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IMPACT OF SOCIAL FEATURES ON PLAYER RETENTION IN F2P MOBILE GAMES

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Ilmaiseksi ladattavien ns. free-to-play -pelien ansaintamalli perustuu virtuaalisten hyödykkeiden myymiseen, mainoksiin, tai molempiin. Pelaajalta on siis mahdollista saada tuloja tämän koko käyttöelinkaaren ajalta. Pelaajien pitäminen saman pelin parissa viikkojen, kuukausien tai vuosien ajan on kuitenkin haastavaa. Sosiaalisten toiminnallisuuksien, jotka mahdollistavat pelaajien välisen vuorovaikutuksen ja kommunikoinnin pelin sisällä, lisäämisen on väitetty edesauttavan pelaajien pysymistä pelin parissa. Tässä tutkimuksessa luodaan katsaus käytön jatkumiseen tietojärjestelmätutkimuksessa ja sosiaalisen kanssakäymisen suhdetta peleihin. Mobiilipelien sosiaalisten toiminnallisuuksien käytön ja käyttäjäpysyvyyden välistä suhdetta selvitetään logistisen regressioanalyysin keinoin. Tutkimuksessa hyödynnetään käyttäjäanalytiikkalokeja kahdesta kaupallisesta free-to-play -mobiilipelistä. Kahdesta tutkitusta pelistä toisessa sosiaalisten toiminnallisuuksien käyttö ensimmäisen viikon aikana edesauttoi selvästi käyttäjän pysymistä pelin parissa vielä kuukauden jälkeen ensimmäisestä pelisessiosta. Toisessa pelissä vastaavaa yhteyttä ei löytynyt. Molempien pelien osalta pelin parissa vietettyjen päivien määrä ensimmäisen viikon aikana edesauttoi pysymistä pelin parissa. Sosiaalisten toiminnallisuuksien lisääminen ei siis välttämättä johda pelikehittäjän kannalta toivottuihin tuloksiin, mutta ainakin joissain olosuhteissa sosiaaliset toiminnallisuudet edesauttavat käyttäjien pysymistä pelin parissa.

Asiasanat: free-to-play, mobiilipelit, käyttäjäpysyvyys, sosiaaliset toiminnallisuudet

ABSTRACT

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The so-called "free-to-play" revenue model relies on selling virtual goods, showing ads, or both, in digital games that are downloadable free of charge. In free-to-play games players can be monetised over their whole player lifetime. However, keeping the players playing the same game over weeks, months or even years is difficult. Social features that enable interaction and communication between players inside the game have been claimed to improve the retention of players. This study examines use continuance literature from the IT field as well as the relationship between social interaction and games. The relationship between social feature engagement and player retention is analysed by utilising logistic regression analysis. This study utilises actual player analytics data from two commercial free-to-play mobile games for the analysis. In one of the games, social feature engagement during the first seven days was found to have a positive impact on player retention even after 30 days from the first day of playing. In the other game, no such effect could be observed. In both games, the count of distinct days of playing the game was found to have a positive effect on player retention. While adding social features into a game does not necessarily improve its player retention, there seems to be a connection between social feature engagement and player retention at least under certain conditions.

Keywords: free-to-play, mobile games, user retention, social features

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1 INTRODUCTION

The global mobile game market has been growing rapidly for quite some years already: the global market value was estimated to be $37B in 2016 and it was predicted to grow beyond $50B by the end of 2019 (Newzoo, 2016). The growth proved to be even faster than anticipated as the global market value has been estimated to exceed $70B already in 2018, accounting for 51% of all digital game revenue (Newzoo, 2019). The dominating business model in mobile games is the free-to-play model, often shortened to F2P, generating 80% of revenue (SuperData, 2019).

F2P games are free to download and play, but they encourage players to spend money on various virtual commodities inside the game. This comes with two advantages: the game is available for the widest range of player segments as there is no up-front commitment, and it allows flexible price points to address to a wide spectrum of players with different spending capabilities and spending willingness (Paavilainen, Hamari, Stenros & Kinnunen, 2013). This type of approach relies on monetising players over long periods of time: a player who spends $10 inside the game every month is more valuable if they continue playing the game for a long time. Therefore, the ability to keep the players playing the game for a long period of time is crucial for a F2P game developer. In mobile game industry, retention is the term used to describe this type of continued usage and especially long-term retention is widely considered to be one of the most important key metrics to evaluate the chances of commercial success of a F2P game (e.g. Lovell, 2011; Evans, 2014).

The service-like nature of F2P model allows the developers of the game to tweak and improve the game incrementally over time to improve the key-performance metrics such as monetisation and retention (Hamari & Järvinen, 2010). Because retention is such an important factor for success, developers are keen to find out good ways to improve retention in their games. Retention has a somewhat notorious reputation among app developers for being a metric that is very hard to improve (Balfour, Winters & Clowes, 2017). Getting significant improvements in retention often requires rebuilding core mechanics of the game, which is both time consuming and expensive.

Game features that are built upon interaction between players, such as trading in-game items and resources, cooperation between players, and competition against other players, are often called social features and considered to be effective retention mechanisms (Katkoff, 2013; Koster, 2019). The more the players are interacting with each other and forming relationships, the more likely they are to keep playing the game. And the longer the players keep on playing and coming back to the game the more time the game publisher has to monetise them via in-app purchases, ads or both. However, verifying this chain of thought is tricky. Even though some research regarding retention prediction exists (e.g. Runge, Gao, Garcin, & Faltings, 2014; Drachen, Lundquist, Kung, Rao, Sifa, Runge & Klabjan, 2016), data regarding the actual behavior of players is scarce and mostly owned and controlled by game publishing companies. The research community can utilise some open datasets (e.g. Deft University of Technology, 2019), data self-reported by the players, or arrange playtest sessions in lab conditions, but the behavioral data provided by the log data remains mostly in databases of the game publishers. These companies that do have the log data and are able to perform analysis regarding their players tend to be unable or unwilling to openly talk about their methods and metrics for business or legal reasons. Therefore, companies with less capabilities to engage in data analytics of their own are forced to act and make development decisions based on less reliable information than their bigger, more resourceful competitors.

Some corresponding academic research exists. While free-to-play mobile games are a relatively new phenomenon and not much literature exists as of now, factors behind use continuance and use continuance intention have been studied in the field of IT research. For quite some time the scientists were more interested in IT adoption and continued use was not properly separated from adoption (Bhattacherjee, 2001). However, it has become more evident that IT continuance should be considered a separate phenomenon of its own (Bhattacherjee, 2001). Again, not all IT systems are comparable to mobile games since gaming is usually driven by entertainment while IT systems are commonly studied in work life context. IT continuance research should still work as a good starting point while more detailed research in gaming context remains lacking as IT continuance models have been successfully utilised in studying games and game-like systems already (e.g. Hsu & Lu, 2004; Lee & Tsai, 2010; Chang, Liu & Chen, 2014).

Use continuance intention has also been studied in other types of games and game-like environments that have been around longer than F2P, such as social virtual worlds (e.g. Barnes, 2011; Mäntymäki & Salo, 2011; Mäntymäki & Islam, 2013; Mäntymäki & Riemer, 2014). Social virtual worlds, such as Second Life and Habbo Hotel, might not be a perfect comparable match for F2P mobile games, but they do share some common elements such as interaction with other players in virtual environments, similarities in revenue models, and the purpose of entertainment. This makes social virtual worlds quite an interesting point of comparison.

The question still remains: does engagement with social features really affect long-term use? The purpose of this study is to help F2P mobile game developers to make better development decisions by shedding some light upon this question. The research is conducted by reviewing existing literature about factors behind IT continuance, and analysing actual data from F2P mobile games by means of logistic regression analysis. This study aims to find answers to following research questions:

1) How is engaging with social features related to long-term use continuance in free-to-play mobile games?
2) How does engaging with social features compare to other factors that might affect the long-term use continuance?

Research data for this study is provided by PlayRaven, a Helsinki-based F2P mobile game development company with a track record of several globally published games. The Finnish game industry scene is known to be a very active one and there is a strong culture of sharing information between the companies. A success of any local game developer is considered beneficial for all of them through increased interest of investors and talented workforce, and the overall brand value of Finnish game development. The success of Finnish game companies such as Supercell, Rovio and many others have given Finland a reputation as a major hot spot of game development (GDC Europe, 2016). PlayRaven has been a strong advocate of openness and sharing in the Helsinki mobile game scene and stands behind this ideology by providing access to their databases for the purposes of this study.

The study is structured into seven main chapters. Chapter 2 consists of literature review of seven models commonly utilised in IT continuance research, to determine how social factors and use continuance are related according to literature. Chapter 3 is an introduction to social interaction in video games, and describing social features and interactions in social network games, multiplayer online games, and free-to-play mobile games. Chapter 4 covers the elements of the actual research such as the research material, research methods and variables used. The results are presented in chapter 5 and the results are interpreted and discussed in chapter 6.The summary can be found in chapter 7.

2 USE CONTINUANCE

In this chapter, a selection of commonly used IT use continuance models is reviewed in order to determine how much social factors contribute to use continuance according to IT research. The seven models that are reviewed in this chapter were chosen because they were the most commonly utilised models in recent IT continuance research according to Nabavi, Taghavi-Fard, Hanafizadeh and Taghva (2016). Nabavi et al. have fairly recently conducted a wide and systematic review of research related to IT continuance between 2001 and 2014. After going through 191 articles from over 60 publishers they noticed that the amount of annual publications concerning IT continuance increased as presented in figure 1. However, only one of these papers was related to mobile games while ten were about social virtual worlds, two about online games and one about simulation games. Even though the selection of games or game-like environments in the review is small, the same models have been utilised for studying games and game-like environments (e.g. Hsu & Lu, 2004; Lee & Tsai, 2010; Chang, 2013; Chang et al., 2014), making these models relevant for the purposes of this study.

