ("mobile game" OR freemium OR free-to-play))
OR
TITLE-ABS-KEY (("In-app" OR "In-game") AND purchase AND (mobile OR freemium OR free-to-play))

2.3.2 Inclusion Criteria

The inclusion criteria were as follows; distinct topic, same or related topic but lacking relevance to the research question (RQ1), not being a research paper, not accessible, and being a duplicate study. The search result was sequentially filtered based on the inclusion criteria and resulted in the following omissions; 184 studies were excluded for being on a distinct topic, e.g., papers regarding detection of fraudulence in IAPs, ethics in the video game business, and gaming addictions. These could, in most cases, be disregarded based on their titles. The remaining articles were more carefully evaluated whether or not to include by reading abstracts. This resulted in 17 articles being excluded for lack of relevance to the research question (RQ1), although being on the same topic. For example, articles about how personality traits influence IAPs were not included. Furthermore, seven articles were omitted for not being research- or conference papers, and four for being inaccessible. Finally, three papers were excluded for being duplicates, meaning they were earlier versions of extended studies or slight variations of other studies using the same data sets. In these cases, the latest study was used.

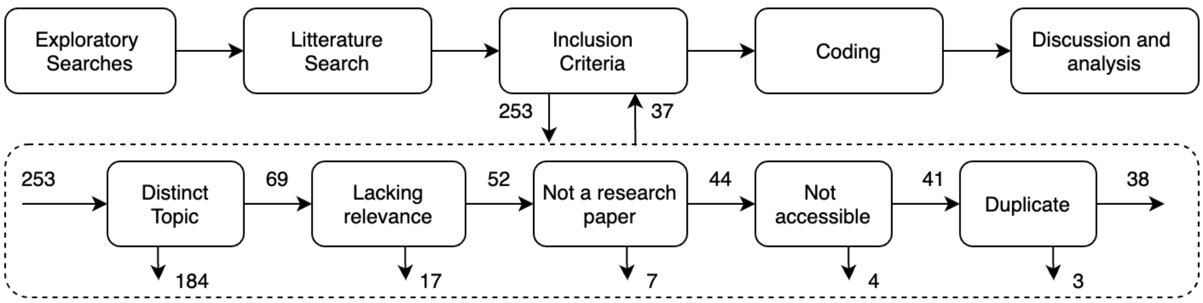

Figure 2.4: Literature review procedure

Lastly, previous literature studies (Hamari and Keronen, 2016 & 2017; Syahrizal et al., 2020) were examined for relevant cited papers that were missed by the formal search on Scopus. This resulted in another five relevant papers, bringing the total up to 43 articles. These additional papers did not show up in the original 253 search hits because they did not exist in the Scopus archive. Of the total 43 articles, 36 were research papers, and seven were conference papers. All of the papers were published between 2007 and 2020.

2.3.3 Coding

The 43 articles were coded on environment types, meaning what kind of context the virtual goods were sold in. There were 22 articles about mobile games, 21 about other online social games or virtual worlds, and five were about apps in general. The studies were also coded on independent variables because not all studies measured the same effects or used the same names. For example, some of the studies measured IAP,s, and others measured revenue. These measures are closely related as IAPs drive revenue in the freemium model. Other studies measured the retention rate, which is known to be a main driver of revenue or IAPs. Some studies used different words for the same independent variables, e.g., interactivity and sociability. Table 2.1 shows the findings with coded effects, independent and dependent variables, along with short descriptions of measures.

The studies were sorted and grouped thematically based on the variables they investigated and measured. The grouping was done to fit the context of the present study, which looks at how they may relate to the player's psychological needs. Some of the main themes identified were social factors in multiplayer games, such as player interactivity, status hierarchies, status-displaying, competition, and cooperation. Other factors were more related to achievement and progress in the game. In Section 2.4, these factors will be grouped together Maslow's needs they most relate to.

2.3.4 Findings

Table 2.1 shows a summary of the findings from 43 articles that help answer the first research question (RQ1):*Which components of freemium games drive purchase intention of virtual goods?* The next two subsections will discuss some of the findings which may relate to social-, esteem- and achievement aspects of games, as these may be relevant in forming the hypotheses regarding Maslow's needs.

Table 2.1: Variables positively correlating with IAP, revenue, or retention

Independent Variables	**Description of independent variables**	**Dependent variable**	**Articles discussing**
Flow	The psychological state of intense focus, where people sink into activities to the point that nothing is more important	IAP, Retention	Alhirz and Sajeev, 2015; Liu and Shiue, 2014; Kao and Chiang, 2015; Su et al., 2016; Hamari and Keronen, 2017; Putra et al. 2019
Retention	How likely users are to continue using the app after a certain period of time	IAP, Revenue	Alhirz and Sajeev, 2015; Atchariyachanvanich et al. 2015; Hsiao and Chen, 2016; Balakrishnan and Griffiths, 2018; Appel et al., 2020;
Playfulness/ Enjoyment	The enjoyment players get from the game	IAP, Revenue, Retention	Alhirz and Sajeev, 2015; Hsiao and Chen, 2016; Stefany, 2014; Chen et al., 2017
Access flexibility	The degree to which a user could choose when and how long to play the game	IAP, Revenue Retention	Hsiao and Chen (2016)
Connectedness/ Community	Individuals are connected to others through the game through communities or groups	IAP, Revenue, Retention	Hsiao and Chen, 2016, Hsieh and Tseng, 2018; Hamid and Suzianti, 2020; Hsu and Lin, 2016
Reward/ achievement	Benefits acquired through the game	IAP, Retention	Hsiao and Chen (2016)
Push notifications	Pop-up alerts sent while the game is not running	Revenue	Alha et al. (2016)

Challenge level	How difficult the game is perceived to be	Retention	Alhirz and Sajeev, 2015; Su et al., 2016; Hamari et al., 2019; Hamid and Suzianti, 2020
Competition	Competitive elements among players in the game	IAPs, Retention	Shi, Xia and Huang, 2015; Kao and Chiang, 2015; Alomari, 2018; Hamari et al., 2019; Hamid and Suzianti, 2020
Interactivity/ Sociability	Interactions between players	IAP, Retention	Alhirz and Sajeev, 2015; Su et al., 2016; Jin et al., 2017; Alomari, 2018
Invite friend	Ability to invite friends via the game itself	Revenue	Alomari et al., 2016; Alomari, 2018
Request friend help	Ability to request help from a friend to help with some task in the game	IAP, Revenue	Filho et al. 2014; Alomari, 2018
Cooperation	Cooperation among players in the game	Revenue	Alomari (2018)
Leaderboards	Ranking of players by some in-game score metric	Revenue	Filho et al., 2014; Alomari et al., 2016; Alomari, 2018
Social hierarchies	Hierarchy- and status structures in the game	IAP	Shi, Xia and Huang, 2015; Mäntymäki, 2015
Number of social connections	The number of in-game social connections	IAP	Wohn, 2014; Shi et al., 2015; Jang et al., 2018
Presentation desire	Desire to present oneself in a social game	IAP	Kim and Chan, 2007; Kordyaka et al., 2018
Identification	The player self-identifies with its game character	IAP	Ko and Park, 2020
Decoration/ customization	Customization or decoration of game character with non-functional virtual items	IAP, Retention	Mäntymäki, 2015; Wang and Chang, 2014; Hamari et al., 2017; Cai et al., 2019
Multi-currency systems	Offering at least two different in-game currencies	IAP	Alha et al., 2016; Wohn, 2015
Virtual currency gambling	Players can win some virtual content by gambling either virtual or real currencies	Revenue	Filho et al. (2014)
Currency tutorial	Tutorial teaching players how to use virtual currency	IAP	Alha et al. (2016)
Offers	Providing special or time-limited offers to players	Revenue	Alha et al., 2016; Hamari et al., 2017; Alomari, 2018
Perceived item value	The player's perception of the value of the virtual item	IAP	Lehdonvirta 2009; Stefany, S., 2014; Yoo., 2015; Marder et al., 2019
Item variation and quantity	Quantity and variation of the virtual items	Retention	Atchariyachanvanich et al. 2015; Guo et al. 2019
Item pricing	The pricing of the different virtual items	IAP	Wohn, 2015; Guo et al. (2019)
Free item/reward video	Ability to gain a free virtual item in the game	IAP, Revenue	Jang et al. (2018, 2019); Lee and Shin, 2017
Waiting-time	The game progress is locked until the player executes a certain task or waits long enough	IAP, Revenue	Filho et al., 2014; Alha et al., 2016; Hamari et al., 2017
Unlocking content	Ability to unlock new content in the game	IAP	Hamari et al., 2017; Salminen et al., 2018

2.3.4.1 Social and Esteem Related Components

Social components in games are regarded as functionalities or features that connect players somehow and allow social interaction, for example, through chats, guilds, or cooperation. Esteem components are also social but differ as they relate to how a player is viewed by others and can include self-presentation, competition, and leaderboards. The social elements of mobile games are some of the main reasons why people play them in the first place (Valho and Hamari, 2019). Social components of games indirectly increase revenue by boosting loyalty to the game (Hamid and Suzianti, 2020), as well as directly impacting revenue by resulting in more IAPs by players (Wang and Chang, 2014; Hamari et al., 2017; Jang et al., 2019). There are several possible reasons for this, for example, peer pressure and the effects of social hierarchies. Generally, premium content tends to include items or features that increase the social value of the service (Hamari et al., 2020).

Alha et al. (2016) studied five top-grossing games with relatively low metascores compared to five low-grossing games with high metascores. A Metascore is a number ranging from 1 to 100 based on weighted averages of critic's reviews, and it indicates how good the game is. Although the small sample size prohibits broad generalizations of the results, the study identified interesting commonalities among these two groups of games, which should be taken into consideration. For example, as opposed to the high Metascore games, the top-grossing ones had more social features like guilds, chats, messaging systems, global maps, ranking systems, or the ability to send and receive virtual resources. Alomari (2018) also found social interactions to be a predominant feature for increasing the revenue of mobile games. These social features included: inviting friends, requesting friend help, line chat, competitive/cooperative play, and leaderboards. Alomari et al. (2016) also studied common features in 48 top-grossing iPhone games, and they found that among 31 features, two of the most important ones for improving revenue generation were "invite friends" and "leaderboards". Filho et al. (2014) also found leaderboards to increase revenue in mobile games. Leaderboards are indirect ways of showing your status and are often used in competitive games. Kao and Chiang (2015) found that competition in mobile games increased purchase intention as players may seek self-assurance by succeeding in competition, and buying virtual items may increase the chance of succeeding.

Shi et al. (2015) studied purchasing behavior in freemium social games and found the social hierarchies to have a significant effect. They found that players in lower hierarchical positions tend to make bigger in-game purchases to climb the social ladder faster. Moreover, players right below the top position tend to be the most aggressive in status competition, and they are more willing to climb in status by means of IAPs. Offering a bonus upgrade to these players tended to increase spending by them. Based on their results, the authors suggested utilizing social hierarchies to influence users to purchase more. Mäntymäki (2015) also found status to be one of the main drivers for purchasing virtual items in social virtual worlds.

Hsieh and Tseng (2018) found that social groups in online games have a large effect on consumers' purchase decisions to buy virtual items, often to enhance their self-image. Some users are highly influenced by other group members, care deeply about their opinions, and seek to conform to the group's norms. Hsu and Lin (2016) also found such social identification enhances purchase intention and retention.

Social engagement in the form of interactivity and sociability can boost sales of virtual items (Jin et al., 2017), and users are progressively more likely to spend money on online games as their number of social connections in the game increases (Wohn, 2014; Shi et al., 2015; Jang et al., 2018). However, having too many friends curbs it, which may be attributed to information overload (Zhang et al., 2017; Mäntymäki and Salo, 2013).

The players' desire for self-presentation has been shown to positively affect purchase intention (Kim and Chan, 2007; Kordyaka et al., 2018). This is related to the phenomenon of self-identification with-, and attachment to one's own game character, which also increases a player's willingness to spend money on their game character. Players may buy items for their game character, and these items are for decoration or expressing an appearance, or they can increase the character's powers in the game (Ko and Park, 2020). Mäntymäki (2015) also found decoration to be one of the main drivers for purchasing virtual items in social virtual worlds. Customization is often used in social games to allow players to differentiate themselves from others, but pure customization does not bring value to the core gameplay. Personalization of a player's avatar or belongings has been associated with higher purchase motivation (Wang and Chang, 2014; Hamari et al., 2017). Cai et al. (2019) also found individual expression to be a determining factor for purchase intention in the popular game Fortnite where players can buy skins for their characters. When buying virtual items to customize their avatar, exclusivity and function are considered key factors for motivating purchase intention (Cleghorn and Griffiths, 2015). Marder et al. (2019) found that for non-functional items, the hedonic and social motivations were the dominant factors for purchasing them. Yoo. (2015) suggested an increased purchase intention when virtual items provided the player with an opportunity to display themselves to others. An increasing perceived value of a virtual item was associated with whether a player's self-perception was enhanced by the item. Wohn (2015) found that the big-spending players typically bought items with decorative purposes instead of functional value, and the smaller spending players tended to prefer consumable-type items. For game designers, she suggested keeping the price range for consumable items narrow, because small spenders buy those items. For avatar-related items, she suggested keeping a larger price range and to create visually unique items or limited-edition items that may be appealing to high spenders.

2.3.4.2 Achievement Related Components

Unlike the social and esteem components, achievement relates to progression within a game, which can be in terms of unlocking new content, leveling up, or improving. It is evident that achievement in some cases can be tightly linked to esteem needs since it is a way to become better in the game and receive recognition, respect, and admiration from peers. However, achievement-related components can also be studied in isolation from esteem-related components in single-player games or parts of multiplayer games which can be played alone. For example, many games have achievements locked or restricted for some time duration, but players can skip waiting time by paying. Several studies have found time-skipping to be positively associated with revenue (Filho et al., 2014; Hamari et al., 2017; Alha et al.. 2016). Progress, or restriction thereof, can also be linked to social factors such as cooperation; for example, a feature of "requesting friend's help" was positively correlated with mobile game revenues. In this feature, the game progress is locked until players execute either of the following actions: wait for a fixed time, request help from a friend, or spend real money.

Unlocking new content has been shown by some researchers to be the most important reason for making in-game purchases (Hamari et al., 2017; Salminen et al., 2018). This is a mechanic where some game content is restricted or unavailable to the player until they have performed a certain amount of tasks within the game, or alternatively by paying for unlocking the content. Progression is also a key element of most games and is rooted in extrinsic motivation. This is why games often have level- or evolvement systems, which Filho et al. (2014) found to give players a feeling of progression in games, and also to be correlated with a game's grossing rank. Progression and achievement can be measured in terms of rewards gained in the game, and Hsiao and Chen (2016) found that rewards could increase player loyalty which also increases IAPs. In their paper, they gave a practical suggestion for encouraging loyalty by introducing daily activities or rewards, e.g. login rewards or play bonuses. Achievement and progression rely on the extrinsic motivation of the player to pursue goals within the game environment, which is a key game-mechanic for monetization.

2.4 Hypotheses

Creating a concise separation between which game-feature may help fulfill the different Maslow's needs is not straightforward. For example, customization may be a form of self-expression through creativity and thus target self-realization. However, customization may also be a way to show off and pursue esteem needs by getting respect and admiration from others. Games are often complex, and many of these factors work in an intricate interplay with each other, which makes it difficult to design studies that adjust for such confounding factors and to isolate the effect of each variable. Nevertheless, this section will present an attempt to segregate different game components into groups based on how they may help satisfy Maslow's needs. Extracting relevant features from Table 2.1 gives the foundation for Table 2.2 below, which presents a proposed segregation of how different game components affecting purchase intention also may relate to Maslow's needs.

Table 2.2: Game specific factors in the context of Maslow's hierarchy of needs

Need	Game components	Articles discussing related factors
Self-actualization	Reward/achievement, Challenge level, Identification, Unlocking content	Filho et al., 2014; Hsiao and Chen, 2016, Su et al., 2016; Hamari et al., 2017; Salminen et al., 2018; Hamid and Suzianti, 2020; Ko and Park, 2020
Esteem	Leaderboards, Competition, Self-presentation, Social/status hierarchies, Decoration/customization	Kim and Chan, 2007; Filho et al., 2014; Wang and Chang, 2014; Shi, Xia and Huang, 2015; Kao and Chiang, 2015; Mäntymäki, 2015; Alomari et al., 2016; Hamari et al., 2017; Alomari, 2018; Kordyaka et al., 2018; Cai et al., 2019; Hamari et al., 2019; Hamid and Suzianti, 2020
Belonging-ness & love	Cooperation, Invite friends, Interactivity/Sociability, Number of social connections, Connectedness/Community/Groups, Request friend's help	Filho et al. 2014; Wohn, 2014; Shi et al., 2015; Hsiao and Chen, 2016; Hsu and Lin, 2016; Su et al., 2016; Jin et al., 2017; Alomari et al., 2016; Jang et al., 2018 Alomari, 2018; Hsieh and Tseng, 2018; Alomari 2018; Hamid and Suzianti, 2020

One of the main premises of this study is that the features of Table 2.2 can measure a player's fulfillment of different Maslow needs and is the basis for the first set of hypotheses. We will investigate three game components for each of the three psychological needs, forming the nine hypotheses H1a to H3c. We hypothesize that each of these nine game components can help fulfill the player's psychological needs through the game. In Section 2.2 we have seen that these psychological needs are important in games, and in some cases can predict player behavior. However, there are no studies to date that have directly validated these hypotheses before, and the premise of this thesis lies on the assumption that the selected nine game components can be used as indicators for these Maslow's needs. Since it is difficult to create questions that directly measure to which extent the different

Maslow's needs are met, we use instead related key terms, which are typically used to describe the different needs as specified in Table 2.3. Associated and shorter variable names to be used in the research model are also introduced in Table 2.3.

Table 2.3: Descriptive measure of Maslow's needs along with variable names

Maslow Need	**Variable name**	**Descriptive measure of need**
Self-actualization	Achievement	Perceived feeling of self-realization through progress and/or achievement
Esteem	Esteem	Perceived feeling of respect and/or status
Belongingness & love	Social	Perceived sense of belonging and/or connectedness

Furthermore, the study will investigate whether these game components individually can be predictors of higher spending on IAPs in games, which results in nine more hypotheses; H4a to H6c. There is evidence from previous studies that support these hypotheses, as discussed in sections 2.3.4.1 and 2.3.4.2, and the specific supporting studies are listed in Table 2.2.

Lastly, the study will examine whether spending money on IAPs can predict a player's higher fulfillment of their Maslow's needs, forming three more hypotheses; H7 to H9. Put in other terms, will people spend real money in a game to better meet their needs for belongingness, esteem, and self-actualization? There are no previous studies directly supporting these hypotheses but we can again turn to the aggregate of individual studies in sections 2.3.4.1 and 2.3.4.2 and the supporting arguments in Section 2.2 to justify the investigation of these hypotheses.