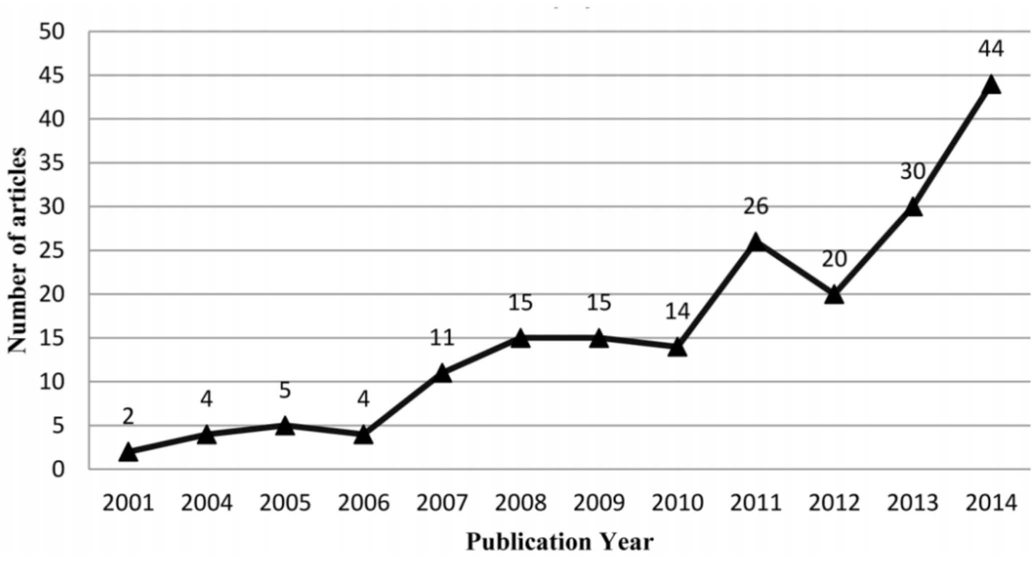

FIGURE 1 Number of IT continuance articles by publication year (adapted from Nabavi et al., 2016)

According to Nabavi et al. (2016) the most common models used were IS Continuance Model (ISCM), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA), IS Success Model and Flow Theory. These models are reviewed in this chapter in terms of how social factors are related to use continuance intention. The models are largely building on top of preceding models so therefore they are reviewed from the oldest to the newest.

2.1 Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB)

Theory of Reasoned Action (TRA) is a social psychology theory that suggests that attitude and subjective norms, a term referring to perceived social pressure to act or not to act, have an effect on behavioral intention of acting in a certain way (Fishbein & Ajzen, 1975). This behavioral intention then directly affects the manifestation of the behavior. Or in other words, presumed consequences and reactions to one's behavior directly affect the intention which then affects the actual behavior. The relevant components and their impact on each other are visualised in figure 2.

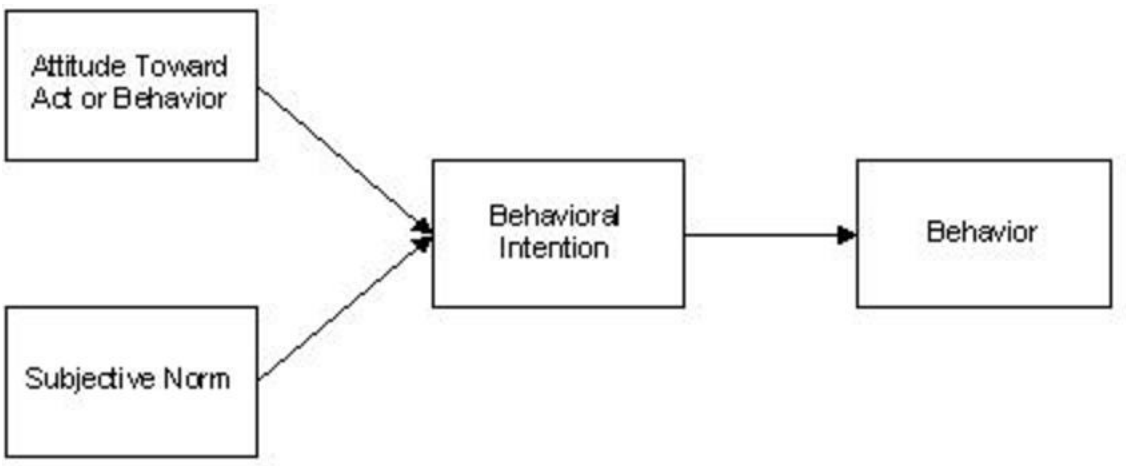

FIGURE 2 Theory of Reasoned Action (adapted from Fishbein & Ajzen, 1975)

Ajzen (1985, 1991) later developed the theory further into Theory of Planned Behavior. It adds perceived behavioral control as new factor that also affects behavioral intention both directly and through the two factors already established in TRA: attitude and subjective norms. Perceived behavioral control means how easy or hard one perceives the intended behavior to be. TPB and its components are visualised in figure 3.

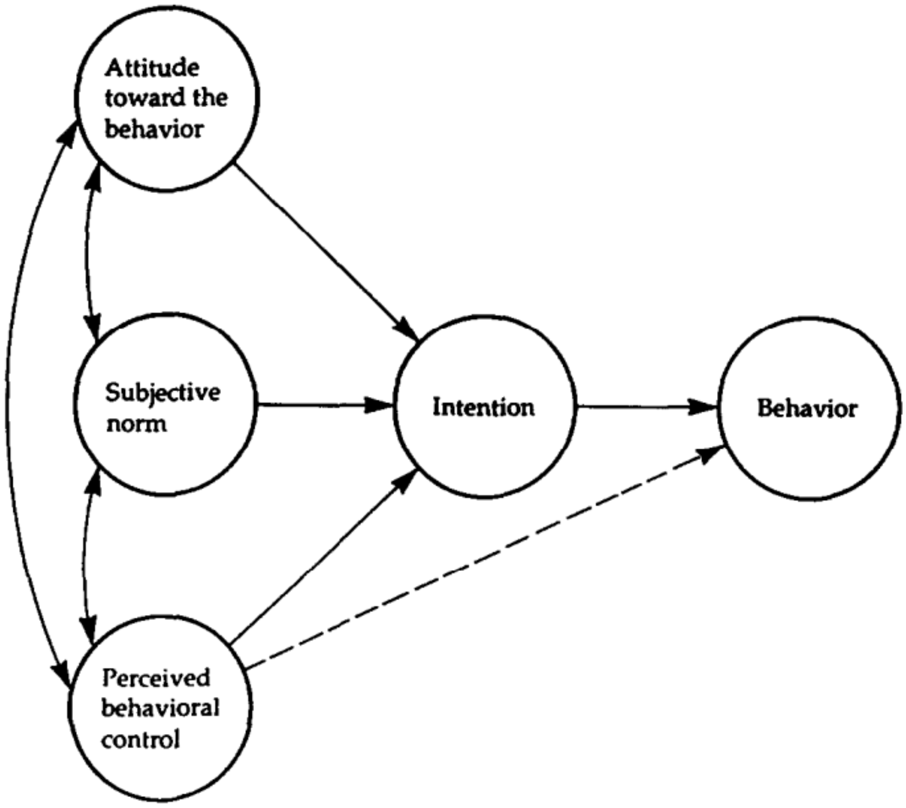

FIGURE 3 Theory of Planned Behavior (adapted from Ajzen, 1991)

Both TRA and TPB include the same social factor: subjective norm. Subjective norm refers to perceived social pressure to act or not to act. Or in IT continuance context, to keep on using a given IT system or not. The more one feels that other people important to them approve acting in a given way, the stronger the intention to act that way becomes (Ajzen, 1991). Ajzen's (1991) findings suggest that while the relative effectiveness of each factor is likely to vary depending on the given situation, the personal considerations tend to be stronger than the perceived social pressure.

These theories have been applied to IT research in studies related to adoption and use continuance intention of technology, both of which play a vital part in achieving benefits from technology. They have been utilized both on their own and in conjunction with other models when studying use continuance intention in the fields of electronic commerce (Cenfetelli, Benbasat & Al-Natour, 2008), e-learning (Lin, Chen & Fang, 2011), social media (Bonsón, Escobar & Ratkai, 2014), virtual worlds (Barnes, 2011; Mäntymäki & Riemer, 2014) and mobile games (Liang & Yeh, 2011). Many different theories and models aiming to explain technology adoption and use continuance intention are founded upon TRA and TPB or have drawn inspiration from them and some of these are introduced in the following subsections.

2.2 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is a model explaining IT adoption developed on the foundation provided by TRA (Davis, 1985). Davis found two factors affecting the attitudes of IT players: perceived usefulness and perceived ease of use. Perceived ease of use was also found to affect perceived usefulness which also affects behavioral intention in addition to attitude. Or to put in a simpler way, an IT user is more likely to use a system that they find both useful and easy to use. The mechanics of TAM are visualised in figure 4.

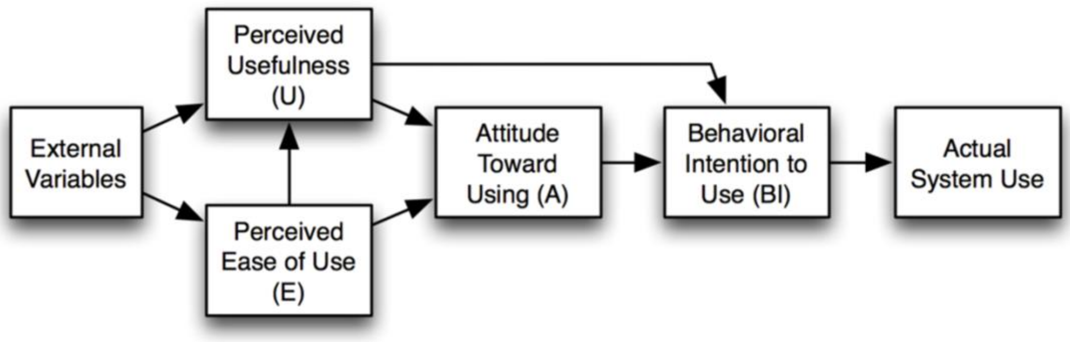

FIGURE 4 Technology Acceptance Model (adapted from Davis, 1985)

The social component of TRA, subjective norms, is not included in TAM. One of the main purposes of TAM is to provide a theoretical basis for user acceptance testing, such as testing system prototypes with potential users. Therefore, the users testing the system are likely to be trying a given system for the first time, which means that there should be no pre-existing social influences (Davis, 1985). However, at least in certain cases social influence from peers and mentors has been found to affect perceived usefulness, and social influence from mentors to also affect perceived ease of use (Shen, Laffey, Lin & Huang, 2006).

Even though TAM was primarily developed to understand IT adoption, it has been used widely when studying IT use continuance intention as well: the review of Nabavi et al. (2016) declared that TAM was the second most used model utilised in IT use continuance research between 2001 and 2014, the most popular one being IS continuance model. Van der Heijden (2004) utilised TAM in context of hedonic systems. He argues that in hedonic systems, which are used for the sake of entertainment rather than utilitarian goals, perceived usefulness is replaced with perceived enjoyment as a major driver of behavioral intention.

TAM has been criticised for the very reason that it is been utilised in IT continuance research even though it was originally developed to describe IT adoption (De Guinea and Markus, 2009; Bhattacherjee & Barfar, 2011).

2.3 IS Continuance Model (ISCM)

Information System Continuance Model (ISCM) was developed specifically to describe IT use continuance intention instead of IT adoption (Bhattacherjee, 2001). ISCM combines some familiar factors from TAM with expectation-confirmation model (ECM) which originates from the field of consumer behavior in marketing. According to ECM, the consumers' expectations towards the product and how these expectations are confirmed affect future purchase decisions. So in context of IT this would translate to expectations related to the system, and how these expectations are confirmed then affects how likely the user is going to continue using the system. Overall, ISCM introduces three factors that affect the continuance intention either directly or indirectly: confirmation of expectations, perceived usefulness, and user satisfaction. Confirmation of expectations affects perceived usefulness and satisfaction, and both perceived usefulness and satisfaction affect continuance intention. Therefore, a system that fulfils or exceeds the expectations is perceived to be more useful and improves satisfaction. These then contribute to intention of continuing to use the system. This mechanism is visualised in figure 5.

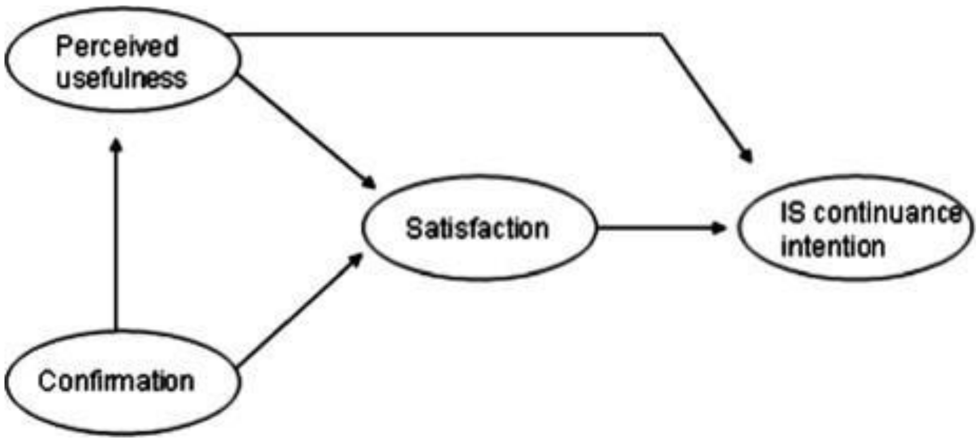

FIGURE 5 IS Continuance Model (adapted from Bhattacherjee, 2001)

Drawing from TAM, ISCM does not include any social component. Instead, ISCM rather suggests that the continuance intention is determined by how satisfied the user was when using the system. However, according to Shen et al. (2006), at least in certain cases social influence can affect perceived usefulness. Also, since perceived usefulness is a secondary predictor to satisfaction in ISCM, social influences can arguably play a minor part in IS continuance intention. A later, extended model of ISCM (Bhattacherjee & Lin, 2015), has adopted subjective norms introduced in TPB and TRA, suggesting further that social influences can affect continuance intention.

ISCM was the most used model in IT continuance research between 2001 and 2014 according to the review by Nabavi et al. (2016). As many as 52% of the papers utilised the model either on its own, in some further developed form, or in conjunction with other models. The model has been developed further on multiple occasions (Lin, Wu & Tsai, 2005; Bhattacherjee, Perols & Sanford, 2008; Bhattacherjee & Barfar, 2011; Tang, Tang & Chiang, 2014; Bhattacherjee & Lin, 2015).

2.4 IS Success Model

IS Success Model of DeLone and McLean (1992) is a thoroughly tested and utilised model explaining success factors of information systems. In the core of the IS success model six factors can be found: information quality, system quality, use, user satisfaction, individual impact, and organizational impact. System use is affected by the quality of the system and information, and user satisfaction, visualised in figure 6. The model was later updated and developed further (DeLone & McLean, 2003). Neither the original nor the updated model recognises any social components affecting system use.

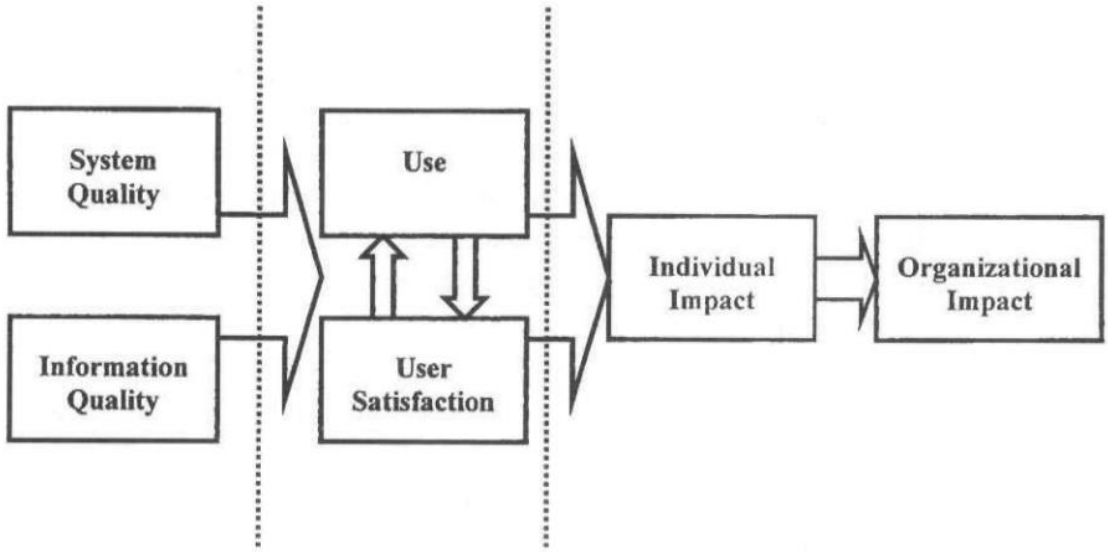

FIGURE 6 IS success model (adapted from DeLone & Mclean, 1992)

Even though the model is focused on explaining IS success, it has been used in IT use continuance research as well, because it includes use of the system as one of the factors. The model has been used in IT continuance research by at least Chen (2007), Chiu, Sun, Sun and Ju (2007), Zheng, Zhao and Stylianou (2013), Zhou (2013), Dong, Cheng and Wu (2014), and Gao and Bai (2014).

2.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

Unified Theory of Acceptance and Use of Technology (UTAUT) is a model explaining IT adoption and use continuance, and it draws a lot from various other models, including TAM, TRA and TPB (Venkatesh, Morris, Davis & Davis, 2003). In its core can be found four different factors that explain behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. The effect of these factors is moderated by a combination of user's age, gender and previous experience. The model was developed further (Venkatesh, Thong & Xu, 2012) to accommodate the context of consumer technology. This new model, UTAUT2, ended up including three new factors: hedonic motivation, price value, and habit. These three factors are also moderated by user's age, gender and previous experience. This model is visualised in figure 7. (Venkatesh et al., 2012).