The complete set of the proposed 21 hypotheses are:

- H1a: Unlocking new content gives a perceived feeling of self-realization through progress and/or achievement.
- H1b: Evolving or powering up game characters or content gives a perceived feeling of self-realization through progress and/or achievement.
- H1c: Leveling up a game character or avatar gives a perceived feeling of self-realization through progress and/or achievement.
- H2a: Competition with other players gives a perceived feeling of respect and/or status.
- H2b: Having the best or rarest content among one's friends gives a perceived feeling of respect and/or status.
- H2c: Being the highest level among one's friends gives a perceived feeling of respect and/or status.
- H3a: Having friends in the game gives a perceived sense of belonging and/or connectedness.
- H3b: Interaction with other players gives a perceived sense of belonging and/or connectedness.
- H3c: Cooperative play with friends gives a perceived sense of belonging and/or connectedness.
- H4a: Unlocking new content is a determining factor for making in-app purchases.
- H4b: Evolving or powering up game characters or content is a determining factor for making in-app purchases.
- H4b: Leveling up faster is a determining factor for making in-app purchases.
- H5a: Competition with others is a determining factor for making in-app purchases.

- H5b: Having the best or rarest content among friends is a determining factor for making in-app purchases.
- H5c: Being the highest level among friends is a determining factor for making in-app purchases.
- H6a: Having friends in the game is a determining factor for making in-app purchases.
- H6b: Interactions with other players is a determining factor for making in-app purchases.
- H6c: Cooperative play with friends is a determining factor for making in-app purchases.
- H7: Spending money on IAPs gives a stronger feeling of progress and/or achievement.
- H8: Spending money on IAPs gives a stronger feeling of respect and/or status.
- H9: Spending money on IAPs gives a stronger feeling of belonging and/or connectedness.

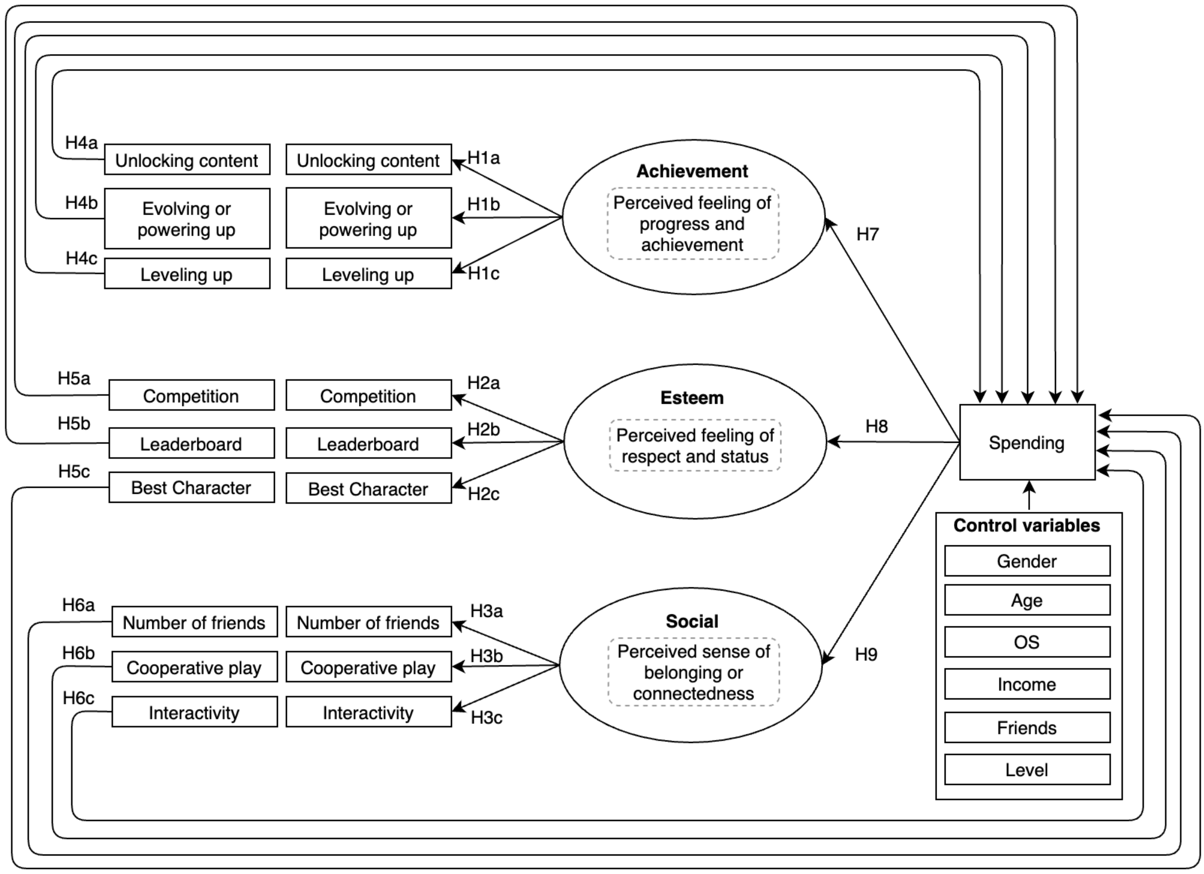

Figure 2.5: Research Model

The set of hypotheses are depicted in the research model in Figure 2.5. The Maslow's needs in the center of the model are psychological constructs that are not directly measurable but instead measured indirectly by giving rise to three indicators each (H1a to H3c). Each of these indicators have a corresponding independent variable predicting spending (H4a to H6c) which are being controlled for by six control variables. Spending is also considered a mediating variable as it is used to predict the psychological constructs (H7 to H9). The model will be more thoroughly explained in Section 3.4, presenting Structural Equation Modeling, which is a suitable tool for statistical analysis of multivariate models with latent psychological constructs like the one in Figure 2.5.

3. Method

This section puts the hypotheses formed in Section 2.4 in the context of the popular mobile game PG, and presents a survey design to fit the research model. Structural Equation Modeling is presented as a tool to perform multivariate analysis for answering the second (RQ2) and third (RQ3) research questions. Lastly, some results from the pilot study are presented.

3.1 Study Context

Based on Table 2.2, a set of features from Pokémon GO (PG) was selected as independent variables and grouped into three themes, achievement-, status- and social components. The most relevant game-specific features were picked based on what was offered through PG, and which of them were thought to have the most relevance to Maslow's needs. The proposed selection was qualitatively evaluated with help from experienced PG players to make sure they were relevant to the game and the context of the present study. Other configurations of variables could have been chosen and would possibly yield different results. Extracting the different game-specific factors from Table 2.2 and finding corresponding game features in PG resulted in Table 3.1 below.

Table 3.1: Game features in Pokémon GO grouped according to which Maslow's needs they meet the most

Maslow Need	**Features in Pokémon GO grouped into components**	**Feature description**
Self-actualization	Achievement components: 1. Unlocking content 2. Evolving or powering up their Pokémons 3. Leveling up their Pokémon trainer	1. Achieving new items, e.g. virtual apparel or rare Pokémons, which requires significant playtime. 2. Making your Pókemons better and more powerful. Typically this means achieving a few very strong pokémons and neglecting the others. 3. Achieving a higher level with your game character which takes exponentially longer time as you progress
Esteem	Esteem components 1. Competition with other players 2. Pokémon power and rarity relative to friends 3. Pokémon trainer level relative to friends	1. Battling other player's Pokémons to see who has the most powerful ones 2. How powerful and rare your pokémons are compared to those of people in your friend list 3. How high level you have reached compared to that of people in your friend list
Belongingness & love	Social components 1. Having friends in the game 2. Interacting with other players 3. Raiding with friends	1. Having mutually added each other in their friend lists in the game. Allows for interaction and viewing each other's stats 2. Interactions can be for example battling together, taking over pokégyms, sending each other gifts, or walking together to catch Pokémons 3. Raiding is an activity where you cooperate with other players to take down a large boss which neither of you could do by yourselves.

3.2 Survey Design and Data Collection

The complete survey with results can be found in Appendix B, but this section gives an overview of its design and purpose. The survey started with a short description of the purpose of the study, explained abbreviations used, and ensured participants' anonymity. No data was gathered which could be used to identify participants, and no GDPR approval was needed to conduct the study. The survey consisted of 28 questions where six were regarding CVs, nine for measuring indicators, nine for IVs, and a final question was added to gather qualitative answers about reasons to spend money in the game. In addition, there were three questions asking about the importance of the different needs in regards to spending. These were intended to act as dependent variables alongside the factors but were omitted from the SEM analysis as they were not needed. All questions were phrased in the same manner to reduce the systematic error caused by inconsistent wording.

Except for the control variables, all questions were phrased on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). The questionnaires for the indicators (H1a-H3c) were phrased according to the proposed descriptive measures of Maslow's needs, as seen in Table 2.3. The three psychological needs, which were not measured directly, would give rise to these nine indicators as will be explained in Section 3.4.1. The descriptive words that are commonly used do describe the different needs used in the items as they would be more relatable for most people than the concepts of social-, esteem- and self-achievement needs themselves. For example, "[...] gives me sense of belonging and/or connectedness" would be a more relatable term than "[...] meeting my needs for love & belonging", and the "Interaction"-indicator for social needs was measured with the following item: "Interaction with other players gives me a sense of belonging and/or connectedness". All indicators were measured in a similar manner. The IVs (H4a-H6c) predicting spending were measured with phrasing such as "[feature] is a determining factor for me to spend money on IAPs", according to the features in Table 3.1. The last question asked participants the biggest reason why they would spend real money in the game. This question was not mandatory to answer but got 4359 out of 5149 responses. These qualitative answers were not to be used in the SEM analysis but rather to gain additional insight into purchasing behavior in the game.

Study participants were targeted from online communities for PG players in May 2021. The approach has the advantages of being a cheap and time-effective way of getting a high quantity of respondents from a specific and relevant demographic as they can be found in large online communities for PG. Five large public Facebook groups for PG players were selected for gathering survey participants. Details about these groups can be seen in Appendix A. It was considered to incentivize participation by offering gift cards to random participants, but this was not needed as there was sufficient participation with no monetary incentive. One tactic used to increase response rate was, in the beginning and end of the survey text, to encourage participants to comment "done" on the Facebook post that linked to the survey. The effect of this was that every comment would push the Facebook post to the top of the Facebook group for other members to see. Furthermore, participants who commented on the post would trigger the Facebook algorithm to show this comment in their friends' newsfeed, thereby increasing participation and inducing a viral spread. The pilot survey got 232 respondents, and the main survey got 5149 respondents.

3.3 Data Encoding

The data from the survey was exported from Google Forms and encoded using nested if-statements in Excel before it was imported to the statistical software package Stata/MP v. 16.1. Many of the questionnaires resulted in categorical variables which needed preprocessing before being applied for regression in the model, e.g., non-numeric data first had to be encoded from strings to byte and then ordered. Encoding could alternatively have been done in Stata using the *encode* command along with the *label* command to create new numerical variables which are labeled with order. Dichotomous variables like OS were encoded 0 for Android and 1 for iOS, and similarity for gender; 0 for female and 1 for male. This order is done to test for positive associations as previous research has shown iOS users and males to spend more money on IAPs.

3.4 Structural Equation Modelling

Structural Equation Modelling (SEM) is a multivariate statistical analysis technique used to analyze structural relationships, and it is frequently used in social sciences (Bollen and Noble, 2011). As opposed to many other statistical methods, SEM can be used to analyze relationships between multiple dependent and independent variables and latent variables that are hypothetical constructs not contained in the data set but rather can be inferred from observed variables (Tabachnick and Fidell, 2013). There are several types of SEM (Mehmetoglu and Jakobsen, 2016), but the most commonly used and the most suitable for the current research model (Figure 2.5) is a SEM combining multiple regression with confirmatory factor analysis (CFA). This allows for the measurement of several latent constructs. While *exploratory* factor analysis is used to identify groups of strongly correlated items representing their own factors, CFA a priory imposes restrictions such as the number of factors and their indicators beforehand. SEM/CFA is a suitable method since we already know which factors we have hypothesized and which are their indicators measured in the survey questionnaires. This type of SEM is well suited for answering research questions where the key constructs are complex or multifaceted but known beforehand, such as psychological concepts like Maslow's needs. Psychological constructs like these are often challenging to measure since they are not directly observable or measurable in people. They are typically multifaceted as it is difficult to come up with a single questionnaire to measure them, but instead, they each require several indicators, which is why CFA is used. SEM as a CFA method uses inferential statistics for a priori theory testing of known constructs. While a theory is an abstract set of ideas linking together concepts which may approximate reality, a model is a representation of a theory (Bollen, 1989). The theory being tested in the present study is whether certain Maslow's needs can be met through mobile games and if players are willing to spend money on IAPs in order to increasingly meet these needs. The sequential process of CFA/SEM is model specification, model identification, model estimation, model assessment, and model modification (Mehmetoglu and Jakobsen, 2016).

Once a relationship between different variables is proposed we define a path diagram, or model specification, which is an illustrated representation of the system of equations to be solved (Bollen, 1989). The path diagram consists of the different variables with arrows representing their relationships, along with associated error estimates. The variables in the SEM path diagram are called latent-, exogenous- (independent) and endogenous (dependent) variables. Unidirectional arrows point from exogenous or independent variables (IV) to endogenous or dependent variables (DV). The unidirectional arrows are denoted with regression coefficients $\boldsymbol{\beta}$ (beta) measuring the effect the IV has on the DV, while bidirectional arrows represent covariances that have no direction of effect. When the different variables are measured on different scales, we must use standardized coefficients which can range from -1 to 1. If the standardized coefficient is below 0.09, it is said to have a small effect; if it is between 0.09 and 0.2, the effect is moderate, and coefficients greater than 0.2 indicate large effects (Mehmetoglu and Jakobsen, 2016).

SEM is a large sample technique that relies on covariances to estimate parameters, and like correlations, covariances become less stable with small samples. Covariance associations can be due to a dependence on some third variable, or there can be a casual and unspecified relationship (Bollen, 1989). A covariance between two variables is the cross-product of the deviation between one variable and its mean and the deviation between the other variable and its mean (Tabachnick and Fidell, 2013). Correlation is a similar measure to covariance, but it also retains information about the scales of the variables.

A variable in SEM can be both exogenous and endogenous, meaning it has arrows pointing at it and away from it, respectively, depending on model specification (Bollen, 1989). The DVs also have residual variance (sometimes called disturbance), denoted ε (epsilon), and represents the part of the dependent variable that is not explained by its IVs or predictors. The error consists of the systematic error and the random error. In surveys, the systematic error can come from bias due to the phrasing of the questionnaire, and a larger sample does not average out this type of error. The random error happens as participants are just as likely to underrate as overrate on questionnaires and are averaged out by large samples.

3.4.1 Latent Variables

Latent variables (LV) are also called factors, constructs, or unobserved variables (Tabachnick and Fidell, 2013). LVs have several definitions but are typically considered hypothetical constructs which are not directly measurable but instead are constructs of multiple observed behaviors or measured variables (Bollen, 2002). LVs are not observed in the dataset but can be thought of as the underlying cause of observed variables, which can be endogenous or exogenous. These are indicators that we believe are caused by the underlying latent construct. LVs are denoted with ξ (xi) and are represented as ellipses in the SEM diagram with its arrows pointing towards its measured variables or indicators, and each LV has two or more indicators. The fact that the arrows point away from the construct may seem counterintuitive as one might think that the indicators cause the construct. However, from a psychometric's standpoint, the constructs give rise to the indicators, even though mathematically, it is the other way around. These arrows are annotated with factor loadings λ (lambda), and the constructs have residual variances. The factor loadings operate like regression coefficients, meaning a one-unit change in the LVs coincides with a λ-unit change in the expected value of the observed variable (Bollen, 1989). The LVs in the research model (Figure 2.5) are love & belonging (shortened so Social), esteem[1] and self-actualization (shortened so Achievement), and they give rise to the measures of the items in the respective game components. This means that, for example, a higher degree of self-actualization in one participant would result in them giving a higher rating on the questions regarding the corresponding indicators. The LVs in this model are also dependent variables as spending has arrows pointing at them.

3.4.2 Exogenous/Independent Variables

Exogenous variables lie outside of the mode, and can be thought of as IVs (Bollen, 1989). In the SEM diagram these have no arrows pointing at them. The IVs in Figure 2.5 are the control variables, and the game specific features which have arrows pointing at spending. The residual errors which are pointing to their DVs are also considered IVs (Tabachnick and Fidell, 2013).

[1] Infact, Bollen (2002) specifically points out self-esteem as an example of a latent variable

3.4.3 Endogenous/Dependent Variables

Endogenous variables are determined by variables within the model and can be thought of as DVs in the SEM model as they are depending on the system of equations (Bollen, 1989). In the SEM diagram these have arrows pointing at them. The endogenous variables in Figure 2.5 would be spending, and the indicators that depend on the LVs, and the LVs themselves since they are also predicted by spending. Spending is also a mediating variable as it is used to predict the LVs.

3.4.4 Control Variables

There are several variables the model should control for as they are expected to influence the purchasing behavior. These variables are exogenous in the SEM model and six such have been deemed important: gender, age, income, operating system (OS), number of friends in the game and highest level achieved in the game. Previous research has shown that gender, age, and income may affect purchase intention and the amount of money spent (Hsiao and Chen, 2016; Kooti et al., 2017). For example, higher-income and older males generally spend more money on in-app purchases. The OS also should be controlled for since, according to industry reports (AppsFlyer, 2016), iOS users spend nearly 2.5 times more money than Android users. However, a recent study on PG by Hsiao et al. (2019) found income, OS, and gender to have non-significant associations to purchase intention. The reason that the number of friends in the game is controlled for is that we are measuring constructs that may depend on this number. Moreover, the number of friends in games has been shown to correlate with higher spending by the player (Wohn, 2014; Shi et al., 2015; Jang et al., 2018; Wang and Loutfouz, 2019). Lastly, we control for the players' level in the game since it is correlated to how long the user has played the game, and again, longer use coincides with a higher retention rate, which again is one of the main predictors of purchasing behavior (Alhirz and Sajeev, 2015; Appel et al., 2020; Balakrishnan and Griffiths, 2018; Atchariyachanvanich et al., 2015; Hsiao and Chen, 2016). Further, a higher-level player may have had time to accumulate more friends within the game. However, a recent study on PG by Hsiao et al. (2019) found playtime to have a non-significant association to purchase intention.

3.4.5 Model Specification

Using the variable definitions above, a hypothesized model can be redrawn from Figure 2.5 as a path diagram in Stata; Figure 3.1 shows this *model specification*. The hypothesized factors are social (shortened from love & belonging), esteem, and achievement (shortened from self-actualization). Note that for readability, the indicators are annotated *_LV,* in the end, to signal that they are associated with Latent Variables and not to be confused with the independent variables ending with *_IV*.