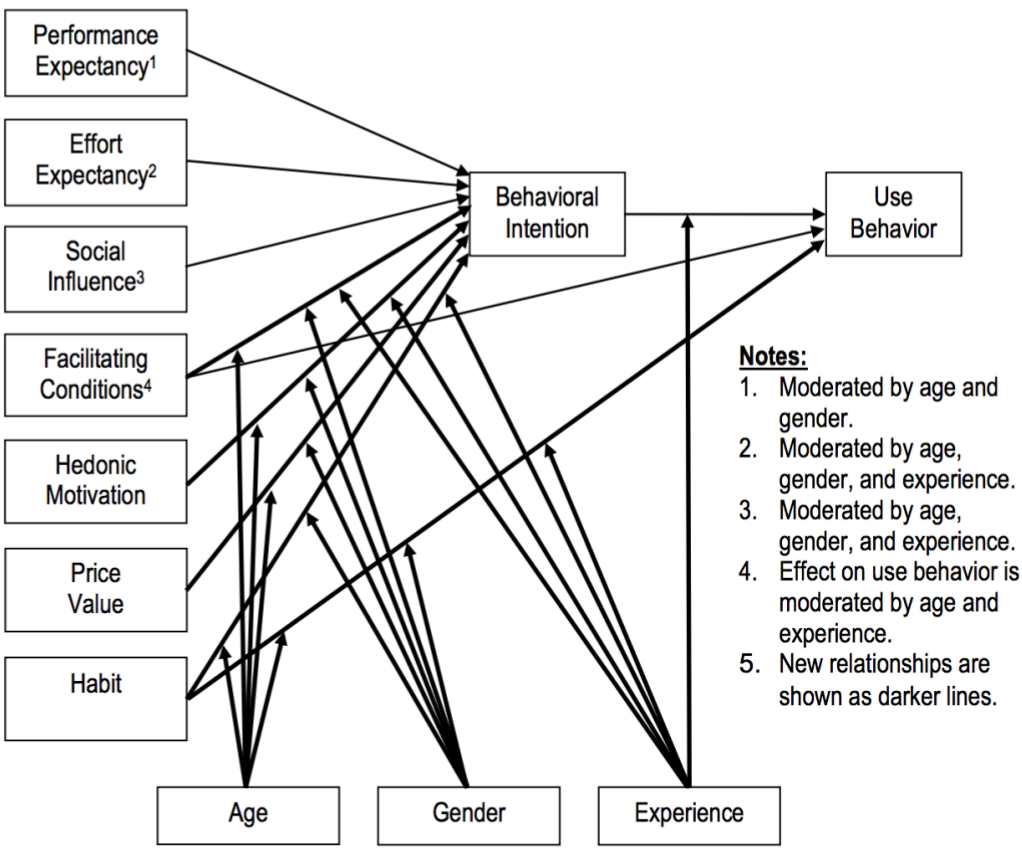

FIGURE 7 UTAUT2 (adapted from Venkatesh et al., 2012)

UTAUT and its more recent versions include social influence as a major component that affects the behavioral intention. Social influence consists of three constructs: subjective norm, social factors, and image. Subjective norm was adopted from TPB and TRA and uses the same definition: perceived social pressure from people the user considers important to them. Social factors refer to internalization of the culture of the organisation: is there encouragement and support from co-workers and supervisors, and are they using the system too. Image is related to whether using the system improves the image and social status of the user in the organisation. (Venkatesh et al., 2003).

2.6 Flow Theory

Flow theory of Csikszentmihaly (1990) describes a state of mind where a person is extremely focused and immersed in the task at hand. In this so called flow state the person's skills and the level of challenge of the task are in an optimal balance. Typically, the flow experience is perceived to be enjoyable and losing the sense of time is common because of the intense focus on the task. If the task proves to be too challenging for the person's skills, they might get too frustrated and anxious or if the task is too easy, they easily get bored. Between the anxiety and boredom lies the so called flow channel, an optimal balance between the challenge and the performers skills, visualised in figure 8. (Csikszentmihaly, 1990).

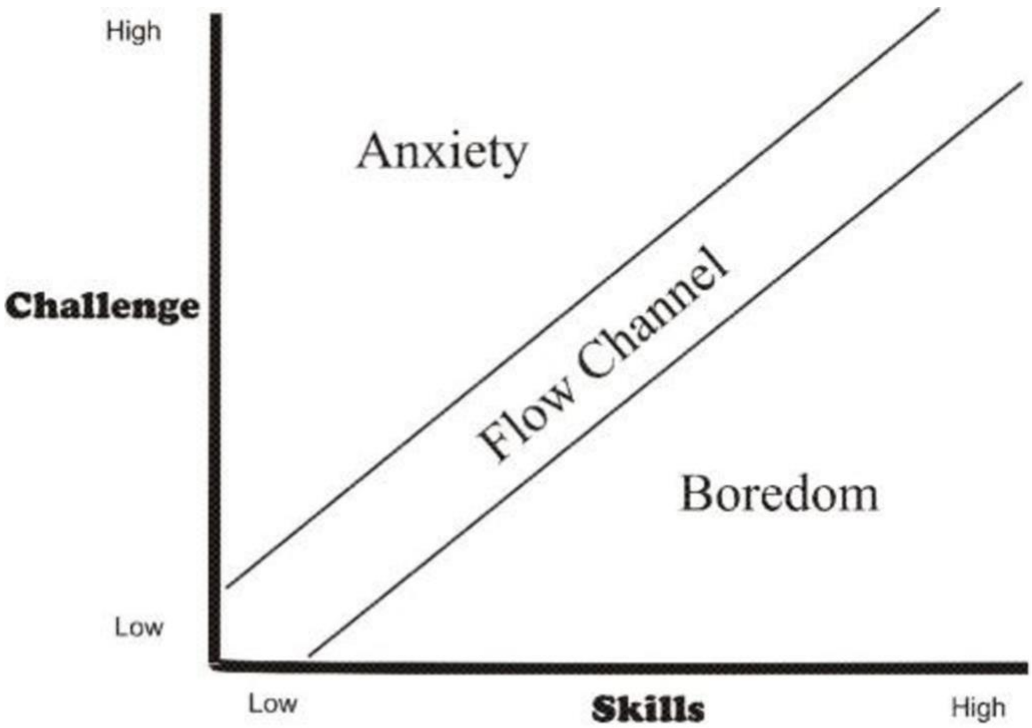

FIGURE 8 Flow theory (adapted from Csikszentmihalyi, 1990)

Flow theory does not directly refer to any social factors behind the flow experience. However, it has been noticed that playing an online game against human-controlled opponents can lead to more feelings of flow experience and enjoyment than playing against computer-controlled opponents (Weibel, Wissmath, Habegger, Steiner & Groner, 2008). This finding directly supports the idea that at least competitive social interaction could have a positive impact in use continuance, because as argued by van der Heijden (2004), perceived enjoyment is a major driver of behavioral intention in hedonic systems.

Flow theory has been cited often in game research and the flow experience is seen as a very influential part of a gameplay experience (Murphy, 2012). It has also been utilised in IT continuance research. The enjoyable experience of the flow experience has certain similarities to various factors recognised in many IT continuance models: in ISCM satisfaction is a crucial factor (Bhattacherjee, 2001) and the expanded UTAUT adds hedonic motivation into the mix (Venkatesh et al., 2012). Zhou (2011) utilised flow theory together with UTAUT when studying mobile network usage and Chang and Zhu (2012) utilised flow theory and ISCM when studying social media service usage in China. ISCM and flow theory was also utilised by Cheng (2014) when studying use continuance of e-learning systems for nurses. Overall, flow experience seems to be in the core of what makes games fun and enjoyable.

2.7 Use continuance in games and game-like environments

2.7.1 Social Virtual Worlds

Social Virtual Worlds (SVW) are computer simulated environments where players can communicate with each other and explore a virtual environment by the means of an avatar (Bartle, 2003). Second Life (2003) and Habbo Hotel (2000) are well-known examples of social virtual worlds. Social virtual worlds can include game-like elements or it can be a straight up massive multiplayer online game (MMO) as well.

Use continuance intention has been studied in the context of social virtual worlds to a somewhat limited extent. Barnes (2011) studied use continuance intention in Second Life and noticed that the most impactful use continuance factors were habit, enjoyment and perceived usefulness out of which the perceived usefulness proved to be the most impactful one.

Mäntymäki and Salo (2011) used TAM when studying use continuance intention and transaction behavior in Habbo Hotel. Similarly to Barnes (2011), they noticed that perceived usefulness proved to be one of the most important factors, alongside perceived enjoyment, affecting use continuance intention. They also studied the impact of the so-called network effect, a phenomenon where additional users provide more value to the whole network through the increased potential of interaction, which had an indirect effect on use continuance intention by affecting both perceived usefulness and perceived enjoyment. Habbo Hotel was studied also by Mäntymäki and Islam (2013) who utilised ISCM and found that the network effect moderates the relationship of both perceived usefulness and perceived enjoyment with use continuance intention. Later Mäntymäki and Riemer (2014) studied the motivations of the Habbo Hotel together and found that the motivations behind use continuance intention were strongly driven by hedonic and social factors.

2.7.2 Online games

Any game that requires an internet connection to play is considered an online game. A typical online game is a multiplayer video game played on a computer or a video game console where players cooperate with each other or compete against each other (Ray, 2012).

Some research exists regarding use continuance intention in online games. Choi and Kim (2004) studied reasons behind customer loyalty in online games and concluded that optimal gameplay experience that kept the players coming back to the game consisted of both personal interactions with the game and social interactions with other players. Hsu and Lu (2004) appended TAM with social influence component and flow theory, discovering that social norms, attitude, and flow experience were crucial factors explaining about 80% of game playing. Lee and Tsai (2010) utilised TAM and flow theory with TPB in their research and found out that perceived enjoyment, attitudes and subjective norms had a clear impact on use continuance intention. Chang et al. (2014) also utilised flow theory, this time together with social cognitive theory (SCT), appended with hedonic and utilitarian expectations. They found out that flow experience, hedonic expectations, utilitarian expectations and various social factors such as peer pressure and critical mass all had an effect on use continuance intention either directly or indirectly through subjective norms. This was aligned with Chang's earlier research in social network games (2013) where he also recognised the importance of hedonic and utilitarian factors, social factors and flow experience. Huang and Hsieh (2011) concluded that challenges, perceived entertainment and sense of control affected customer loyalty positively, but they were not able to find a relevant positive effect produced by sociality. Overall, there seems to be a wide academic agreement over the relevance of social factors, flow experience, and enjoyment when it comes to playing online games.