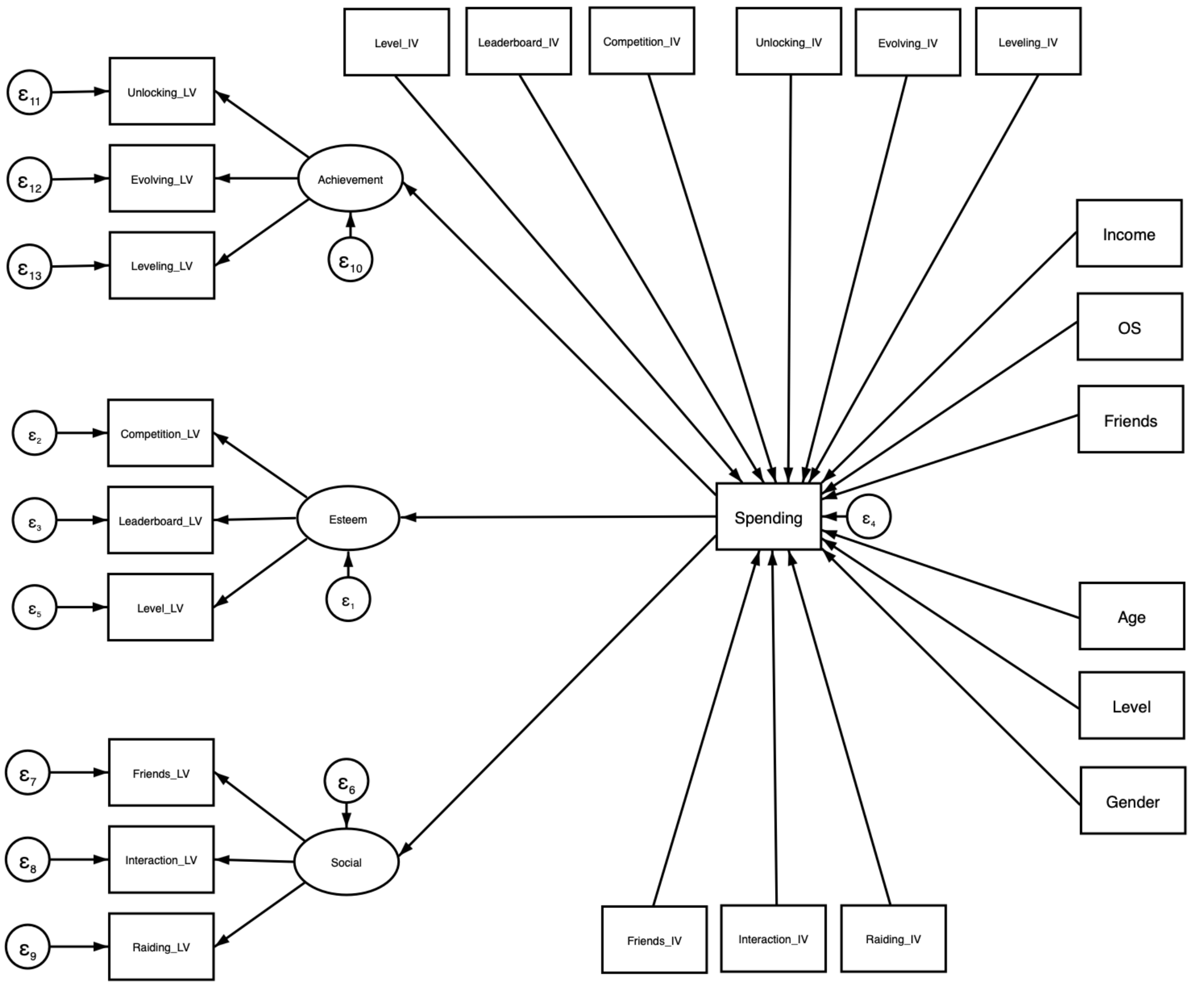

Figure 3.1: Model Specification of SEM path diagram constructed in Stata from Figure 2.5

The model specification is a graphical representation of the set of equations to be solved, and the parameters of the model are estimated from the data (Tabachnick and Fidell, 2013). The parameters are then used to produce an estimated population covariance matrix which is used to determine model fit. However, these estimations can only be done on models that are identified, meaning that there is a unique numerical solution for each parameter in the model.

3.4.6 Model Identification

Model identification is about the balance of known and unknown pieces of information to find unique estimates of unknown parameters in a set of equations in the specified model. The set of equations cannot be solved unless the number of freely estimated (known) parameters are greater than the unknowns (Bollen, 1989). The known information in SEM are variances, covariances, and means of observed variables, while the unknown information is the parameters to be estimated. Models can have three levels of identification:

- Unidentified: knowns < unknowns
- Just identified: knowns = unknowns
- Overidentified: knowns > unknowns

To find whether a model can be identified, it first requires counting the number of data points and parameters to be estimated. These consist of variances, covariances, and means of the observed variables. For smaller models, we can easily count this, but for larger models, the number of known data points are often calculated using the following equation:

$$Eq.\ 3.1:\quad number\ of\ known\ parameters\ =\ \frac{p(p+1)}{2}$$

where p is the number of measured variables. The hypothesized model has 25 measured variables, which give 325 known data points according to Eq. 3.1. Next, the unknowns are the number of parameters to be estimated, i.e., the sum of the path coefficients, factor loadings, error variances, and covariances in the hypothesized model. In Figure 3.1, we see this number totaling 40 parameters to be estimated, of which nine are factor loadings, 18 are path coefficients, and 13 are variances. This gives 325 - 40 = 285 degrees of freedom, and the model is overidentified, meaning it meets the necessary prerequisite for proceeding doing the SEM analysis. Generally, the more variables or parameters used, the more the solution improves. However, this also comes at the cost of a lowered degree of freedom. If there are more parameters than data points to be estimated, the model is underidentified, and estimation of the parameters cannot be done. In such cases, the number of parameters must be reduced by fixing, constraining, or deleting some of them. Model identification is the second step after model specification, but before running the model to analyze the results, it is also important to assess the validity and reliability of its constructs; otherwise, there is a risk that the results are of little use.

3.4.7 Validity

Validity refers to whether something measures what it is supposed to (Bollen, 1989). In SEM, this refers to whether the indicators adequately can measure their constructs, and we commonly measure two types of validity of our constructs, namely convergent- and discriminant validity. Convergent validity (CV) means that the indicators of a construct share a high portion of variance, and it measures to what extent the indicators reflecting the same construct are positively correlated. In the present model, it measures whether the survey questions reflect their corresponding factors. The factor threshold for the loadings of all indicators of each factor must exceed 0.5 (Hair et al., 1998), and each construct's average variance extracted (AVE) must exceed 0.5, and CV must exceed 0.7 (Fornell and Larcker, 1981). AVE measures CV by how indicators converge together and can be calculated from the following equation:

$$Eq.\ 3.2:\quad AVE(\xi_j) = \frac{\sum_{i=1}^{k}(\lambda_i^2)}{\sum_{i=1}^{k}(\lambda_i^2) + \sum_{i=1}^{k} Var(e_i)}$$

Where:

λ_i is the i^{th} factor loading

k is the number of indicators for the construct ξ_j

$Var(e_i)$ is the error variance of i^{th} indicator

The discriminant validity (DVa) is the other type of construct validity and is a measure of statistical difference between the factors. In practice it means that the indicators of one construct should have high factor loadings for that construct compared to what they would have for other constructs. DVa is measured by comparing each factor's square root of AVE with the correlation coefficients of the other constructs. The requirement for satisfactory discriminant validity of a factor is that the square root of its AVE is larger than the factor's correlation coefficients with each of the other factors (Fornell and Larcker, 1981). The correlation coefficients of two variables are given by their covariance divided by the product of their standard deviations. The standard deviation is also the same as the square root of the variance. If DVa measures are not within the acceptance threshold, it is possible to improve it by removing the weakest loading. However, this requires that each construct has three or more indicators.

3.4.8 Reliability

Reliability refers to how consistent the measurement is (Bollen, 1989). It differs from validity in that we can have high reliability but consistently get invalid measures if we have low validity. There are several ways to measure reliability, such as *squared multiple correlation*, c*omposite reliability* (CR)*,* and *Cronbach's α* (alpha). Cronbach's α is commonly used in exploratory factor analysis and is readily available in Stata to measure internal reliability between items. A higher α is preferable, and it must exceed a threshold of 0.6 for acceptable reliability (Fornell and Larcker, 1981). One weakness of Cronbach's α is that it assumes no measurement error, which is generally not the case for SEM, so it is common to also use another measurement like CR which is used in confirmatory factor analysis. The same threshold can be used for CR, which is given by the following equation:

$$Eq.\ 3.3:\quad CR(\xi_j) = \frac{\left(\sum_{i=1}^{k}(\lambda_i)\right)^2}{\left(\sum_{i=1}^{k}(\lambda_i)\right)^2 + \sum_{i=1}^{k} Var(e_i)}$$

It is not enough that the construct's reliability and validity are within the threshold limits. The specified model also has to fit the data, otherwise it may need respecification or modifications.

3.4.9 Model Fit

Model fit is a measure of whether or not the specified model adequately reproduces the characteristics of the data in the sample. Model fit can tell us whether or not to reject a model, but a model can never be proved valid, as it is only an approximation of reality (Bollen, 1989). In SEM, the specified model has underlying parameters corresponding to regression coefficients, variances, and covariances of the IVs (Tabachnick and Fidell, 2013). Model fit is essentially achieving a low difference between observed values and model-predicted values, represented as the residual errors. When running the analysis, estimations of these parameters are made and result in a population covariance matrix. This matrix is then compared to a sample covariance matrix, and the goal of the analysis is to estimate the parameters so that the difference between these two matrices is small and *not* statistically significant, which implies a good model fit. Maximum likelihood estimation is commonly used in SEM/CFA as an iterative procedure to minimize the difference between these two matrices (Mehmetoglu and Jakobsen, 2016). The difference between the matrices can be used to determine model fit by using a χ^2 (chi-squared) test. The χ^2 test is one of the oldest model fit tests, but one of its drawbacks is that it is negatively affected by larger samples. This is a problem because SEM is a large sample technique meaning the χ^2 test will often fail and is not always the best test to focus on optimizing for. Therefore, several other goodness-of-fit (GOF) tests have been developed for measuring model fit while minimizing the effect of sample size (Tabachnick and Fidell, 2013). Some of the alternative methods are tests for relative/comparative goodness of fit, and they work mostly in the same way; by comparing the model with a baseline model. Some examples of such tests in SEM are the Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI). Another class of tests is absolute GOF, like Root Mean Squared Error of Approximation (RMSEA), which does not rely on baseline models for comparison but rather on the difference of the model and its data, like degrees of freedom and sample size. As opposed to relative GOF tests, RMSEA also gives a confidence interval. Lastly, the Standardised Root Mean Residual (SRMR) is neither absolute nor relative but measures model fit by creating a matrix of the standardized residuals, which are averaged to output a single number. Table 3.2 shows the acceptable threshold levels for the different model fit tests mentioned.

Table 3.2: Model fit tests with acceptable threshold levels (Hu and Bentler, 1999)

Model Fit Test	Acceptable Threshold Level
CFI	>0.95
TLI	>0.95
RMSEA	<0.06
SRMR	<0.08

Often models have to be respecified to meet an adequate threshold of model fit. This can be done by increasing the sample size or removing paths, introducing new paths or by removing some parameters in the model. One technique to do this is to look at the modification indices which are suggested covariance paths to add between items, resulting in improved model fit. Many statistical programs can provide these indices in their postestimation tools. However, it is important that these paths be theoretically justifiable and only to covariate items measuring the same factor.

3.4.10 Causality

It is worth pointing out that even with an excellent model fit, the paths in the model do not prove causation; instead, we may state that the model 'may be valid' since other models and assumptions may also fit the data (Bollen, 1989). The main reason for this is due to lack of 'isolation' which is generally an unattainable ideal as variables do not exist in a vacuum with a single dependence between each pair. It is only if we can isolate cause and effect from every other possible influence that a correlation may equal causation. This is not the case for the present model specification.

3.5 Pilot Study

Before carrying out the main study, an anonymous pilot study was conducted in March 2021. The study analyzed a slightly different version of the model presented in Section 3.4.5, where each factor only had two indicators instead of three. A pilot survey was posted on the Facebook group *Pokémon GO Norge* consisting of about 17.2K members at the time of the study (see Appendix A for details). The goal was to identify certain issues which would be corrected or improved in the main survey. The results were also coded and analyzed in the statistical software Stata to test hypotheses and check that the results made sense. The survey got 232 respondents, and the results provided essential information for modifying and refining the survey for the main study. The data was used for introductory SEM analysis, which showed promising results. The sample size was insufficient to run the whole model as specified in Figure 3.1, and the model was run as three separate parts, one for each LV. Even with the modest small sample size, several hypotheses were supported with significant p-values. A p-value is a number between 0 and 1, indicating how confident we can be in the results. A p-value below 0.05 is often used as an acceptance criterion, meaning that less than 5% of the time, the results are attributed to some other factors causing a false positive.

One of the main findings of the pilot study was that customization was not an important reason for purchasing behavior in PG, although this was an earlier hypothesis. Customization was used as an indicator for esteem needs, and it had a low standardized factor loading (λ = 0.5) which is just at the acceptable threshold, indicating a relatively low association with esteem needs. The data for the items about customization had a very high positive skewness, and the overall results disconfirmed the previous hypothesis related to customization predicting spending in PG as well as it being an indicator of esteem needs. Questionnaires related to the customization feature were thus excluded from the main survey. Instead, questionnaires regarding four other game features were added as the pilot survey had a higher than expected participation and it was deemed realistic to gather sufficient data to extend the model. While the pilot study only had two indicators per factor, the main study increased this to three. It is generally recommended to have several indicators per factor. For example, each factor requires at least two indicators, and in the case of poor factor loadings, like for customization, it would be possible to disregard one indicator. This is a way to improve discriminant validity if it does not meet the acceptance threshold, as explained in Section 3.4.7.

After the pilot survey, it was also decided to change some of the control variables. Controlling for education was omitted as it had no effect and a nonsignificant p-value. Instead, control variables for level achieved and the number of friends in the game were added as these were deemed important factors for spending behavior (see Section 3.4.4).

The pilot survey also asked participants for other reasons as to why they would spend money in the game. The responses were aggregated and revealed new insights which were included in the main survey. For example, common among respondents was a proclivity to spend money on (remote) raid passes, allowing them to participate in raids of Pokégyms. This is a cooperative game feature allowing the unlocking of exclusive content, and the feature was included in the main questionnaire.

4. Results

This section first presents the descriptive statistics results from the survey data. Next, the results from model testing are presented, along with model assessment and postestimation tests.

4.1 Descriptive Statistics

Descriptive statistics is often the first step in quantitative analysis (Mehmetoglu and Jakobsen, 2016), and it may entail frequency distributions, means, medians, variances, standard deviations, kurtosis, and skewness. The data was analyzed and outputted using Stata's built-in functions (Stata Corporation, 2021).

4.1.1 Demographics and Control Variables

From the participants, there were 69.2% women and 29.7% male, which is significantly skewed towards women compared to the demographics of the players (Statista, 2019).

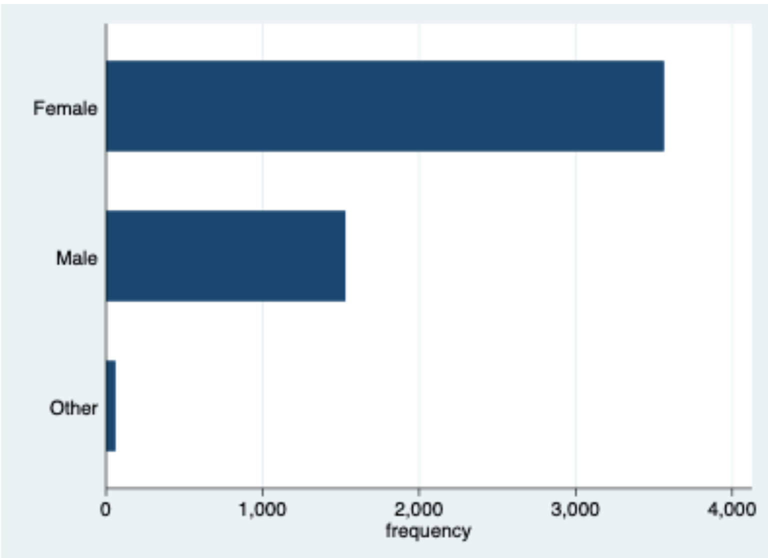

Figure 4.1: Gender distribution of survey participants

Only 0.5% answered "other" on gender, and likewise, 0.5% answered "other" on OS. One hypothesis would be that participants answering "other" to Gender and iOS would generate outlier data. However, filtering out these respondents has no effect on model fit or any meaningful impact on regression coefficients or significance, and for simplicity, these respondents were therefore omitted. Participant's age distributions, as seen in Figure 4.2, seem to coincide somewhat with the demographics of the game (Statista, 2016), albeit slightly skewed toward older people.

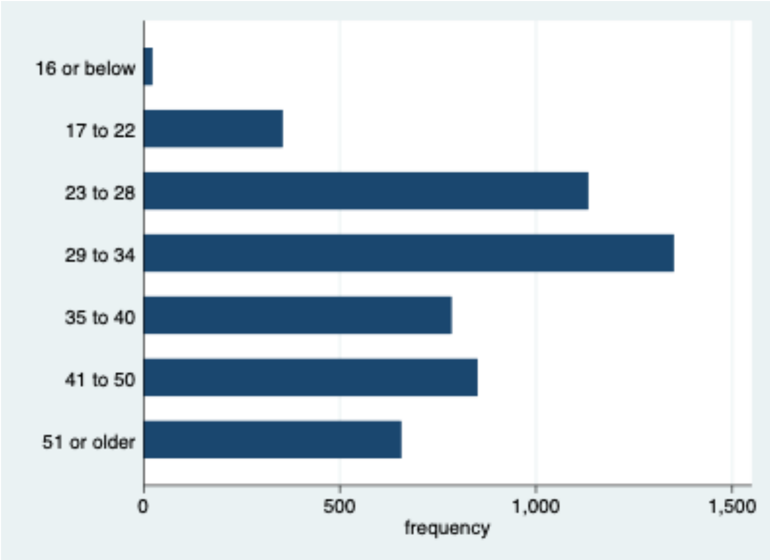

Figure 4.2: Age distribution of survey participants

The income distribution was relatively evenly spread out with *kurtosis* of 1.763, meaning a flat distribution. The kurtosis value can range from one to infinity and is a measure of the ‘flatness’ of a sample distribution relative to a normal distribution, called *mesokurtic,* with a value of three. A kurtosis higher than three generally is said to represent a distribution with more ‘peakedness’ than a normal distribution and is called *leptokurtic,* while a distribution with kurtosis less than three is flatter and called *platykurtic*.