2.7.3 Mobile games

Unfortunately, research regarding use continuance in mobile games is scarce. Nabavi et al. (2016) listed only one article regarding mobile games in their review of IT continuance research. This article by Liang and Yeh (2011) utilized TRA and TPB and they found out that attitudes, perceived ease of use and perceived enjoyment affected use continuance intention, but subjective norms didn't have a major impact. The majority of the research suggests that there would be a connection between subjective norms and use continuance intention so the findings of Liang and Yeh (2011) differ a bit from the majority.

In addition to papers reviewed by Nabavi et al. (2016), mobile games has been studied to some extent. Findings of Park, Baek, Ohm & Chang (2014) regarding mobile social network games were similar to results Liang and Yeh (2011): perceived enjoyment and perceived usefulness affected attitudes and use intention, while attitudes were also affected by perceived ease of use and perceived connectedness. Merikivi, Tuunainen and Nguyen (2017) concluded that mobile game use is driven by enjoyment, which is driven by ease of use and various game design aspects such as novelty, aesthetics and challenge. Wei and Lu (2014) utilized U&G model, a model commonly used in mass communications research, instead of IT continuance models. They studied the impact of individual gratifications, network externalities, and time flexibility on intention to play mobile social games. Individual gratifications were composed of enjoyment, and interaction with other players. This proved to be the most influential factor on intention to play. Network externalities, consisting of perceived number of other players and peers playing the game, also contributed to the intention to play, but the effect was smaller. Time flexibility, which can be considered the competitive edge of mobile games, was surprisingly found to have only a small impact.

To summarize, there seems to be a wide consensus that mobile game use seems to be driven mainly by perceived enjoyment and perceived ease of use, with other factors such as perception of playing with a great number of other players possibly playing a small role as well.

2.8 Translating IT research into mobile game context

IT continuance models are usually developed and examined in the context of information systems meant for utilitarian use in work life and therefore the use case is quite different when compared to mobile games. In games, player engagement is voluntary and driven by entertainment rather than utilitarian purposes. Therefore, they naturally fall under hedonic systems rather than utilitarian systems. Van der Heijden (2004) demonstrated that use of hedonic systems, that serve the purpose of entertainment rather than utility, is driven more by perceived enjoyment rather than perceived usefulness. Some IT continuance models have been later modified to accommodate the hedonic systems as well. For example, UTAUT2 (Venkatesh et al., 2012) recognises hedonic motivation as a new component affecting system use through intention. Sometimes the researchers utilise other models, such as flow theory, together with IT continuance models to study hedonic systems (e.g. Hsu & Lu, 2004; Lee & Tsai, 2010; Chang, 2013; Chang et al., 2014). As these studies have demonstrated, various IT continuance models can be utilised in studying games and game-like systems if used in conjunction with models or modification that accommodate the hedonic nature of games.

Many of the IT continuance models reviewed in this study revolve around attitudes, expectations, meeting the expectations, and satisfaction. All these are relevant in context of mobile games as well. Attitudes, possibly influenced by advertisement or social factors, toward a certain game or game genre can influence the player to download and open a game with an expectation of entertainment and arguing that the use continuance intention is affected by how these expectations are confirmed by the gameplay experience and how satisfied the player is after playing the game seems a reasonable suggestion.

In TAM, a widely utilised IT continuance model developed on the foundation of TPB and TRA, the main factors driving the behavioral intention and actual system use are perceived ease of use, perceived usefulness, and attitudes toward using the system. Perceived ease of use translates directly to games: there is evidence that perceived ease of use has an impact on flow effect and attitudes, which both contribute to use intention (Hsu & Lu, 2004; Park et al., 2014). In mobile games usability is widely considered an important factor in mobile games especially as a part of the first time user experience (Barnett, Gatzidis & Harvey, 2017). Translating perceived usefulness directly into games can be a bit tricky since all games are by default systems designed for entertainment rather than utility. However, as van der Heijden (2004) has demonstrated, perceived enjoyment effectively replaces perceived usefulness in hedonic systems: in case of a utilitarian work life system, usefulness comes from helping or enabling the user to complete a work related task more effectively than without the system, while in context of games what one expects to get out of using the system is entertainment. Then again, Hamari & Keronen (2017) conducted a meta-analysis on motivations behind playing games and after reviewing 48 studies they concluded that actually both perceived enjoyment and perceived usefulness are important factors, and games are multi-purpose systems even if they are hedonically oriented. The third component, attitudes toward using the system, is also present in games; one might have heard good or bad things about the game or the genre of games, have personal experiences with similar games, or have their attitudes affected by advertisement. The effect of attitudes towards use continuance intention has been confirmed both in online games (Lee & Tsai, 2010) and mobile games (Liang & Yeh, 2011).

Social factors seem to affect IT use continuance intention via two different mechanisms: subjective norms, and increased enjoyment. Subjective norms, as introduced in TPB and TRA, means whether the user thinks that the people important to them will approve or disapprove the user using the system. In context of games, the more a player thinks that people important to them approve or support their gaming, the more positively it affects their intention to continue using the game (Hsu & Lu, 2004; Lee & Tsai, 2010). Social interaction also seems to make the gameplay experience more enjoyable and fun: playing against a human-controlled opponent is perceived more enjoyable than playing against a computer-controlled opponent (Weibel et al., 2008; Gajadhar, De Kort & Ijsseltsteijn, 2008). Social interaction also seems to increase flow experiences (Weibel et al., 2008; Chang, 2013), which has been observed to affect the use intention and increase perceived enjoyment (Lee & Tsai, 2010). These results are directly supporting the proposition behind social feature engagement affecting use continuance. In mobile games, where players form communities inside the game, other players in the game community might become important people to the player, and therefore the game community itself might work similarly to subjective norm. Moreover, through this subjective norm social feature engagement can be expected to affect use continuance. Also, since social interaction has been observed to increase perceived enjoyment, social feature engagement can be expected to affect use continuance intention through this mechanism as well.

3 GAMES AND SOCIAL INTERACTION

This chapter describes the role of social interaction in games based on existing literature and research in an attempt to find whether there is any ground for stating that social engagement could be a strong motivation for playing free-to-play mobile games. In addition to free-to-play mobile games, two other types of games that share certain similarities are also reviewed: multiplayer online games and social network games.

3.1 Co-operation and competition

A popular definition for 'game' is provided by Jesse Schell (2008, p. 47):

> A game is a problem solving activity, approached with a playful attitude.

A bit more detailed definition was proposed by Salen & Zimmerman (2004, p. 80-81):

> A game is a system in which players engage in an artificial conflict, defined by the rules, that results in a quantifiable outcome.

Very similar elements are proposed by many others as well (e.g. Fullerton, Swain & Hoffman, 2004; Suits, 1967; Avedon & Sutton-Smith, 1971) and they agree on certain key concepts; there is a player partaking in some kind of a challenge or conflict that gets resolved to an outcome within the restrictions of artificial rules. The definitions presented here do not require a game to include more than one participant: Klondike Solitaire is a well-known example of a single player game. Digital games have introduced the possibility of a non-human adversary in form of AI in arcade video games and later in computer and console games. Therefore, social interaction, either cooperative or competitive in nature, is not by default a necessary component of a game.

Schell (2008) points out, that majority of games ever created are designed to be played with or against other players, and that solo games are a rare exception: humans are social animals and this is reflected in games. Therefore, social interaction is a fundamental part of why and how people enjoy playing games. Schell describes five reasons for why people prefer to play games with or against each other. The first reason is competition. A human opponent provides a worthy adversary to test ones skills against, and allows for games that require complex strategies and psychology. Overall, a to win a game against another human player is a more complex and interesting problem to solve. The second reason is collaboration: problem solving in a group and being a part of a successful team invokes great pleasure, and in a group people can employ strategies that are not possible with just a single person. Third reason is that games are a good excuse for meeting up and spending time with friends as it gives something to focus on without forcing anyone to make conversation just for the sake of it. Fourth, playing games allows for exploring other peoples fundamental minds. A conversation is always filtered by the persons conception of what they think they should say and what the other person wants to hear. Games provide a view into how the other persons make decisions under stress, how they solve problems or react to unexpected situations. Fifth, the player gets to explore themselves as well: how they react to complex social situations, who do they prefer to team up with and why, and how do they react to moments of being defeated publicly. (Schell, 2008).

Communities, groups of people with a shared interested who get to know each other better over time, that arise around games are also an important part of why people enjoy playing games with other people (Schell, 2008). Schell argues that people have a social need to be a part of something and game communities can fulfil that need. Communities and the shared emotional connection that comes with them can keep the players stick to a game for long time. (Schell, 2008)

Schell's arguments have wide support. There seems to be a wide acceptance within the game industry and related academia that the social aspects of gaming are a fundamental factor and a prominent motivation behind gaming for many players (e.g. Klug & Schell, 2006; Sherry et al., 2006; Raney et al., 2006; Yee, 2006a; Yee, 2006b). Players can also form strong and meaningful relationships in games (Yee, 2006b; Cole & Griffiths, 2007). Player-formed tribes or teams, usually referred to as guilds, clans or alliances, are especially important social communities and belonging to one can become an important reason to keep playing (Yee, Ducheneaut & Nelson, 2012). Even if technology has allowed game designers to utilise computer AI as a virtual opponent, playing against human opponents is observed to be more enjoyable (Weibel et al., 2008; Gajadhar et al., 2008). To summarise, even though a playing a game is not always a social activity by definition and not all the games are fundamentally social by nature, the social component still seems to have a special place in the very core of the phenomenon of gaming.

3.2 Multiplayer Online Games

Online games are video games played through a computer network, commonly an internet connection (Ray, 2012). Modern video games are often online games regardless of the genre: first- and third-person shooters, strategy games, massively multiplayer online role-playing games (MMORPGs), multiplayer online battle arena games (MOBAs), and battle royale games are all examples of currently popular genres played online with millions of players. Many of these games either are primarily multiplayer games or provide the option for either cooperative or competitive gameplay or both. (Quandt & Kröger, 2013).

Socialness in multiplayer online games has been a somewhat popular subject in game research. Especially social networking in these games has been explored in various prior studies. Merrit and Clauset (2013) discovered than in Halo: Reach (2010) the players with greater long-term engagement tended to cluster together. Van de Bovenkamp, Shen, Jia & Kuipers (2014) argue that socially-aware matchmaking that clusters players based on their interactions with other players can reduce player churn in competitive online games. Ang (2011) studied interaction networks in massively multiplayer online games and discovered that in the center of guild communities were certain knowledgeable players. Those players then helped and interacted with many other players, and that social interactions tended to cluster into small cliques of player while task related interaction happened between wider selections of players and was found to be more reciprocal. Chen, Duh, Phuah & Lam (2006) argue that social interaction is the key factor that influences both the enjoyment and the level of engagement a player has in MMORPGs, and negative social interactions reduced the enjoyment.

Kuipers, Märtens, van der Hoeven and Iosup (2018) present three dimensions of social interaction in multiplayer online games:

1) Explicit vs implicit social ties.
2) Inside the game-world vs outside.
3) Long lasting game-world vs short-lived matches.

According to Kuipers et al. (2018), explicit social ties are formed on player's own initiative, such as belonging to a guild, or establishing a friend list relationship. Implicit ties are formed passively through interaction, such as playing with or against other players. Social interaction can also happen outside of the actual game and game-world. Players tend to form various internet-based communities to discuss and plan in-game interactions between the game sessions (Kuipers et al., 2018). Some game publishers provide platforms, such as internet forums, themselves to foster their player community, but players can also establish and run self-organised communities on other internet platforms such as Reddit or Discord. Lastly, games that function as a series of short, instanced matches, can lead to different social relationships than games that have a long lasting or persistent game-world in which to interact (Kuipers et al., 2018). MMORPG games operate on one or more persistent game-worlds where the players inhabit the same virtual space and the game-world exists independently from the players (Lin & Sun, 2015). Thus, they have the possibility of constantly meeting and interacting with a wide selection of other players. In some other types of games, such as MOBA and battle royale games, the gameplay happens in instanced virtual spaces. A single match of MOBA game typically happens on an instanced map where two teams of five players face off against each other, and after the match that specific instance of the game-world vanishes (Kuipers et al., 2018).

Yee (2006a) discovered 10 factors behind motivations for playing online games. The factors were grouped into three main components: achievement, social, and immersion. The three factors under the social component are socializing, relationships, and teamwork. Socializing was related to casual chatting, helping others, and making friends. Relationships were related to the desire to form meaningful long-term relationships with others, and finding and giving support. Teamworking was related to deriving satisfaction from collaboration, being part of a group effort, and achieving goals together as a group. Yee's (2006a) model has since been utilised successfully with similar results when studying MMORPGs (Debeauvais, Nardi, Schiano, Ducheneaut & Yee, 2011; Billieux, Van der Linden, Achab, Khazaal, Paraskevopoulos, Zullino & Thorens, 2013; Yee et al., 2012).

MMORPGs are online role playing games where hundreds or even thousands of players share the same virtual game environment to interact with each other and the gameplay elements (Lin & Sun, 2015). MMORPGs can be described as virtual theme park playgrounds with plenty of activities to choose from: exploring the virtual world alone or with others, adventuring in dungeons, fighting other players, crafting items, or just socialising with other players (Lin & Sun, 2015). Debeauvais et al. (2011) utilised Yee's (2006a) model and concluded that player retention in World of Warcraft (2014), a popular MMORPG, was driven especially by motivations related to achievement and social components. Billieux et al. (2013) also used the same model and concluded that while the social components were influential, the amount of years of playing was mostly related to achievement components. Billieux et al. (2013) and Yee et al. (2012) demonstrated that there are differences in player motivations between various player demographics, and that the players engage differently with the various parts of the game depending on their individual player motivations.

Many popular MMORPGs, such as World of Warcraft (2004), have a wide collection of various social features with considerable complexity. These include several in-game chat channels to have conversations privately or in groups, friends lists, trading in-game items and currencies, in-game challenges that require players to team up and cooperate with other players, player-versus-player action, and guilds for players to organise themselves for both cooperative in-game challenges and player-versus-player gameplay (Lin & Sun, 2015; Rapp, 2018; Blizzard Entertainment, 2019). Sometimes the social activity can even spread to platforms outside of the actual game-world such as internet forums that can provide a more specialised environment for communication and planning (Kuipers et al., 2018).

It seems, that multiplayer online game engagement is heavily driven by social interaction and communities, and that the game developers provide the players with wide selection of social features to enable and support the forming of these communities.

3.3 Social Network Games

A social network game (SNG) is essentially an online game with a distinct trait of utilising a social media platform, such as Facebook, to facilitate in-game interactions (Fields & Cotton, 2011). According to Björk (2010), asynchronous gameplay, no upfront cost to play the game, no game ending win condition, in-game events timed to real world (e.g. seasonal events, holidays), and benefitting from inviting friends to join the game are common characteristics of SNGs. Some well-known examples of SNGs are the various casual farming games, such as FarmVille (2009) and Happy Farm (2008). In these games, the players goal is to tend to and upgrade their in-game farm or village, but there is no game ending condition where one would win or lose the game. Thus, the game technically never ends and there is no direct imminent conflict between the players. SNGs were originally played on web browsers, but as the social media platforms adopted mobile devices so did the SNGs (Mäyrä, Stenros, Paavilainen & Kultima, 2017). Even if SNGs nowadays have plenty in common with free-to-play mobile games, using a social network as their platform and depending on players to invite their friends are the fundamental components that makes them different from other games (Hou, 2011).

Use of SNGs is driven mostly by similar factors as online games in general: perceived enjoyment, perceived usefulness, and attitudes (Chang, 2013; Shin & Shin, 2011; Park et al., 2014). Experience of flow is influential as well (Shing & Shin, 2011; Chang, 2013). In addition, social factors have also been observed to play a part: Park et al. (2014) discovered that perceived connectedness, the feeling of being connected to the game and other players, was positively influencing the attitudes towards use intention in SNGs. In addition, Chang (2013) concludes that social interaction contributes to both flow experience and satisfaction, which both contribute to use continuance intention.

Paavilainen, Alha and Korhonen (2017) have made an inductive review of social features in 16 different SNGs, presented in figure 9. They recognised multiple different social features and organised them into three categories: presence, communication, and interaction. Presence features allow the player to know that other players are present in the game. This category includes features such as displaying information about the presence of other players, visiting other players' game spaces, and getting in-game rewards or bonuses based on the number of friends playing the game. Communication features enable the players to communicate or exchange information or virtual goods with each other, or ask for help from other players. For example, an in-game chat or other message system, or being able to request in-game actions or items from friends fall into this category. Interaction features include all the actual game mechanics with player-to-player interaction, such as player-vs-player gameplay, forming in-game teams or tribes (often referred to as guilds, clans, or alliances), and sending and receiving in-game items or resources between each other. The most common features found in all the reviewed games were related to informing the player about the various activities of their friends, inviting friends that were not yet playing the game, and some kind of scoreboard that was tracking and displaying the in-game status of players. (Paavilainen et al., 2017).

Code	Social feature	Description
PRE1	Activity information	The game informs the player about friends' actions in the game world.
PRE2	Community challenge	Community tournaments and other organized events in the game, which are accessible for the player.
PRE3	Automatic friend bonus	Automatic gameplay bonus based on the number of friends playing the game.
PRE4	Friend requirements	The player cannot complete a gameplay task without requesting her friend to do an action.
PRE5	Off-game sociability	In-game links to off-game social spaces such as discussion forums, wikis and Facebook fan pages.
PRE6	Presence information	Player receives information about the presence of other players in the game.
PRE7	Scorekeeping	Ranking and scorekeeping information, where the player can compare her status against others.
PRE8	Social user-interface element	Graphical user-interface elements, which have a social reference, such as player portraits, links, pop-up dialogs etc.
PRE9	Visit game space	The player can visit a friend's game space.
PRE10	Community progress indicator	An indicator representing community progress on a gameplay task.
PRE11	Relocate game space	Relocation of the player's own game space in the game world, to play in closer proximity with friends.
COM1	Asynchronous communication	An ability to communicate with others via asynchronous means (e.g. in-game message system, discussion board, or sign posts in game space).
COM2	Facebook wall post to a friend	Sending a wall post to a friend's Facebook wall from the game.
COM3	Facebook wall post to own wall and the news feed	Posting a message from the game on a player's own Facebook wall and the news feed.
COM4	Facebook notification	In-game activity that is presented as a Facebook notification for other players.
COM5	Invite request	Sending a request to a friend to join the game (also asking a friend to become a neighbor in some games).
COM6	Rematch/Replay	Requesting a rematch or replay from another player.
COM7	Request activity	Requesting an in-game gameplay action from a friend.
COM8	Request items	Requesting an item from a friend. Commonly known as a gift request.
COM9	Synchronous communication	An ability to communicate with others via synchronous means (e.g. chat).
INT1	Competitive action	Player vs. player gameplay action.
INT2	Facebook click post reward	Clicking a Facebook game post leads to an in-game reward.
INT3	Interaction reward	Interacting in a friend's game space leads to an in-game reward.
INT4	Receive items	Receiving items sent by friends. Commonly known as accepting gifts.
INT5	Remove friend	Removing a friend from in-game contacts/neighbors.
INT6	Send finite items	Sending an item to a friend. The sending player loses that item from her inventory.
INT7	Send in-app purchase items	Buying an item with premium currency in the game and sending the item to a friend.
INT8	Send infinite items	Sending an infinite item to a friend. Infinite items are free for the player and can be sent on a daily basis.
INT9	Synchronous interaction	Interacting simultaneously with a friend in the same game space.
INT10	Team formation	Forming a team or an alliance through in-game actions.