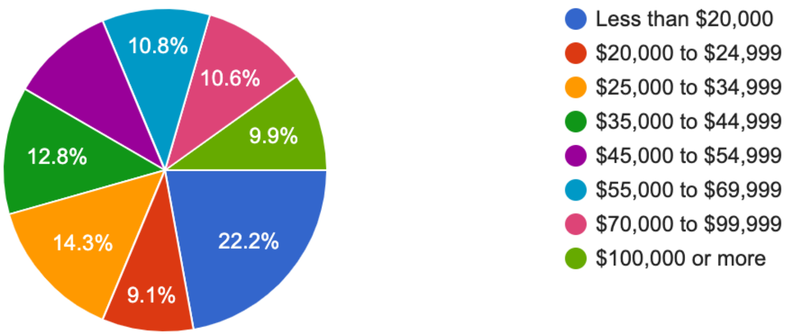

Figure 4.3: Income distribution of survey participants

Participants' spending had a normal distribution, with most participants scoring in the middle two answers, as seen in Figure 4.4. The kurtosis was 2.617, which is close to a mesokurtic normal distribution.

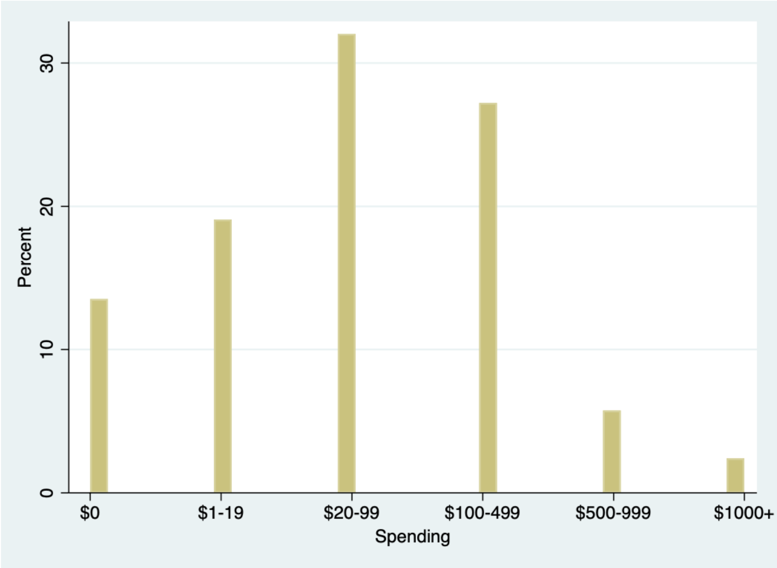

Figure 4.4: Spending amounts of survey participants

A striking observation from the survey was that 82.4% of respondents had spent real money on IAPs, and only 13.6% had never done so. This result is diametrically opposite of what one would expect considering the literature; that on average, only about 1% of players of F2P games make up most of the revenue (Kooti et al., 2017; Swrve, 2016). The survey participants are arguably overly biased towards spending. This is preferable for a study investigating purchasing behavior; however, the resulting dataset is less likely to represent the average PG players. This overrepresentation of paying players can also be explained by the longer playtime of the participants, as indicated in Figure 4.5.

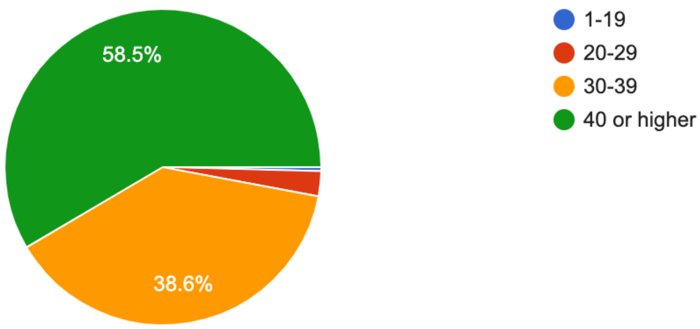

Figure 4.5: PG trainer level of survey participants

We can observe that most players are above level 40, which coincides with a very high average playtime among participants. A casual PG player playing about 1-2 hours per week may take 2-3 years to reach level 40 (Future Game Releases, 2020). This long playtime reflects a very high retention rate which we know from previous studies is a predictor of purchase intention in games, and is a likely reason as to why so many participants are paying users of the game. In July 2020, an update allowed players to reach up to level 50, and in retrospect, it may have been beneficial to segment the level variable into a few more groups to further separate the most dedicated players. The participation of players below level 30 was severely underrepresented, which may reflect that only when players have accumulated a lot of playtime do they realize the benefits of joining communities as these are often used to find friends and join raid groups, which become increasingly relevant later in the game.

A summary of the descriptive statistics for the control variables, except for OS and gender, is shown in Table 4.1 below. Note that variables are ordinal and have been coded to numerical values in order to perform descriptive statistics calculations. All numeric variables are coded with 'one' corresponding to the lowest answer in questionnaires and increasing according to Appendix B.

Table 4.1: Mean, median, variance, standard deviation, kurtosis and skewness for control variables

	Income	Spending	Age	Level	Friends
mean	4.044	2.993	4.494	2.555	4.285
p50	4	3	4	3	5
variance	5.577	1.446	2.248	0.306	1.689
sd	2.361	1.203	1.499	0.553	1.299
kurtosis	1.763	2.617	2.036	2.481	3.549
skewness	0.196	0.070	0.170	-0.743	-0.930

Skewness is a measure of how much pileup of observation is to the left or right tail of the distribution, with negative skewness meaning a pileup data to the right (Tabachnick and Fidell, 2013). For example, the variable 'level' had the highest negative skewness, meaning most respondents scored high on the measure.

4.1.2 Questionnaire Data Distribution

The practice of SEM is typically done using maximum likelihood estimation, which relies on the assumption that the observed variables have a multivariate normal distribution. It is therefore important to look at the distribution of the data before starting to fit the model. For example, some types of multivariate distributions may be problematic due to convergence issues of the model. For example, U-shape distributions are known to cause convergence issues, but there are no such distributions seen in the dataset. The distributions of all the observed variables as bar graphs can be found in Appendix B.

For most of the questionnaires, the data had a normal distribution; however, several variables had their data highly skewed either positively or negatively, which can be problematic for statistical tests. A general observation was that IVs predicting Spending generally had a high positive skewness, while the indicators of the LVs had a negative skewness, as seen in Table 4.2 and 4.3 below. The interpretation of this is that the indicators were very well predicted by the LVs, something which will be further described in Section 4.2.3.1 regarding validity, while the IVs were less significant in predicting Spending. The skewness was almost diametrically opposite. For example, the two most extremely skewed variables, Friends_IV, had a skewness of 0.908, and Raiding_LV had a skewness of -0.985. The most evenly/flatly distributed variable was Raiding_DV with a kurtosis of 1.538, while most variables had a more mesokurtic normal distribution. Summaries of the descriptive statistics for the indicators and IVs are shown in Table 4.2 and 4.3 below respectively. These variables are measured on a 1 to 5 Likert scale.

Table 4.2: Mean, median, variance, standard deviation, kurtosis and skewness for the indicators

	Unlocking _LV	Evolving _LV	Leveling _LV	Competition _LV	Leaderboard _LV	Level _LV	Friends _LV	Interaction _LV	Raiding _LV
mean	3.663	3.583	3.781	2.966	3.332	3.049	3.446	3.685	3.940
p50	4	4	4	3	4	3	3	4	4
variance	1.458	1.463	1.366	1.783	1.884	1.907	1.399	1.319	1.235
sd	1.208	1.210	1.169	1.335	1.373	1.381	1.183	1.148	1.111
kurtosis	2.725	2.554	2.923	1.878	1.954	1.805	2.382	2.707	3.342
skewness	-0.752	-0.634	-0.825	-0.066	-0.398	-0.133	-0.385	-0.653	-0.988

Table 4.3: Mean, median, variance, standard deviation, kurtosis and skewness for the IVs

	Unlocking _IV	Evolving _IV	Leveling _IV	Competition _IV	Leaderboard _IV	Level _IV	Friends _IV	Interaction _IV	Raiding _IV
mean	2.912	2.381	2.497	2.172	2.359	2.087	2.130	2.208	2.867
p50	3	2	2	2	2	2	2	2	3
variance	2.077	1.799	1.955	1.637	1.946	1.611	1.724	1.761	2.303
sd	1.441	1.341	1.398	1.279	1.395	1.269	1.313	1.327	1.518
kurtosis	1.657	2.075	1.855	2.428	2.011	2.656	2.631	2.331	1.538
skewness	-0.020	0.541	0.413	0.767	0.584	0.894	0.911	0.758	0.060

We see that no variables have a negative kurtosis, which coincides with a U-shaped distribution which may cause convergence issues. The high amount of skewness may be caused by outlier data, meaning some participants answering 1 or 5 on most or all items.

4.1.3 Outlier Data

Outliers are observed values that differ from the rest of the dataset, and they can have a large effect on the analysis (Bollen, 1989). These observations can be identified by examining the distribution of the dataset. In the present dataset, these outliers were considered on the basis of survey responses for each participant instead of on a variable to variable basis. This is because the scales for the items were restricted to a five-point Likert scale and should not produce outlier data on a variable to variable basis, but instead, a single participant could be an outlier by, for example, answering only ‘strongly disagree’ or only ‘strongly agree’ on every question. Outliers considered in this regard are multidimensional data points, and detection of these is not a fully solved problem (Bollen, 1989). However, we can easily filter these out from the dataset using built-in filtering functions in Stata. For the indicators, there were 56 such participants answering ‘strongly disagree’ on every item, as well as answering ‘strongly disagree’ on most other items. Of these 56 participants, 41% reported $0 spending in the game, as opposed to 13.6% in the whole dataset of 5149 participants. These 56 observations were thus omitted from the study for being considered outliers.

On the other hand, 66 participants answered ‘strongly agree’ on all items and could potentially also be considered outliers. In this group, only 7.6% were non-spenders, and the group also had a disproportionately higher amount of big spenders: 19.7% spending $500 or more compared to 8.1% in the whole dataset. Only the (5 of 66) non-spenders in this group were omitted since these observations did not make sense on the basis that they ranked every item as ‘strongly agree’ while also not spending any money in the game. The rest of the sample group made sense as the group was dominated by high-spenders. In total, 143 observations were removed, including those answering ‘other’ on OS and gender (as mentioned in Section 4.1.1), from the dataset, leaving 5006 observations.

After removing outlier data, the skewness was slightly normalized since some of the extremely low and high data points were removed. Kurtosis was also slightly lowered, causing less ‘peakedness’ for the variables that had peaks around the extremes of scores.

4.1.4 Sample Size

After removing outliers, there were 5006 observations, and the model has 25 observed variables giving a ratio of cases to observed variables of about 200:1. There is no definitive rule for how many observations are needed in SEM, but a rule of thumb is often said to be that the ratio of observations to free parameters should be somewhere from 5:1 to 20:1. However, in general, for most statistical models, the more observations, the better. Regardless, the sample size was more than sufficiently large to conduct the SEM analysis. Since all questionnaires were mandatory to complete, the survey had no missing data.

4.1.5 Qualitative Data

The last question in the survey asked participants what would be the biggest reason to spend money in the game. Out of the 5149 participants, 4359 answered the question. A word frequency check of the data showed that the word raid, or variations of it, was among the most frequently appearing words containing more than three letters and appeared 1065 times in the responses. A high frequency was also seen in the pilot survey and was the reason why the feature was added to the main study.

4.2 Model Testing

Model testing entails calculating validity and reliability of the factors, and performing postestimation tests for fitting the model.

4.2.1 Stata Setup

The model was estimated using standard settings of Stata. Because the model contains ordinal variables, meaning they are discretely measured (e.g. in a five-point Likert scale) it would generally be advised to use GSEM (Generalized Structural Equation Model) which is better suited to handle ordinal variables. However, it is also possible to run SEM since it will treat ordinal variables as continuous and is common practice in the field of psychology. For testing, the model was run with both SEM and GSEM, and the results had only small differences. SEM was therefore preferred due to some advantages over GSEM, such as postestimation GOF tests, allowing standardized estimates, as well as orders of magnitude quicker estimation times. The method for estimation was set to maximum likelihood, which is most commonly used in CFA/SEM (Mehmetoglu and Jakobsen, 2016). Standardized estimates were used because several variables were measured on different scales, as seen in Appendix B.

4.2.2 Model Estimation

Figure 4.6 below shows the results of the first run. The paths show associated coefficients and the variables show average respondent score. Each DV has an associated error variance. Significant associations are marked with '*', although most have p-values less than 0.0001 and could therefore be marked with '****'. The non-significant associations are marked with 'ns'.

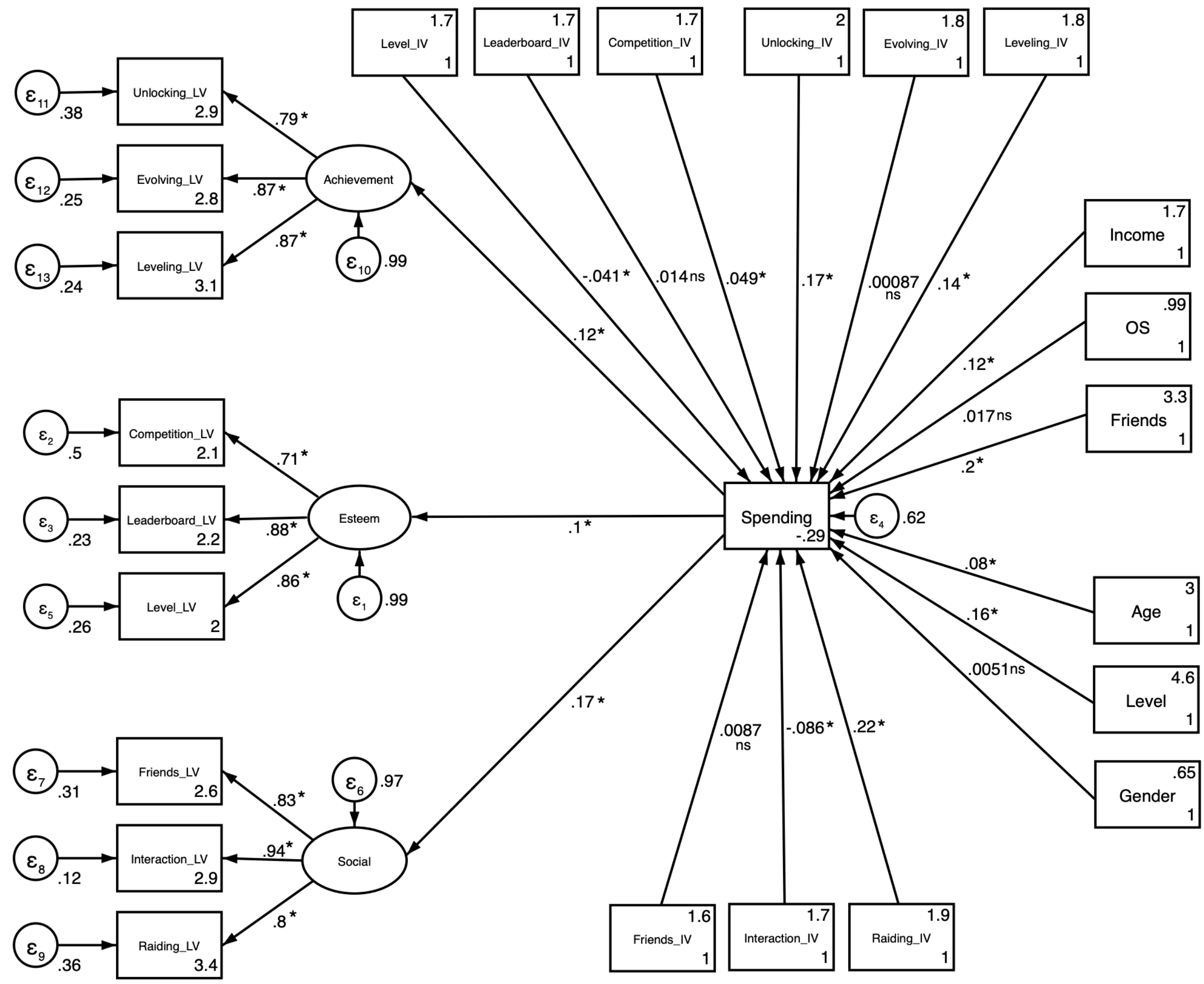

Figure 4.6: Path diagram with coefficients and variances

At glance Figure 4.6 shows several path coefficients with moderate and high effects coinciding with the hypotheses. A more detailed overview of the results are found in Table 4.4 containing SEM results output from Stata.

Table 4.4: Parameter estimates

Standardized	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Spending <-						
Age	0.0802895	0.0133435	6.02	0.000	0.0541368	0.1064422
Gender	0.00507	0.0115242	0.44	0.660	-0.017517	0.027657
OS	0.0169556	0.0113638	1.49	0.136	-0.005317	0.0392281
Income	0.1180532	0.0125585	9.4	0.000	0.0934391	0.1426674
Competition_IV	0.0494621	0.0175669	2.82	0.005	0.0150317	0.0838925
Leaderboard_IV	0.013926	0.0184285	0.76	0.450	-0.0221932	0.0500452
Level_IV	-0.0410902	0.0199448	-2.06	0.039	-0.0801812	-0.0019992
Friends	0.1982856	0.0131699	15.06	0.000	0.1724731	0.2240981
Level	0.1572292	0.0135399	11.61	0.000	0.1306913	0.183767
Unlocking_IV	0.1684079	0.0166221	10.13	0.000	0.1358293	0.2009865
Evolving_IV	0.0008708	0.0202197	0.04	0.966	-0.0387591	0.0405008
Leveling_IV	0.1447838	0.0202353	7.16	0.000	0.1051234	0.1844442
Friends_IV	0.0086959	0.0198111	0.44	0.661	-0.0301331	0.047525
Interaction_IV	-0.0856148	0.0211945	-4.04	0.000	-0.1271552	-0.0440743
Raiding_IV	0.2226791	0.0156676	14.21	0.000	0.1919712	0.253387
_cons	-0.2871082	0.0603111	-4.76	0.000	-0.4053157	-0.1689006
Esteem <-						
Spending	0.1031003	0.014929	6.91	0.000	0.0738401	0.1323606
Social <-						
Spending	0.1731349	0.0143087	12.1	0.000	0.1450903	0.2011795
Achievement <-						
Spending	0.1195698	0.0148278	8.06	0.000	0.0905079	0.1486317

Table 4.4 shows that most of the p-values are statistically significant. The exceptions are five of the associations that have non-significant p-values meaning the model predicts no association between those variables. Path coefficients with significant values aligned with what is expected from the hypotheses is a great start, but the results must be further evaluated before we use them. The confidence intervals of the estimates are small, which is a reflection of a large sample size. The next step is to assess whether the estimated parameters can be trusted and whether the model reproduces the characteristics of the sample data by evaluating reliability, validity, and model fit.

4.2.3 Model Assessment and Postestimation

4.2.3.1 Validity

The average variance extracted (AVE) and composite reliability (CR) are calculated from Eq. 3.2 and 3.3 and shown in Table 4.5 below. We see that each AVE is above acceptable criteria of 0.5 (as mentioned in Section 3.4.7), and CR is above 0.7, meaning that the factors have adequate reliability and validity. Also the factor loadings (λ) are all above the acceptable threshold of 0.5.

Table 4.5: Average variance extracted and composite reliability of factors

Indicator	Factor	Var(e)	λ	λ^2	AVE	$\sqrt{AVE}$	$\Delta = 1 - \lambda$	$(\sum\lambda)^2$	CR
Unlocking_LV	Achievement	0.37	0.88	0.774			0.12		
Evolving_LV	Achievement	0.26	0.86	0.740			0.14		
Leveling_LV	Achievement	0.24	0.87	0.757	0.723	0.850	0.13	6.812	0.887
Competition_LV	Esteem	0.48	0.72	0.518			0.28		
Leaderboard_LV	Esteem	0.24	0.87	0.757			0.13		
Level_LV	Esteem	0.26	0.86	0.740	0.673	0.820	0.14	6.003	0.860
Friends_LV	Social	0.30	0.84	0.706			0.16		
Interaction_LV	Social	0.14	0.93	0.865			0.07		
Raiding_LV	Social	0.34	0.81	0.656	0.741	0.861	0.19	6.656	0.895

Table 4.6 below shows the correlations between the factors, which are all lower than each $\sqrt{AVE}$ implying satisfactory discriminant validity (DVa).

Table 4.6: Covariance and correlations between factors

	Covariance	Correlation
Achievement <-> Esteem	0.55	0.57
Achievement <-> Social	0.39	0.42
Social <-> Esteem	0.42	0.46

4.2.3.2 Reliability

From the correlation matrix in Table 4.7 below, we see that there is a high correlation among the set of three indicators associated with their corresponding factor, while the correlation is low between these and the remaining indicators. This affirms that each set of indicators measures the same thing, namely their corresponding factors but not the other factors.

Table 4.7: Correlation matrix of indicators

	Competition _LV	Leaderboard _LV	Level _LV	Unlocking _LV	Evolving _LV	Leveling _LV	Friends _LV	Interaction _LV	Raiding _LV
Competition _LV	1.000	-	-	-	-	-	-	-	-
Leaderboard _LV	0.631	1.000	-	-	-	-	-	-	-
Level _LV	0.619	0.764	1.000	-	-	-	-	-	-
Unlocking _LV	0.404	0.425	0.412	1.000	-	-	-	-	-
Evolving _LV	0.409	0.423	0.407	0.702	1.000	-	-	-	-
Leveling _LV	0.407	0.403	0.438	0.706	0.771	1.000	-	-	-
Friends _LV	0.393	0.293	0.291	0.356	0.339	0.371	1.000	-	-
Interaction _LV	0.399	0.309	0.304	0.372	0.340	0.390	0.794	1.000	-
Raiding _LV	0.393	0.344	0.328	0.374	0.364	0.414	0.686	0.773	1.000

The same effect is reflected in Cronbach's α, which measures the internal reliability of the indicators. This value can easily be outputted using Stata, and as seen in Table 4.8, all three values for Cronbach's α are well above the acceptable criteria of 0.6 for each set of indicators.

Table 4.8: Cronbach's α for indicators

Set of indicators	Cronbach's α
Achievement indicators	0.860
Esteem indicators	0.888
Social indicators	0.900

Given that the model is overidentified with adequate reliability and validity, it is reasonable to proceed with postestimation and model fit tests.

4.2.3.3 Postestimation and Model Fit

Stata provides GOF tests for SEM and Table 4.9 below shows the results of these tests.

Table 4.9: Model fit tests

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(168)	8348.312	model vs. saturated
p > chi2	0	
chi2_bs(195)	35358.18	baseline vs. saturated
p > chi2	0	
Population error		
RMSEA	0.099	Root mean squared error of approximation
90% CI, lower bound	0.097	
upper bound	0.1	
pclose	0	Probability RMSEA <= 0.05
Information criteria		
AIC	333376.108	Akaike's information criterion
BIC	333682.473	Bayesian information criterion
Baseline comparison		
CFI	0.767	Comparative fit index
TLI	0.703	Tucker-Lewis index
Size of residuals		
SRMR	0.172	Standardized root mean squared residual
CD	0.384	Coefficient of determination

We see that the GOF tests are not quite within the acceptable thresholds specified in Table 3.2. Therefore, we do a postestimation evaluation displaying modification indices which are suggestions of additional paths that may improve model fit. The modification indices are numbers showing which paths may have the largest impact on model fit. After evaluating the modification indices, the covariances between the factor-variances were added, resulting in a slightly better fit according to relative- and absolute fit indices as well as SRMR. Since the current model has a very high degree of freedom as determined in Section 3.4.6, adding these three unknown parameters still results in an overidentified model. Figure 4.7 shows the path diagram with covariances added, and postestimation GOF tests are seen in Table 4.10.

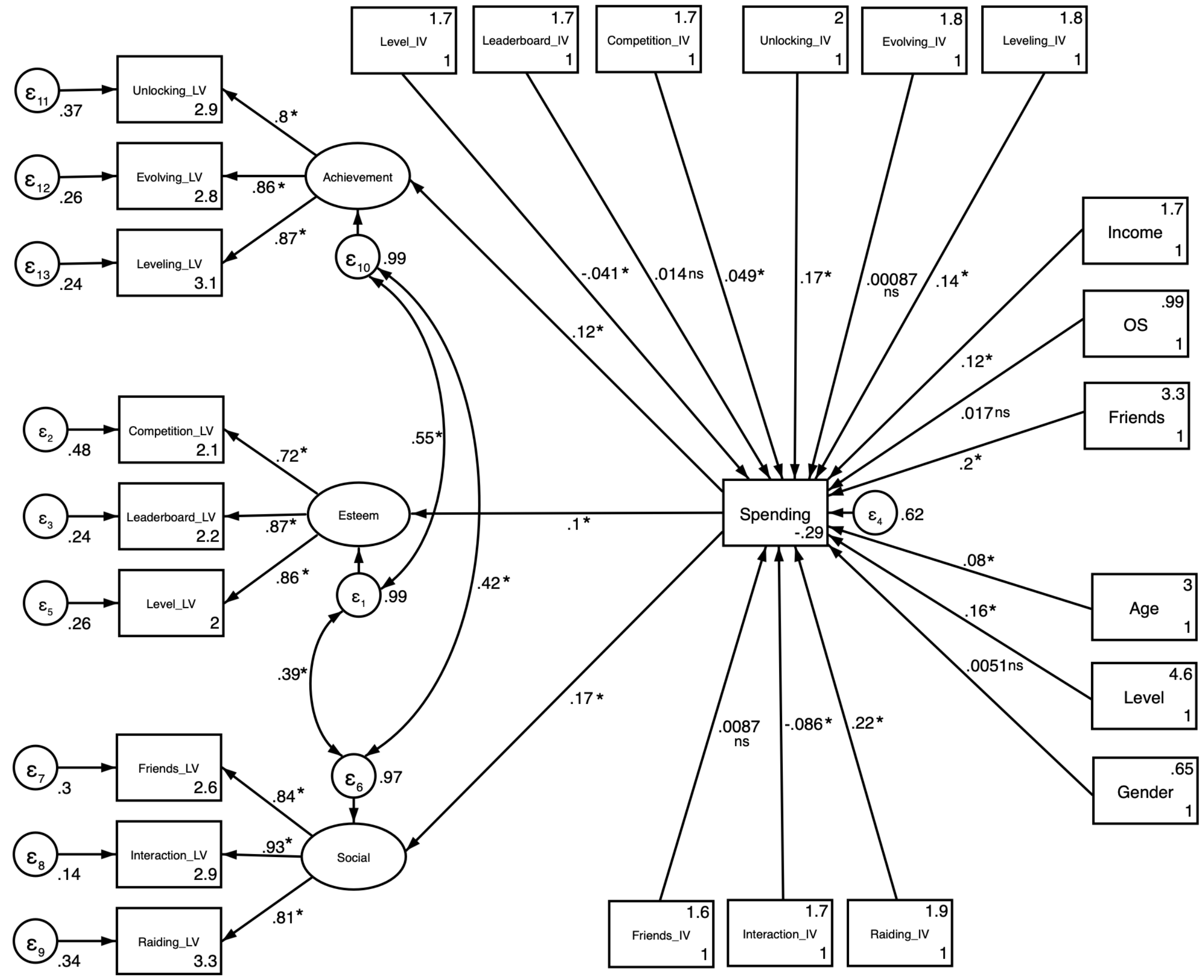

Figure 4.7: Path diagram with coefficients, variances and covaried factors

Table 4.10: Model fit tests after modification indices

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(168)	6065.642	model vs. saturated
p > chi2	0	
chi2_bs(195)	35358.18	baseline vs. saturated
p > chi2	0	
Population error		
RMSEA	0.085	Root mean squared error of approximation
90% CI, lower bound	0.083	
upper bound	0.086	
pclose	0	Probability RMSEA <= 0.05
Information criteria		
AIC	333376.108	Akaike's information criterion
BIC	333682.473	Bayesian information criterion
Baseline comparison		
CFI	0.832	Comparative fit index
TLI	0.802	Tucker-Lewis index
Size of residuals		
SRMR	0.143	Standardized root mean squared residual
CD	0.384	Coefficient of determination

We see an improvement in GOF from Table 4.10, but the tests still do not fully meet the acceptance criteria as listed in Table 3.2. However, this is not in itself a reason to reject the model. It is also important to look at the parameter estimates and see if they support the hypotheses. The first test we often look at is the χ^2 test, which fails completely. However, this is as is expected for large sample models, and it is not a problem, as discussed in Section 3.4.9. Instead, we use the other GOF thresholds from Table 3.2, which are meant as guidelines. It is important to note that these thresholds should not be taken as absolute criteria for model acceptance and that each case has to be evaluated in its context. For example, we do not expect a high CFI or TLI as they rely on correlations of all variables and the model has many variables which are expected to have low correlations, e.g. age, gender and other IVs. Instead, RMSEA and SRMR are more reliable measures of model fit in this case as they rely on other data like degrees of freedom, sample size, and standardized residuals. These values are still not within the threshold for acceptance, but they are not so bad that we will reject the model. To improve model fit it is often recommended to further modify the model, as discussed in Section 3.4.9. Although we do not reject the current model, we can also propose a simplified model to see if there are improvements in model fit. This may give us clues as to what may cause a lower GOF in the larger model.

4.2.4 Simplified Model

A simplified model with nine IVs predicting spending being removed is proposed in Figure 4.8. In this model, the variables which previously were control variables are now instead predictors of spending since they are not controlling for any other variables that are predicting spending.

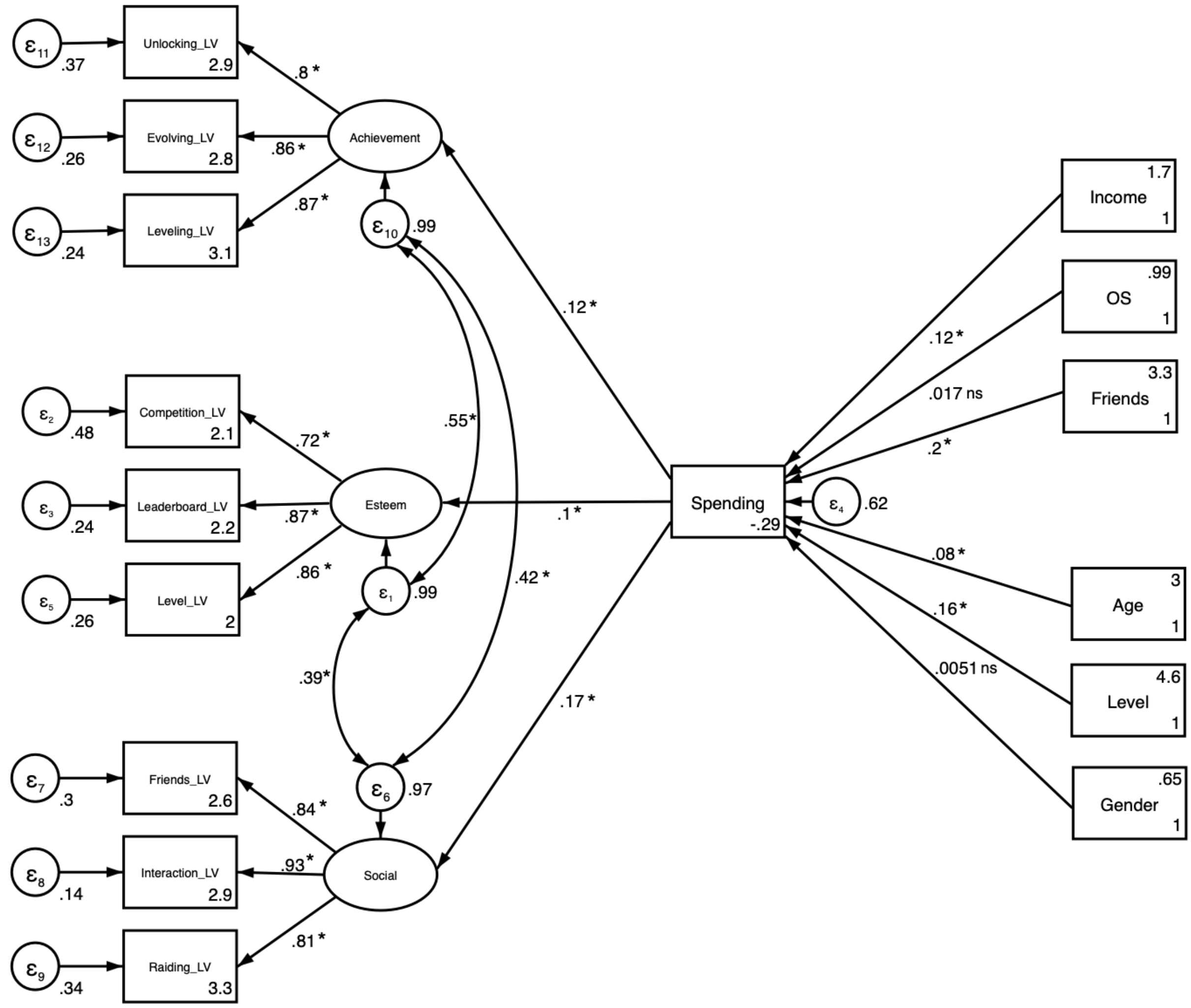

Figure 4.8: Path diagram with coefficients and variances of simplified model

This simplified model passed all GOF acceptance criteria as seen in Table 4.11.

Table 4.11: Model fit tests for simplified model with covariances

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(168)	1353.908	model vs. saturated
p > chi2	0	
chi2_bs(195)	29529.084	baseline vs. saturated
p > chi2	0	
Population error		
RMSEA	0.055	Root mean squared error of approximation
90% CI, lower bound	0.052	
upper bound	0.058	
pclose	0.001	Probability RMSEA <= 0.05
Information criteria		
AIC	208752.449	Akaike's information criterion
BIC	209019.703	Bayesian information criterion
Baseline comparison		
CFI	0.957	Comparative fit index
TLI	0.946	Tucker-Lewis index
Size of residuals		
SRMR	0.055	Standardized root mean squared residual
CD	0.23	Coefficient of determination

The simplified model has the same coefficients from spending to the LVs as the original model, meaning both reproduce these characteristics of the sample data equally well. This gives us more confidence in the original model as the simplified model has a great model fit. Based on this we can conclude that the original model adequately reproduces the characteristics of the sample data.

5. Discussion

This section will evaluate the results and how they fit according to previous literature on the topic and whether the results support the hypotheses and answers the research questions. The section starts with a summary of the hypotheses testing before evaluating the results of IVs in the model, followed by the LVs and the CVs. The section then presents a broader picture of the results and the implication from a managerial and academic perspective. Lastly, some limitations of the study are acknowledged.

5.1 Discussion of Results

Table 5.1 below summarizes the testing of the hypotheses. The table shows which associations belong to which hypotheses andit shows the effect of these associations.

Table 5.1: Summary of hypotheses testing

Hypothesis	Association	Supported?	Effect
H1a	Achievement -> Unlocking_LV	Yes	High
H1b	Achievement -> Evolving_LV	Yes	High
H1c	Achievement -> Leveling_LV	Yes	High
H2a	Esteem -> Competition_LV	Yes	High
H2b	Esteem -> Leaderboard_LV	Yes	High
H2c	Esteem -> Level_LV	Yes	High
H3a	Social -> Friends_LV	Yes	High
H3b	Social -> Interaction_LV	Yes	High
H3c	Social -> Raiding_LV	Yes	High
H4a	Level_IV -> Spending	No	Negative low
H4b	Leaderboard_IV -> Spending	Inconclusive	n.s.
H4c	Competition_IV -> Spending	Yes	Low
H5a	Unlocking_IV -> Spending	Yes	Moderate
H5b	Evolving_IV -> Spending	Inconclusive	n.s.
H5c	Leveling_IV -> Spending	Yes	Moderate
H6a	Friends_IV -> Spending	Inconclusive	n.s.
H6b	Interaction_IV -> Spending	No	Negative low
H6c	Raiding_IV -> Spending	Yes	High
H7	Spending -> Achievement	Yes	Moderate
H8	Spending -> Esteem	Yes	Moderate
H9	Spending -> Social	Yes	Moderate

5.1.1 Independent Variables

Some of the hypotheses H4a-H6c were supported, but H4c, H4c showed negative path coefficients, and H4b, H5b, H6a have non-significant p-values. H5a has a low path coefficient and was not an important predictor of spending. Three IVs stand particularly out with the highest coefficients; raiding with friends (H6b), unlocking new content (H4a), and leveling up (H4c).

Raiding with friends was the game-specific factor which had the most significant influence on spending (β = 0.22) and is to be considered a high effect (Mehmetoglu and Jakobsen, 2016). This feature was included in the main survey after the pilot survey had revealed that this was repeatedly mentioned when asked for other reasons to spend money in PG. The word also appeared 1065 times in the 4359 qualitative responses in the main survey, clearly indicating its importance for monetizing the game. Raiding is a social feature where players defeat a large enemy together, which none of them could have taken down individually. This is an example of cooperative play, which has been shown to increase revenue of games (Alomari, 2018). It is also a way for individuals to be connected to others through the game groups or communities which are associated with increased spending (Hsiao and Chen, 2016, Hsieh and Tseng, 2018; Hamid and Suzianti, 2020; Hsu and Lin, 2016). Moreover, raiding is a way to unlock new content like rare and powerful Pokémons. This may explain why raiding and unlocking new content had a very high (β = 0.98) and significant covariance, implying that these features are closely related.