FIGURE 9 Social features recognised by reviewing 16 different social network games, divided into three categories (adapted from Paavilainen et al., 2017)

Ricchetti (2012) suggests three heuristics for categorizing social mechanics, presented in figure 10. He presents one heuristic regarding the timing of social interactions, and two regarding the type of the social relationship.

The first heuristic is synchronous vs asynchronous interaction: does the interaction occur simultaneously or in different times. A real time chat is an example of a synchronous interaction. Taking turns in a turn-based game, or sending and receiving messages and items via in-game inbox are examples of asynchronous interaction. The popular social games tend to feature a mix of both synchronous and asynchronous interactions. (Ricchetti, 2012).

The second heuristic concerns the symmetry of the relationship. Relationships in multiplayer online games can be symmetrical or asymmetrical in nature. In a symmetric relationship both participants of the relationship need to consent in order for the relationship to be formed. For example, in Facebook a player must request another player to connect and be friends with them and the other player needs to agree before the relationship is established. In games, trading is a popular feature that requires agreement from both sides before the transaction can happen. The mutual acknowledgment of symmetrical action allows for deeper sharing, but also necessitates tools for friend management and limits the overall site interaction. In an asymmetrical relationship, this type of virtual handshake is not needed, but instead the willingness of just one party or the other is needed. For example, in Twitter anyone can start following anyone without asking for permission first. In games, one can often send messages, or gift items or resources to another player without requiring mutual agreement. (Ricchetti, 2012).

The third heuristic is the strength of the social tie. Loose ties are often asymmetric and strong ties are usually symmetric. For example, player-formed tribes or guilds tend to be some of the strongest group relationships games can have and they are usually symmetric in nature. Benefits from belonging to a guild can be game changing in many ways since the other players can serve as a valuable platform for exchanging information or in-game goods, tackling the most difficult and lucrative in-game challenges, and making friends. In guilds players can form very meaningful relationships with other players that can even transfer into real life relationships. (Ricchetti, 2012).

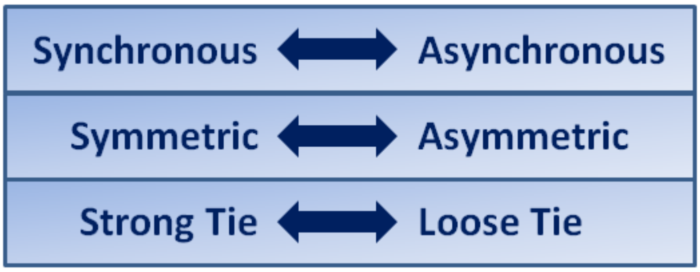

FIGURE 10 Three heuristics for categorizing social mechanics in online multiplayer games (adapted from Ricchetti, 2012)

Ricchetti (2012) proposes that the three heuristics presented can be used to review and evaluate social mechanics in existing games and to use them as a tool when designing new games.

Similarly to other multiplayer online games, SNGs are utilising social features to hold on to their players. Developers of SNGs employ a wide mix of social features to enable player interaction and meaningful social relationship between players.

3.4 Free-to-play mobile games

A free-to-play (F2P) game is a game that can be downloaded and played free of charge (Alha, Koskinen, Paavilainen, Hamari & Kinnunen, 2014). Instead of charging an up-front cost for downloading the game, common ways to monetize players in F2P games include utilising so called in-app purchases (IAPs), showing ads in the game, having a paid subscription with extra benefits, or a mixture of various (Fields & Cotton, 2011). Other models exist as well, such as the subscription model, where the player pays a subscription fee to gain access to certain in-game benefits for a certain period of time that are otherwise inaccessible (Fields & Cotton, 2011). F2P model is the dominating business model in mobile games, generating 80% of revenue (SuperData, 2019).

In-app purchases (IAPs), sometimes referred to as micro-transactions, are digital transactions where player exchanges real money for virtual products such as virtual in-game currencies and resources, consumable power-ups, items or characters, new playable content, and visual improvements. Even though most of the content in the game can be accessed without paying, some content might be available only for paying players. The cheapest IAPs tend to range from $1 to $5 while the most expensive ones can go beyond $100 (Hanner & Zarnekow, 2015). IAPs provide certain advantages over more traditional revenue models where the player has to pay a fixed price up-front before being able to download and play the game. First, it allows for flexible price points to appeal to a wider spectrum of players with different spending capabilities and spending willingness (Hamari & Järvinen, 2011; Paavilainen et al., 2013). Second, it allows the players to try the game before any financial commitment. Therefore, a F2P game is by default more accessible to a wider audience than a game that requires an up-front cost to download and play the game (Paavilainen et al., 2013). If the game is utilising ad monetisation, the developers can also monetise players who do not have a credit card or do not want to spend money in the game, by showing them ads.

Because there is no up-front cost for downloading and playing a F2P game, it has a very wide potential audience. This makes F2P a fitting business model for games that rely on a wide player base, such as social network games and multiplayer online games. When the technical capabilities of mobile devices started to accommodate for more complex games and after mobile game distribution was revolutionized by app store ecosystems, many game genres started to adopt the mobile platform, such as casual arcade and puzzle games (Mäyrä, 2015). Social network games have also adopted the mobile platform and they have evolved to provide more versatile and complex gameplay experiences familiar from MMORPGs and strategy games (Kultima, Paavilainen, Stenros & Mäyrä, 2017). Nowadays even MMORPGs, such as Lineage 2: Revolution (2017), are published on mobile devices despite their gameplay complexity and high hardware requirements.

Even though the F2P business model is being utilized by a wide variety of different types of games on mobile, it is important to notice that regardless of the genre, all F2P games need to hold on to their player base because the revenue is accumulated from players over long periods of time instead of a single fixed up-front purchase. As discussed earlier in this chapter, social factors do contribute positively to motivations to play and keep on playing games of various types. Therefore, it is not surprising that those game genres that are heavily relying on social factors, such as MMORPGs and games that have their roots in social network games, have adopted the F2P model and are experiencing great success on mobile. Overall there seems to be plenty of support for the argument that social interaction can have a great positive impact on long-term use continuance of a F2P mobile game.

4 DATA COLLECTION AND ANALYSIS

This chapter describes the research material extracted from the data of the two games examined in this study. This chapter also describes the research method, variables used in the analysis, and how the data was processed and analyzed.

4.1 Research strategy and method

This study seeks to find out how engaging with social features is related to long-term player retention. The research problem has been formulated into following research questions:

1) How is engaging with social features related to long-term use continuance in free-to-play mobile games?
2) How does engaging with social features compare to other factors that might affect the long-term use continuance?

The questions will be answered by analysing actual player data from two F2P mobile games by performing a logistic regression analysis on the data extracted from the game log database. Logistic regression analysis is used to determine whether the players who engage more with social features in the early stage of the game are more likely to keep coming back to the game over time. The effect of early engagement with social features is also compared to the effect of other variables that also might result in better player retention, such as overall intensity of engagement and amount of money spent.

4.2 Material

Because the nature of F2P video game products is similar to software-as-a-service models where the product is constantly under iterative development, it is common for F2P game companies to utilise various methods of storing and analysing gameplay data to improve their products. A common method for this is event based tracking: tracking player behavior by sending data points to the server whenever the player performs certain predetermined actions inside the game. These predetermined actions are usually referred to as events, triggers or hooks. For example, when a player makes an in-app purchase, a trigger goes off in the game code and data regarding the transaction and the player is recorded and sent to the database. Other common events are moments when a player spends in-game currencies or resources, engages with game features, visits in-game shop and so on.

Data gathered via event based tracking is extremely useful for this research. Alternative data gathering methods, such as gathering data directly from players via surveys or questionnaires, would first of all be challenging, and data related to spending and session lengths would be much more inaccurate compared to actual measures conducted by the game client and server. Usually getting one's hands on such data would be unlikely, because for competition reasons game publishing companies are not too inclined to share or give access to their data. Fortunately, PlayRaven, a Helsinki based mobile game development company, has agreed to provide access to their data, which is utilised as research material for the purposes of this study. PlayRaven has given a permission to utilise their BigQuery analytics database that can be accessed via standard SQL queries.

The database has data regarding all the games developed by PlayRaven. Each game is a separate project entity in the database and within the projects the data is split based on mobile device platform (iOS or Android) and environment (production or development). The exact database schemas may vary between the games a little bit because each game has its unique feature composition, but still all the events that are sent to the database have certain parameters in common. Each event includes the unique user ID, timestamp, and event type. Many events also include numerous event specific parameters. For example, an event about an in-app purchase includes the name and price of the purchased product.
However, not all the games in the database are suitable for this study. Since the social activeness of players needs to be measured, only data from games that allow us to make this kind of measurement can be used. Therefore, data will be utilized only from such games that allow us to measure differences in the activeness of social feature engagement. Two games fit our criteria: Robocide (2016) and Spymaster (2017).