Unlocking new content was the IV with the second highest effect on spending (β = 0.17), which coincides with some studies suggesting it is the most important reason for making IAPs (Hamari et al., 2017; Salminen et al., 2018). The third largest effect on spending among IVs was leveling up their Pokémon trainer (β = 0.14), coinciding with progression and leveling systems motivating for purchase (Filho et al., 2014). The remaining IVs had a small or non-significant effect on spending.

We notice that two of these three mentioned IVs are achievement-type game components while one was classified as social according to Table 3.1. This is also reflected in the results of Spending predicting the LVs with Social and Achievement having the largest coefficients, respectively, which will be discussed in Section 5.1.2. However, raiding could also be considered an achievement related game component as it is also used to unlock exclusive content like legendary Pokémons, as well as having a high covariance with the 'unlocking' feature. This would further support that achievement mechanisms are important for the monetization of F2P games.

It is worth mentioning that systematic error may have been introduced due to the phrasing of the questionnaires regarding the nine IVs predicting spending. The following wording was used in these questions: *[feature] is a determining factor for me to spend money on IAPs*. Many may interpret the word *determining* as quite strong and thus rate these items lower. Replacing the word *determining* with words like *important* or *possible* may have caused a more normal skewness of the results and lessened possible systematic errors. The data for the IVs generally had a high positive skewness, as discussed in Section 4.1.2, meaning participants generally gave low scores on these items. This is reflected in low path coefficients for several of the IVs that were thought to predict spending. For example, earlier studies on PG have associated competition with increased spending on IAPs (Hamari et al., 2019) We may therefore assume that some of the proposed modifications of the questionnaires could have caused higher path coefficients and given support to additional hypotheses.

5.1.2 Latent Variables

All the LVs had significant and strong associations with the proposed indicators, with the lowest factor loading being Competition_LV <- Esteem (***β*** = 0.72) and the highest being Interaction_LV <- Social (***β*** = 0.93). The factors were reliably described by the indicators with high validity, which confirms hypotheses H1a-H3c and answers the second research question (RQ2). These results suggest that Maslow's psychological needs can be pursued through games and that the nine suggested game features allow for this.

All three effects on the LVs from Spending are considered moderate and hypotheses H7-H9 were supported. This also answers the third research question (RQ3); that spending money in the game increases the fulfillment of these psychological needs. The social needs saw the biggest increase from spending (***β*** = 0.17). This coincided with previous research showing that social factors of games increase spending on virtual items (Wang and Chang, 2014; Hamari et al., 2017; Hamari et al., 2019; Jang et al., 2019), and is a major reason why people even play games (Valho and Hamari, 2019).

The second largest effect (***β*** = 0.12) from spending was seen in achievement needs followed by esteem needs (***β*** = 0.10). There is a lack of specific research coinciding with these findings because perceived feelings of esteem and achievement have not been measured in studies on monetization of games. We can instead points to related game components covered in the literature such as leaderboards and level- or evolvement systems (Filho et al., 2014; Alomari et al., 2016; Alomari, 2018), status and social hierarchies (Shi et al., 2015; Mäntymäki, 2015), competition (Shi, Xia and Huang, 2015; Kao and Chiang, 2015; Alomari, 2018; Hamari et al., 2019; Hamid and Suzianti, 2020), desire for self-presentation (Kim and Chan, 2007; Kordyaka et al., 2018) and unlocking content (Hamari et al., 2017; Salminen et al., 2018). Although these studies are not directly measuring Esteem or Achievement, they study effects or components related to these and are the closest we get to coinciding research results.

It is also difficult to separate esteem and achievement needs in games as they have significant overlap. For example, when you achieve some high level or rare game content it would raise you up in leaderboards and implicitly raise your status relative to those that are lower level with less exclusive content. Admiration from these players would increase your feeling of esteem. Achievement will gather respect and status, which in turn results in higher esteem. This may explain why Achievement and Esteem have the highest covariance (***β*** = 0.55) among the LVs. All the LVs have a significant and large covariance to each other (see Table 4.6). This is expected as Maslow's needs are dependent on each other; someone will pursue a need higher up in the hierarchy when the need just below it is sufficiently satisfied. We also know that the different needs in practice have significant overlap (see Figure 2.3). The high covariances between LVs also make sense because the features that constitute the indicators of the LVs share commonalities and are, in practice, interrelated. For example, leveling up, unlocking content, and evolving are regarded as achievement features, but they would also make a player rank higher in the leaderboard and fare better in competitions, which were regarded as esteem features. Although the Cronbach's α separates these indicators well when describing their respective LVs, in reality the game-features are highly interrelated.

5.1.3 Control Variables

As was expected, the more friends someone has in PG, the more likely they are to spend money in the game. This result coincides with previous literature on the number of connections in a game increasing spending (Wohn, 2014; Shi et al., 2015; Jang et al., 2018). The relationship was significant, and it was the

CV with the highest effect on spending (β = 0.2). The second highest effect was the level of the player (β = 0.16), which reflects the amount of time spent playing the game. This makes sense because the more someone plays a game, the higher their retention rate or loyalty is, which is one of the most significant predictors of spending (Alhirz and Sajeev, 2015; Atchariyachanvanich et al., 2015; Hsiao and Chen, 2016; Balakrishnan and Griffiths, 2018; Appel et al., 2020). However, a recent study by Hsiao et al. (2019) found playtime to be a non-significant CV for purchase intention. The CVs 'friends' and 'level' also had a significant and high covariance (β = 0.53) which can be explained since longer playing time gives the player time to acquire more friends in the game. Age had a small effect on spending (β = 0.08) while income had a moderate effect (β = 0.12). OS and gender had non-significant p-values which are aligned with a recent study on PG (Hsiao et al., 2019). However, generally, we would expect iOS users to spend more than Android users (AppsFlyer, 2016) and that men generally spend more (Kooti et al., 2017).

5.1.4 Implications for Designed Inconvenience Through Psychological Needs

One might wonder why the arrows corresponding to H7-H9 in the research model point from Spending and towards the LVs and not the opposite way. The answer is because we investigate whether players are willing to spend money to increase the fulfillment of their Maslow needs. Reversing the arrow's directions would mean that we investigate whether fulfillment of Maslow's needs would predict increased spending, but this would not answer the research questions of the thesis. If spending more implies feeling more fulfillment of the psychological needs, it does not necessarily mean that increased satisfaction coincides with more spending. This is an asymmetric relation where A implying B does not equal B implying A. In fact, reversing the arrows in the model yields small negative standardized path coefficients from the Achievement to Spending (β = -0.04) and Esteem to Spending (β = -0.084), indicating that increasingly meeting these Maslow's needs may lead to a reduction in spending as seen Figure 5.1. We also see that, when reversing the arrows, the path from Social to Spending is non-significant meaning there is no association.

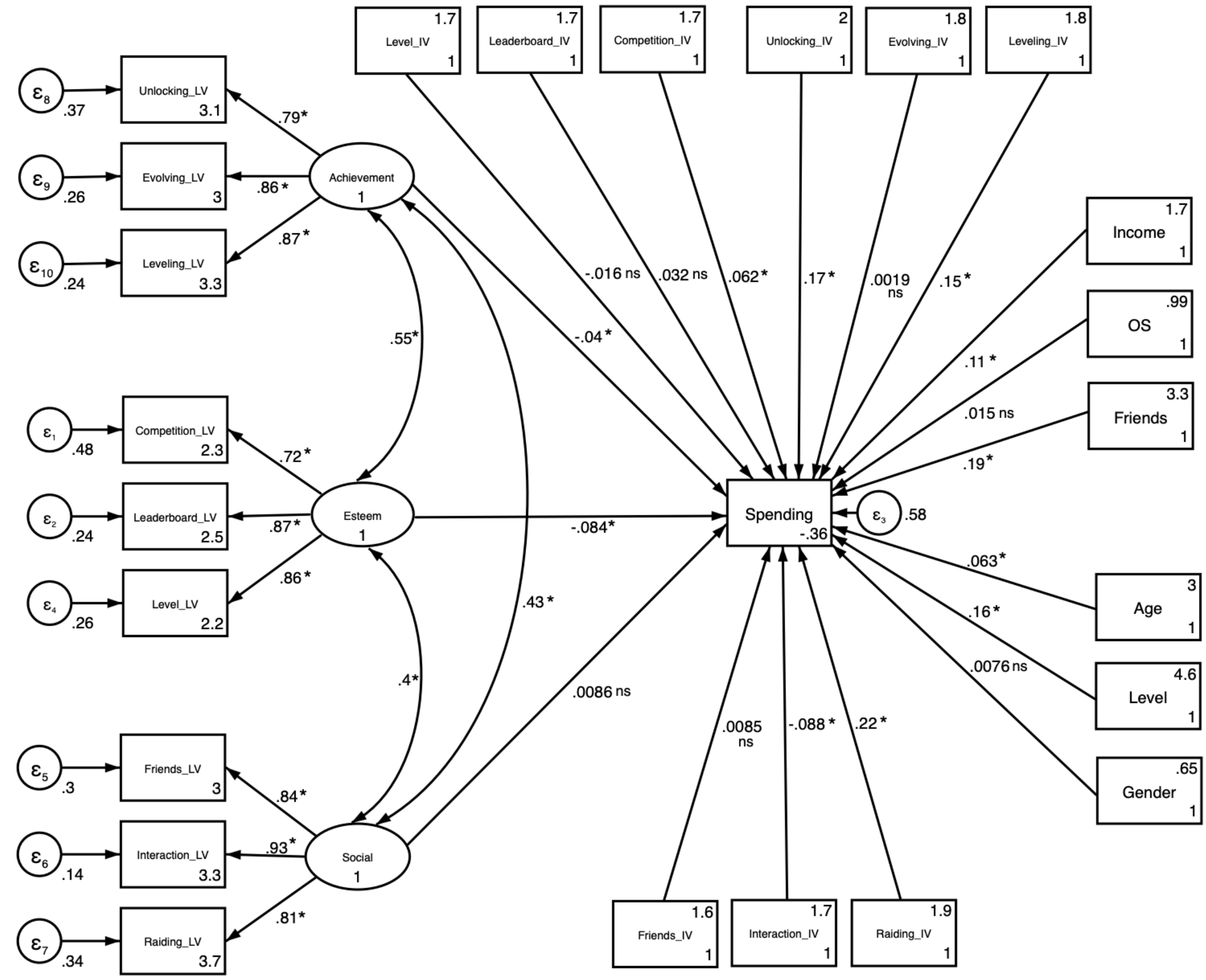

Figure 5.1: Model with reversed paths from Spending to LVs

We can interpret this result as when players meet their needs through the game; they have a reduced proclivity to spend money in the game. It makes sense since if you feel that the game fully satisfies your needs, why would you spend any more money on it? On the contrary, if you do not feel satisfied, but you believe that spending money in the game could provide additional satisfaction, you would have a greater reason to spend money to achieve this. This is exactly the type of challenge game designers ought to think about for creating profitable games; to give the player an urge to spend money to feel more satisfied. The phenomenon arguably coincides with the *designed inconvenience hypothesis* (Hamari, 2015), which means that game designers intentionally introduce inconveniences, make gameplay burdensome, limit some aspects of the game, and then offer to alleviate these by means of virtual items for sale. Hamari (2015) found that enjoyment while playing games was negatively associated with the intention of purchasing virtual goods. A possible reason for this, he argues, is that when there is sufficient enjoyment, the player does not have the urge to make IAPs in order to enhance enjoyment further. However, if the enjoyment is somewhat lacking, then making IAPs could fill this gap. Drawing parallels to the present study, one could argue that increased spending could be obtained by restricting fulfillment of some of the psychological needs and allowing satisfaction of these by spending money on IAPs. We can see examples of this in PG, where players can pay for raid passes, allowing them to participate in raids more frequently. However, raid passes are scarce and restricted, and so the satisfaction is held back or limited for players until they make a purchase. Raiding was also the main reason out of nine features for players to spend money in the game. Participating in more raids is a way for players to achieve more in a social way. This can be tested by drawing paths from Raiding_IV to each of the LVs, giving significant and large path coefficients as seen in Figure 5.2. However, these high coefficients also result in non-significant associations from Spending to the LVs.

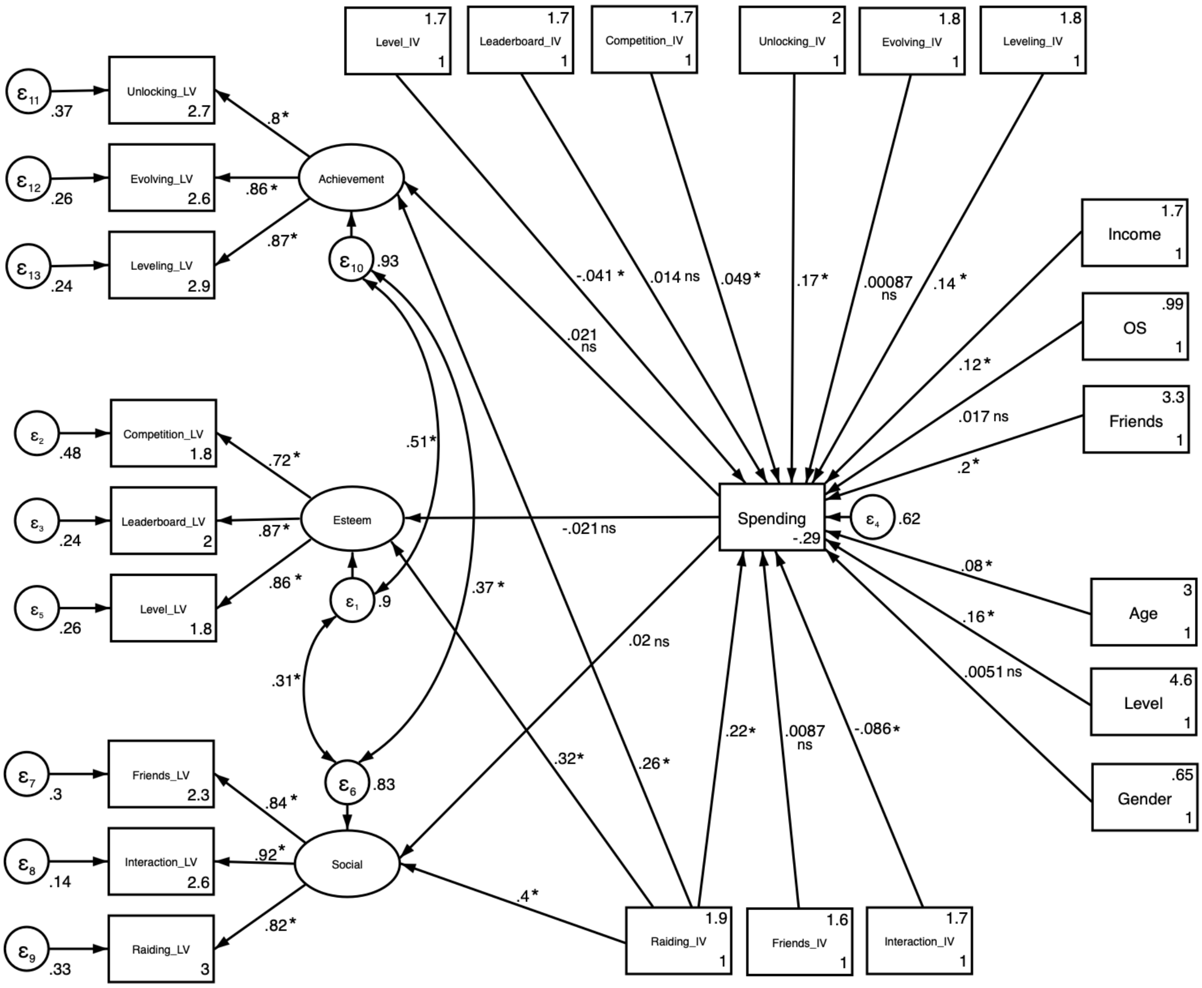

Figure 5.2: Model with added paths from Raiding_IV to the LVs

As Figure 5.2 suggests, adding direct paths Raiding_IV to the three psychological needs yields higher effects than going through the mediating variable Spending. The raiding game feature captures all three psychological needs by means of cooperative play, which helps you level up and unlock new exclusive content like legendary Pokémons. The remaining eight game features do not entail multiple effects like this to the same degree. For example, the second most important IV, unlocking content, is a more general feature of the game and does not necessarily entail the social aspects which we know from previous literature are predictors for IAP. We may therefore assume an interesting managerial implication; that designing features encapsulating several psychological needs at once may increase profitability.

5.2 Managerial Implication

The main results from this study can be used by designers of freemium games to facilitate the pursuit of Maslow's needs through their games for increased spending on IAPs. To increase monetization a game should offer players to pursue their needs for achievement, esteem and belongingness. Preferably, as seen in the raiding feature, it may seem that features encapsulating all three psychological needs in interplay are ideal. However, in accordance with the designed inconvenience hypothesis, games should be designed so that the psychological needs can be met to a higher degree by paying for virtual items in the game. The game must *not* be designed for the player's enjoyment-maximization, but rather, satisfaction must be somewhat held back or provided in limited supply. For example, a game may grant limited access to certain features that increase multiplayer interaction and achievement while allowing players to get more access to this feature by paying and thus further satisfy their psychological needs. A prominent example of this from PG is raid passes which are severely restricted but can be bought for real money. Having more raid passes allows players to collaboratively defeat difficult opponents and have greater achievements and sociability in the game. For profit maximization, freemium games should not be designed to fully meet the player's psychological needs without them paying for it; although this may result in a more enjoyable game, some studies (Hamari, 2015, Hamari et al., 2020) have found enjoyment to be negatively correlated with purchase intention. This may explain why lower-rated games with designed inconvenience have relatively higher revenue than the highest-rated games (Alha et al., 2016). However, the game must be sufficiently enjoyable to ensure player retention, as retention rate is one of the main drivers for a games' revenue. Proper game design therefore requires a fine balance between enjoyment and 'designed inconvenience', because without sufficient retention, players will leave, and revenue will suffer. Games are, after all, supposed to be fun, and satisfying gaming experiences improve purchase intention (Stefany, 2014; Chen et al., 2017). There is no straightforward procedure for maximizing a games' revenue, but demand for virtual products in a freemium game can be created by a carefully designed interplay between the game experience and virtual goods sold therein. Catering to the players' psychological needs is a crucial component of this interplay and is imperative for game designers to consider.

5.3 Academic Implication

Maslow's hierarchy of needs is among the most recognized theories for human motivation, and is used in consumer psychology (Schütte and Ciarlante, 1998; Kotler, 2012; Ward and Lasen, 2009) and to predict consumer purchase motivation (Cui et al., 2021). Although some studies have applied motivational theories to investigate why people play games (Himeno and Tano, 2019; Neys et al., 2014), this study is the first to investigate spending behavior in a video game in relation to the player's psychological needs. The results imply that mobile games can be vehicles used to pursue a player's social-, esteem-, and self-actualization needs and those players are willing to spend money to further increase the satisfaction of these needs. This may be a valuable addition to the fields of marketing and technology adoption, which seek a deeper understanding of consumer behavior. This thesis shows that Maslow's hierarchy may have applications beyond traditional marketing and that it can be used as a framework for understanding consumer behavior in digital software products like games. Maslow's psychological needs are interrelated, and they have significant overlap (Schütte and Ciarlante, 1998). Usually, these needs are discussed as separate factors and studied as such, but as results from this thesis imply, it is possible to design features, like 'raiding' in Pokémon GO, that cater to several needs at once. It may be interesting from an academic perspective on consumer psychology to investigate other products or services that are able to capture several of Maslow's needs simultaneously, and whether this is more effective than catering to a single psychological need or several in a sequential manner.

5.4 Limitations

As this study used SEM, the results can only be generalized to the type of sample that was used in the model (Tabachnick and Fidell, 2013). The model is fitted to reproduce the characteristics in the data set, but not other data sets. This means that the results apply to PG players found in the Facebook groups in Appendix A who participated in the survey. In general, these were very experienced players and are likely spending more in the game than the average PG player. The results would therefore probably be different if the sample was a completely random grouping of PG players, and the results are therefore not generalizable to all PG players.

Another limitation of this thesis results from the limited amount of available research on which to base the study. No study to date has investigated purchasing behavior of video game players in the context of Maslow's need. However, this thesis had a basis on a review of 22 papers about spending behavior in mobile games and 21 more about other types of social online games, virtual environments, or apps in general. The studies which were not directly related to mobile games were included to provide more depth to the review, and it is reasonable to assume that there are commonalities that can be inferred to mobile games. However, generalizations between these different environments are not necessarily valid. For example, enjoyment can be a significantly stronger predictor for purchase intention in virtual worlds compared to other types of games (Hamari and Keronen, 2017). The limited available research may have contributed to not identifying the best candidates for independent variables as only three out of nine of these had a moderate to high effect on spending.

The narrowness of the research model is another limitation, as it only investigates a very few selected components hypothesized to be associated with spending. This study also neglected many reasons which contribute to a freemium game's commercial success, many of which did not fit the model used. A game does not need to fulfill Maslow's needs to monetize players, and many highly successful mobile games barely have any social features at all. Games are generally meant for fun, and the hedonistic aspects of playfulness, enjoyment, and flow may be enough to drive purchases. Many of the identified features that drive purchase intention (see Table 2.1) do not necessarily fit directly into Maslow's hierarchy of needs, e.g., features like waiting-time or design specific details like the multi-currency systems or offers. Other subtle psychological effects are not accounted for either; for example, instead of making players repeatedly spend money in small amounts, games often sell virtual currency like coins or gems in larger quantities. The intention is that players will more easily part with virtual currencies than actual money. This is analogous to selling poker chips to players in casinos, as players do not feel the same loss of losing chips compared to real money. The mentioned features neither fit into other proposed models, such as by Syahrizal et al. (2020), and there is a lack of a model, or several, which can take account for a more wholesome picture of spending behavior in games. This, however, is a difficult task as there could be dozens or even hundreds of interlinked components making *certain* players more inclined to spend money in a game. Moreover, every game and every player is different, making it even more difficult to create generalized models that accurately represent this complex reality.

6. Conclusion and Future Studies

This study is the first to have used Maslow's hierarchy of needs as a framework to study player's purchasing behavior in a video game. The study started with answering the first research question (RQ1) by performing a literature review on what makes players spend money on virtual items in video games. Results from the literature review were used in context of the popular mobile game Pokémon GO to answer RQ2 and RQ3. The results of a three factor structural equation model answers RQ2 and suggest that certain game features may cater to the player's need for belongingness, esteem, and self-actualization, and thus can be used as vehicles through which such psychological needs can be met. Moreover, answering RQ3, players are willing to pay for in-app purchases to obtain further satisfaction of these needs. On the contrary, increased satisfaction of these needs resulted in slightly less spending, implying that if a game fully satisfies a player's psychological needs, there is no reason to spend money in the game. This aligns with studies showing that enjoyment while playing games can reduce spending and means that game-designers can strategically limit a player's satisfaction, thereby making them more likely to spend money in anticipation of more fulfillment of their psychological needs.

The three most important game-specific factors for increasing spending in Pokémon GO were raiding with friends, unlocking new content, and leveling up. Interestingly, the highest effect was seen in raiding, which is also the only investigated game feature encapsulating all three psychological needs. The raiding feature is also largely restricted, but players can spend money to raid more frequently and thus increase the fulfillment of their psychological needs. The raiding feature had a large direct effect on these needs, as well as a mediating effect through increased spending.

Being the first study using Maslow's hierarchy of needs as a framework for spending in mobile games, the study cannot draw broad or clear conclusions, and further studies would need to reaffirm these results. Future studies may use a similar approach but use other indicators for each factor. Other independent variables could also be investigated as this study only found three out of nine to predict spending with moderate to high effects. Future studies could also investigate other types of games that have in-app purchases, e.g., other mobile games, virtual worlds, and PC games. It could also be interesting to perform a similar analysis using another theoretical framework for consumer psychology, like the increasingly popular self-determination theory. This theory has many similarities with Maslow's hierarchy of needs, and it could investigate if the need for autonomy, connectedness, and competence can be accounted for when designing games with higher revenue potential. Future studies could also look at how Maslow's needs in games are associated with Flow, which several studies have reported being an important predictor of spending.

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Appendix A

Table of Pokémon GO Facebook groups used for data collection:

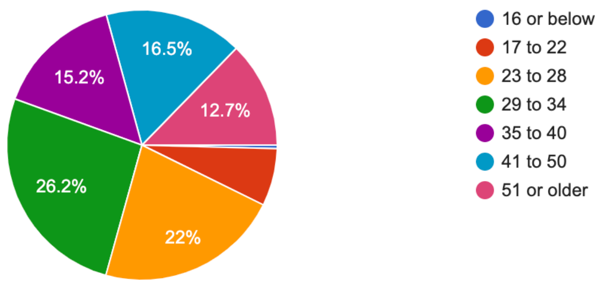
Facebook group name	**Facebook group ID**	**Members in May 2021 [thousands]**	**Survey used for**	**Data collection initiated**	**Data collection ceased**
Pokemon Go Worldwide (Official)	1330869733593308	198.8	Main	2nd May 2021	7th May 2021
Pokémon GO Worldwide FRIEND CODES (Official)	pokego	64.9	Main	30th April 2021	7th May 2021
Pokémon go friends code exchange group	295235504597912	62.6	Main	1st May 2021	7th May 2021
Pokémon GO Worldwide	gopokemongogame	62.9	Main	30th April 2021	1st May 2021
Pokémon Go Worldwide Friend Codes	1189350011234648	28.1	Main	1st May 2021	7th May 2021
Pokemon Go Norge	1565239027114192	17.2	Pilot	6th March 2021	7th March 2021

Appendix B

Summary of survey responses:

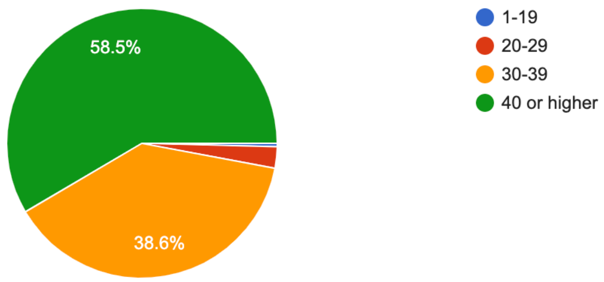
My age is

5,149 responses



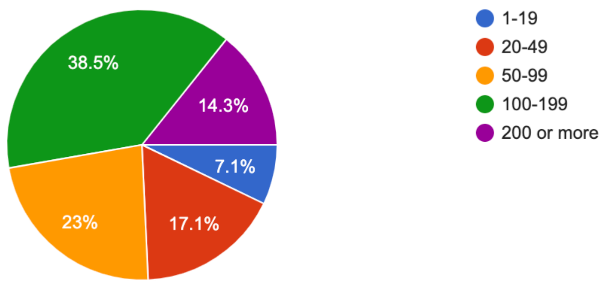
My highest level PokémonGo (PG) trainer is:

5,149 responses



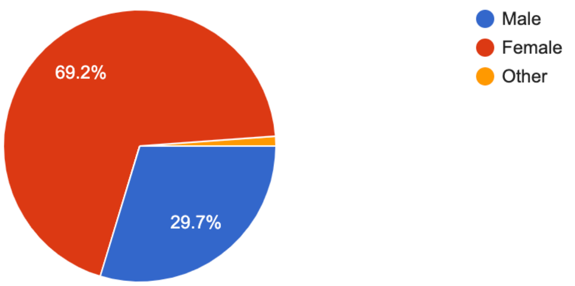
My number of friends in PG is:

5,149 responses



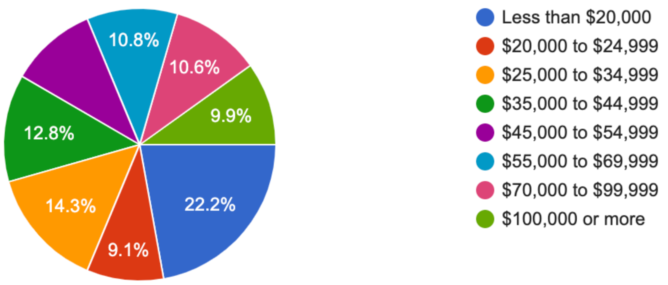
My gender is:

5,149 responses



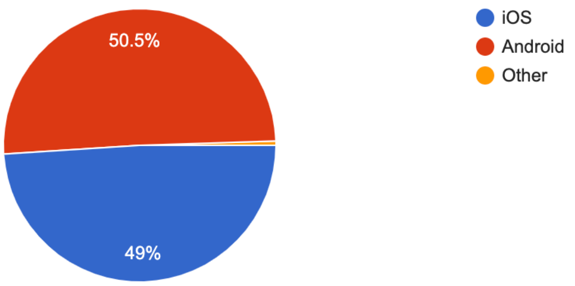
My yearly income in USD is:

5,149 responses



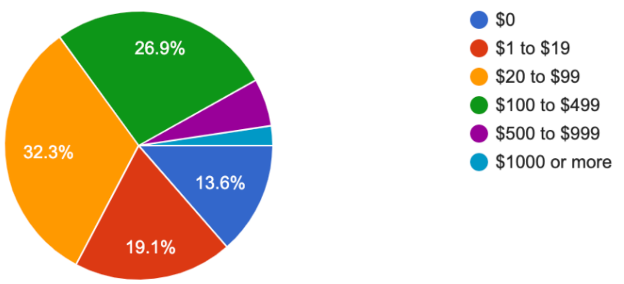
My operating system is

5,149 responses



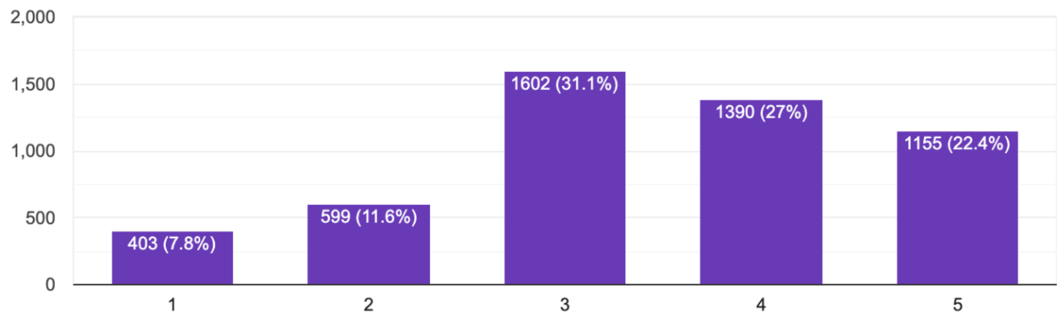
Over a whole year I would spend on average the following amount in USD on IAPs in PG:

5,149 responses



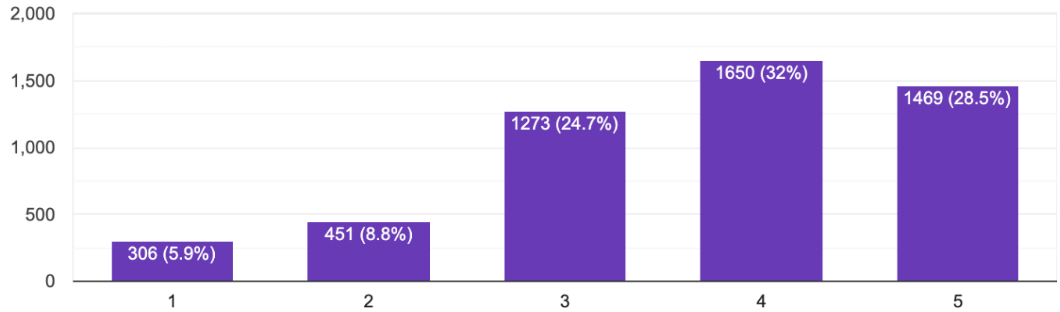
Having friends in PG gives me a sense of belonging and/or connectedness:

5,149 responses



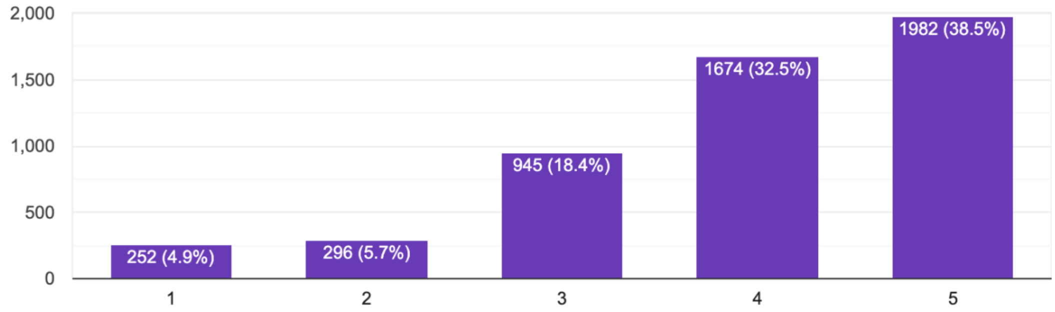
Interaction with other players gives me a sense of belonging and/or connectedness:

5,149 responses



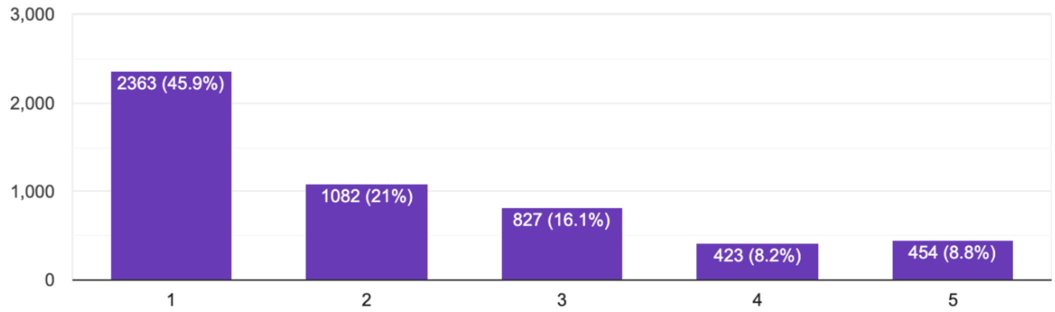
Raiding with friends gives me a sense of belonging and/or connectedness:

5,149 responses



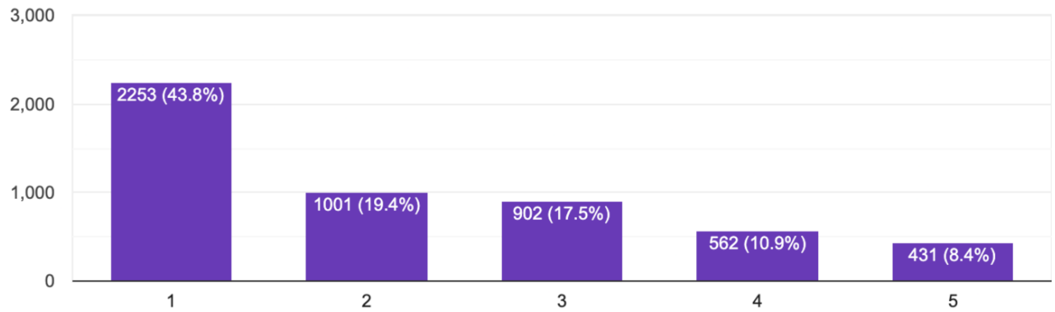
Having friends in PG is a determining factor for me to spend money on IAPs:

5,149 responses



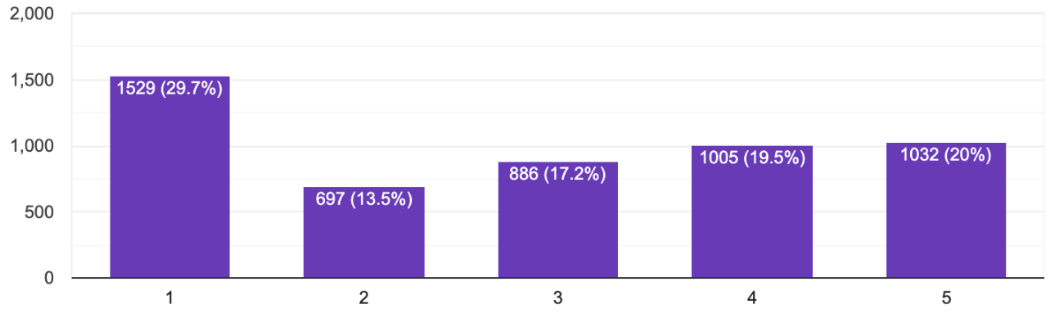
Interactions with other players is a determining factor for me to spend money on IAPs:

5,149 responses



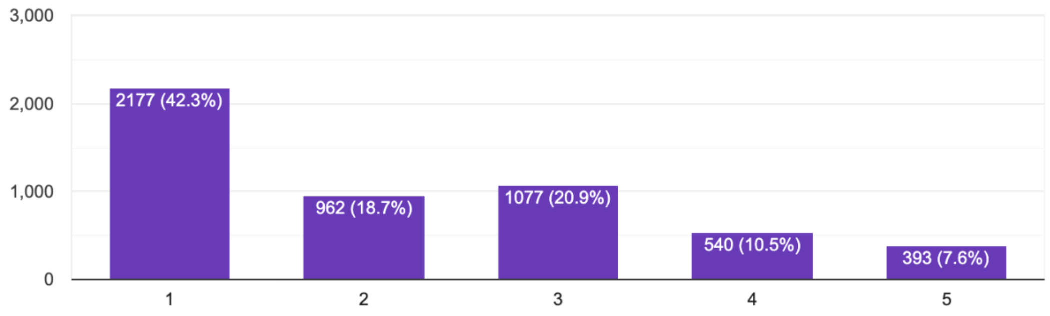
Raiding with friends is a determining factor for me to spend money on IAPs:

5,149 responses



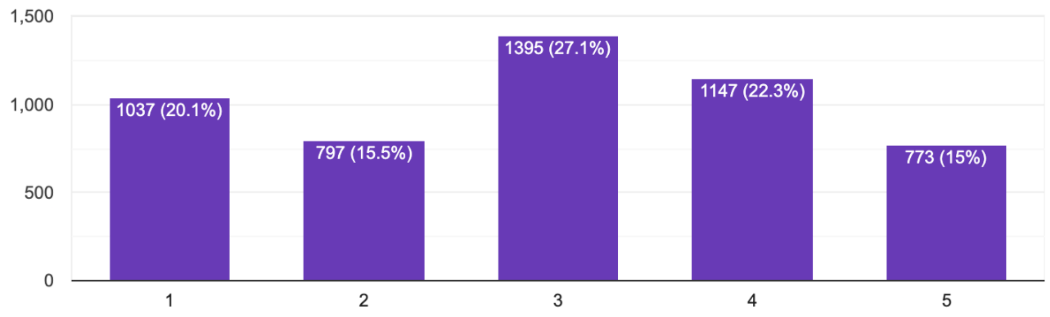
I would be willing to spend money on IAPs to get an increased sense of belonging and/or connectedness in PG:

5,149 responses



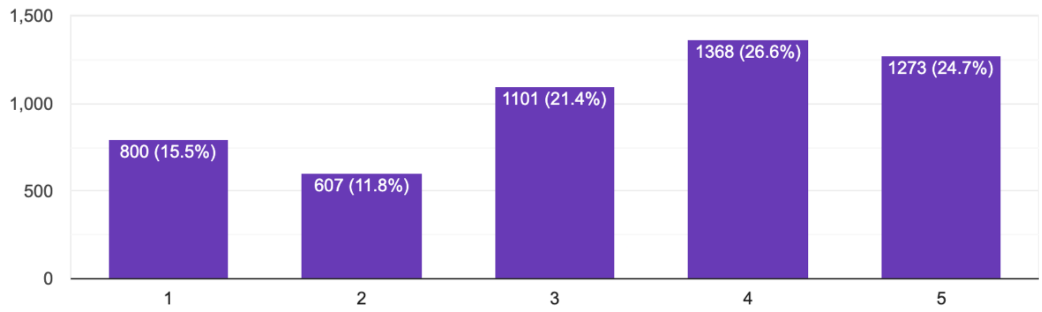
Competition with other players gives me a feeling of respect and/or status:

5,149 responses



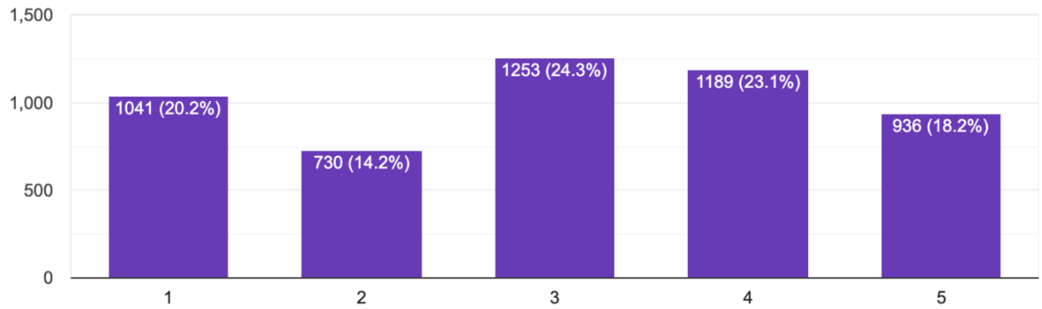
Having the best or rarest Pokémon among my friends gives me a feeling of respect and/or status:

5,149 responses



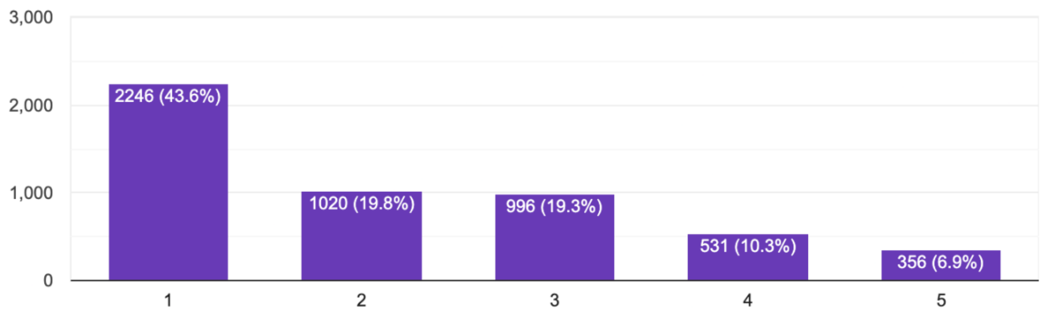
Being at the highest level among my friends gives me a feeling of respect and/or status:

5,149 responses



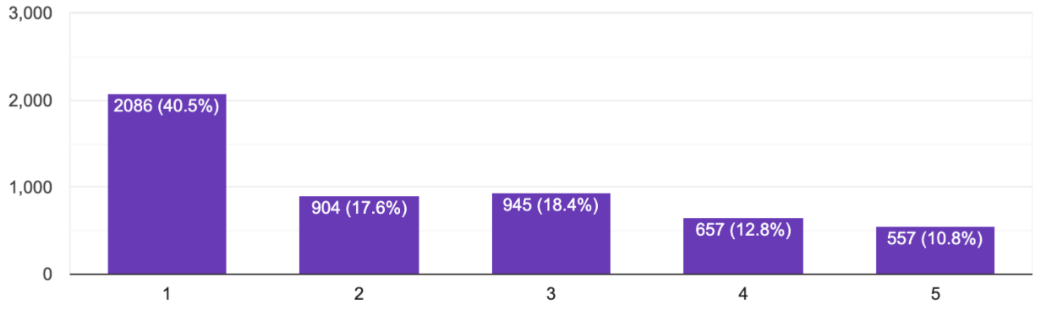
Competition with other players is a determining factor for me to spend money on IAPs:

5,149 responses



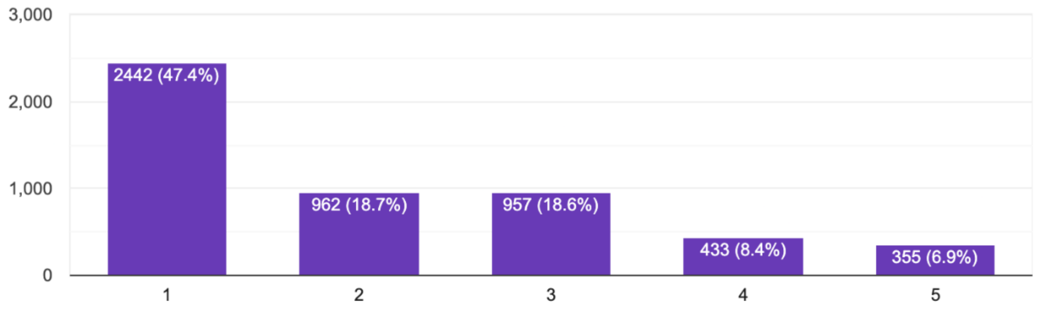
Having the best or rarest Pokémon among my friends is a determining factor for me to spend money on IAPs

5,149 responses



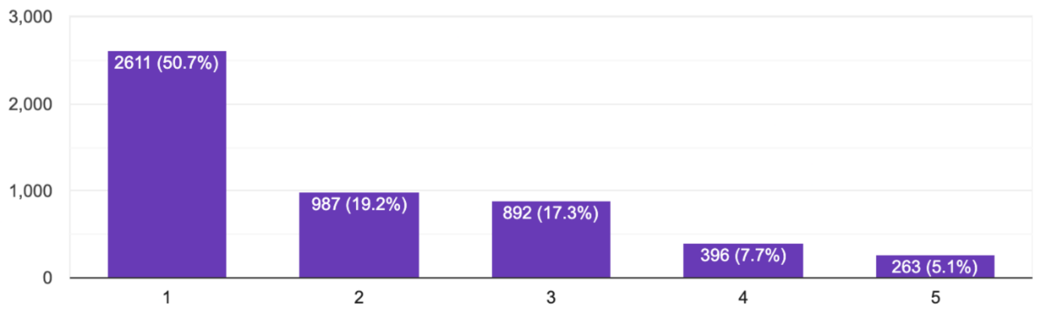
Being at the highest level among my friends is a determining factor for me to spend money on IAPs

5,149 responses



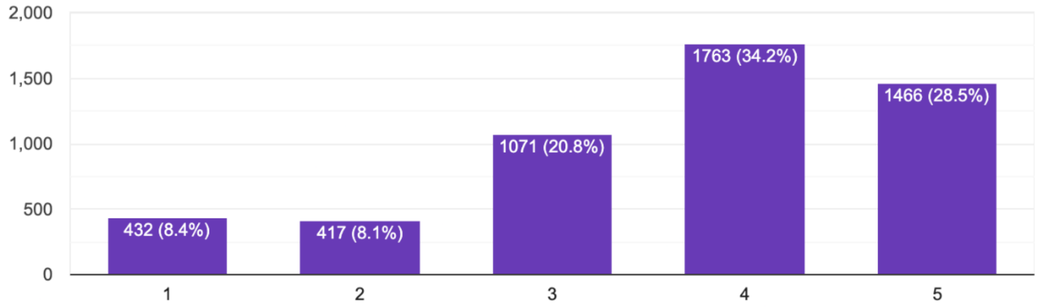
I would be willing to spend money on IAPs to get a stronger feeling of respect and/or status in PG:

5,149 responses



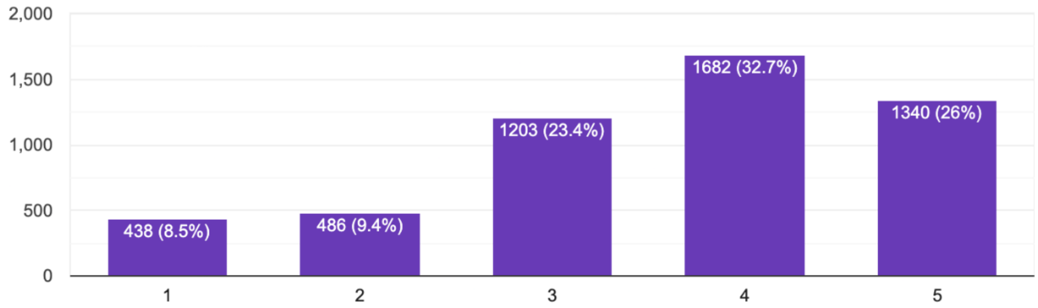
Unlocking new content in PG gives me a feeling of self-realisation through progress and/or achievement:

5,149 responses



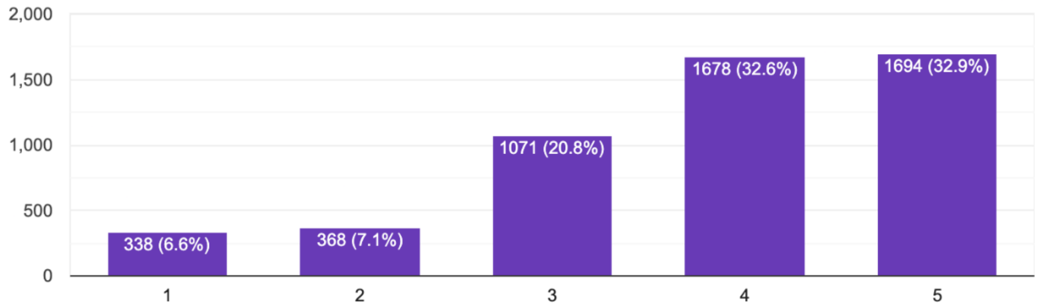
Evolving or powering up my Pokémons gives me a feeling of self-realisation through progress and/or achievement

5,149 responses



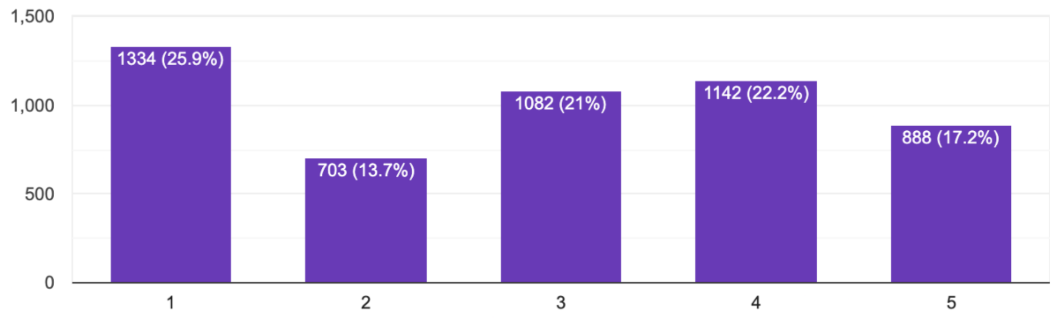
Leveling up my Pokémon trainer gives me a feeling of self-realisation through progress and/or achievement:

5,149 responses



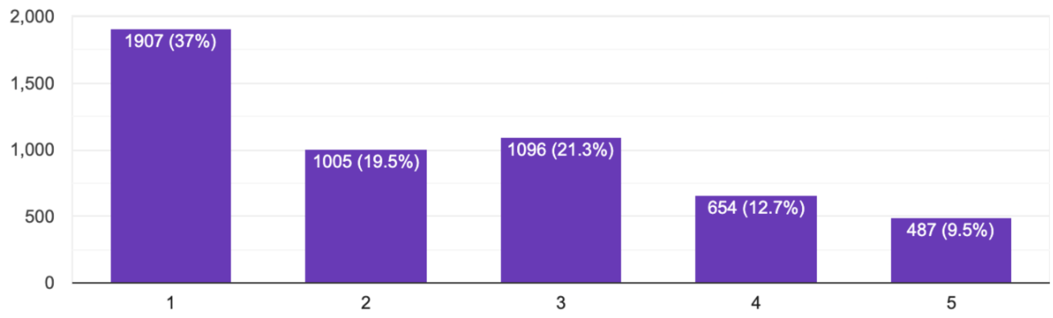
Unlocking new content in PG is a determining factor for me to spend money on IAPs:

5,149 responses



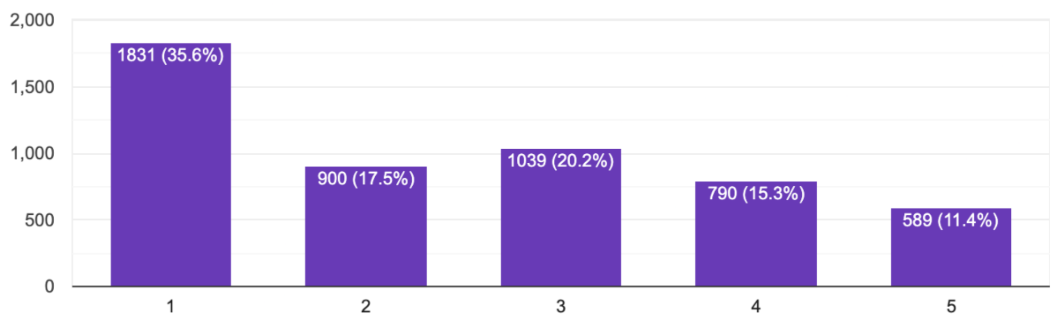
Evolving or powering up my pokémons is a determining factor for me to spend money on IAPs:

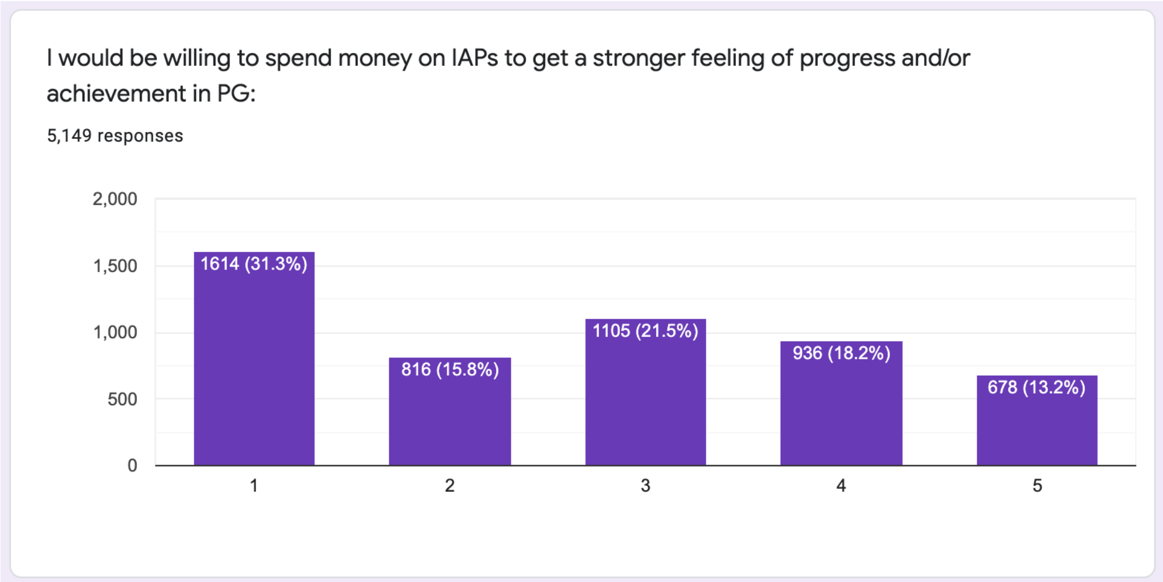
5,149 responses



Leveling up my Pokémon trainer is a determining factor for me to spend money on IAPs:

5,149 responses




I would be willing to spend money on IAPs to get a stronger feeling of progress and/or achievement in PG:
5,149 responses
2,000
1,500
1,000
500
0
1614 (31.3%)
816 (15.8%)
1105 (21.5%)
936 (18.2%)
678 (13.2%)
1
2
3
4
5

NTNU

Kunnskap for en bedre verden