4.2.1 Robocide

Robocide (2016) is a mobile free-to-play strategy game published on iOS in February 2016 and on Android in March 2016 by PlayRaven. In the game, the player is clearing levels of increasing difficulty by destroying the base of hostile robots by controlling a swarm of robots of their own (figure 11). If the hostile robots destroy the base of the player, the player loses the match and needs to try again. The game has three different game modes: Starmap, Warp Zone and Arena, visible in figure 12.

FIGURE 11 Robocide gameplay

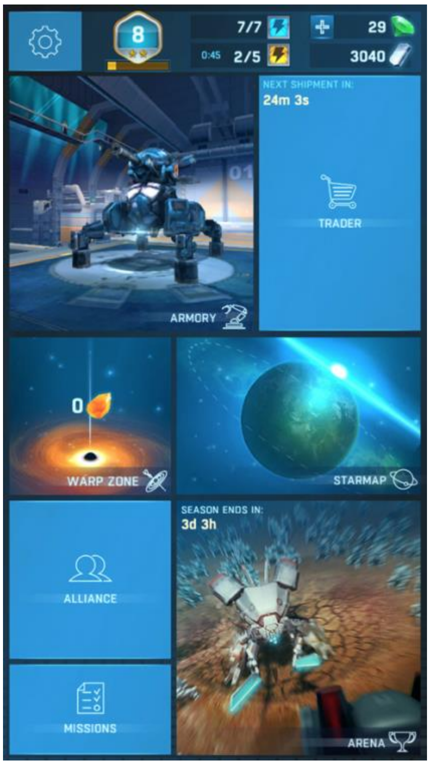

FIGURE 12 Robocide game modes

Starmap is the core of the single player content, where the player needs to clear levels of increasing difficulty in linear order in order to proceed in the game. In addition to unlocking the next level, the player is rewarded with random upgrade items that can be consumed to make their collection of robots stronger.

Warp Zone is an extension to single-player content. It provides better rewards but has restricted access: once the player finishes one Warp Zone run, the Warp Zone closes for several hours before the player can make another run. In the Warp Zone the player needs to clear randomly selected Starmap levels with special rules: in the regular Starmap levels players can try to beat any level as many times as they want and all their destroyed robots are instantly repaired at the end of the level, but in Warp Zone all the robots that get destroyed during a match will stay destroyed until the end of the Warp Zone run and the Warp Zone ends when the player loses three matches. After the run, the player gains rewards based on how many levels they were able to clear.

The player can also choose to fight against other players in player-vs-player (PvP) mode called Arena, which is the primary social mechanic in Robocide. In the Arena mode, players are divided into small groups via a matchmaking process. The matchmaking ensures that the players competing against each other are roughly on the same level in terms of their in-game power level. Each player then creates their own level by building a defensive setup of their robots and predetermined level assets, such as defensive turrets and spawn locations. The other players then try to beat these levels created by other players in their group to gain score. A caption of gameplay is shown in figure 13. Players are ranked on a leader board and after a predetermined period of time the players with highest score are moved into a higher level tier of matchmaking, while the lowest performing players are dropped into a lower level tier. All players gain rewards based on their ranking on the leader board and the tier they currently reside on.

FIGURE 13 Robocide Arena mode gameplay

In Robocide, social interaction is driven by competition in the Arena mode: players can engage in competition by creating a playable level of their own and then trying to beat the levels created by other players. The players can form Alliances to compete on the Alliance leader board. Each player contributes to the total score of their Alliance based on their own individual performance in the Arena mode. The Arena mode creates implicit social ties: the players do not get to choose the players they play against, but are rather forced to compete against players chosen by the matchmaking algorithm. In terms of Ricchetti's (2012) social game mechanic heuristics, the social mechanics present in Robocide are mostly asynchronous, asymmetric, and with loose ties. Some symmetric mechanics do exist in the form of Alliances, but the Alliances in Robocide are very limited in terms of the available interactions between Alliance members. There are no direct ways of communicating with the players and the presence of other players can only be examined via their performance on the leader board. There is also no persistent game world that the players would interact in. The levels created by the players in the Arena mode only exist for the duration of a single Arena cycle, after which all the players get a new level and level assets to setup.

Since Robocide has such a clear distinction between single player and player-versus-player content that can be played and proceeded in separately, it allows us to measure differences in activity of players engaging in either type of content. All this should make Robocide data a good fit for the study.

4.2.2 Spymaster

PlayRaven published an iPad game called Spymaster in September 2014. A new game concept based on Spymaster was in development from June 2016 until April 2017 when the game concept was abandoned. This game concept was also called Spymaster, but it was never launched globally. The game was only available and tested by players in Australia, Canada and Netherlands. Even though the game never saw global launch, data was gathered from thousands of players in these countries and this data can be utilised in the study.

In Spymaster (2017), the player recruits secret agents and sends them on missions to save the world from an evil secret society that tries to achieve world domination. The game has two game modes: World Map and Agency Battle.

World Map is the core single-player experience, where the player builds a global spy network by taking on agent missions in various cities around the globe. Each mission has several steps with certain agent requirements and the player has to make decisions regarding which agents to send for each mission. Once the player has chosen the agents they start to complete the mission autonomously without further input from the player. After the mission timer has finished, the player can see the result and collect rewards. Rewards include in-game currencies, agent cards for unlocking and upgrading new agents, and plane tickets that can be used to unlock new playable areas on the World Map. Once the player has completed enough missions in a given city, they can upgrade their spy network in that city to provide better rewards for future missions in the city. A player can have up to five missions running at a time. An example view of the World Map is presented in figure 14.

FIGURE 14 Spymaster World Map gameplay

Agency Battle is the player-vs-player section of the game. Players are encouraged to join an existing Agency, an in-game tribe of players who can request and donate agent card resources with each other, and compete against other Agencies in Agency Battles. Agencies are the Spymaster equivalent to guilds and clans in multiplayer online games, and is the primary social component in the game. In Agency Battles, two Agencies compete over fragments of a secret code on a world map very similar to the map in World Map mode. One of the Agencies starts as the defending Agency and the other one is the attacking Agency. The defending Agency needs to protect the fragments of a secret code scattered around various cities on the map. The players of the defending Agency can allocate their agents to defend and lay traps in cities. The players in the attacking Agency need to search for and disarm the traps with their agents and try to locate the cities where the code fragments are hidden. Once the code fragments are located, the attacking players then need to beat the defending agents with their own agents (figure 15). An attacking player chooses an agent to fight a defending agent, and the two agents engage in combat that is resolved automatically based on the in-game attributes of the two agents. Trapped or defeated attacking agents can get captured, which means that the agent will be unavailable to use in Agency Battle. Captured agents can be set free by other members in the Agency by performing a successful rescue mission with their agents (figure 16). Once the attacking Agency has located and claimed all the code fragments from the defending Agency, the roles are switched and the attacking Agency now needs to defend their code fragments while the former defending Agency now turns into an attacking Agency. The defending Agency gains score based on the amount of time they are able to protect the code and the Agency Battle ends when one of the Agencies manages to reach a certain amount of score. The victorious Agency is rewarded with in-game resources and clues for rare agent cards.

FIGURE 15 Spymaster Agency Battle gameplay

Utilising Ricchetti's (2012) social game mechanic heuristics, Spymaster is observed to have more variety in its social features: the Agencies form symmetric, strong ties, and the in-game Agency chat works as a synchronous communication channel. A player can join any Agency that has less than 30 players in it – no mutual agreement is needed. However, the Agency leader and officers can remove a player from the Agency at will so the Agency members have some control over which players they want to co-operate with. Requesting and providing help for captured agents is an asynchronous, symmetrical mechanic: a player whose agent is captured needs to ask help from the fellow Agency members in order for them to be able to provide or decline help, and this transaction of help can happen asynchronously. Requesting and donating agent cards with fellow Agency members works in the same way. Agency battle mechanics are asynchronous, but planning and exchanging of information can happen synchronously via the in-game Agency chat. Both of the Agencies fighting against each other need to signal that they are willing to engage in an Agency battle, but they cannot decide a specific rival Agency to fight against. Instead this pairing is done by the matchmaking logic in the game server.

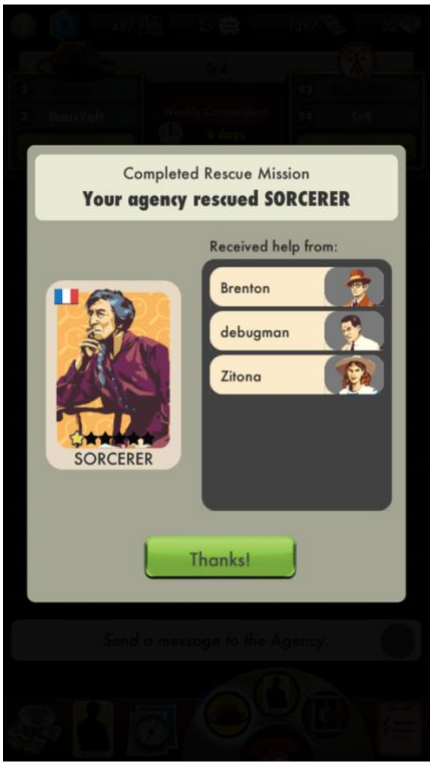

FIGURE 16 Rescued Agent screen in Spymaster

Even though the Agency Battles are a major part of the game, a player may choose to ignore the whole Agency content and focus just on the World Map and keep on unlocking and upgrading their agents and cities. The players taking part in Agencies have the opportunity to take part in Agency Battles, help to rescue captured agents of their Agency members, and donate and share agent cards with each other. Similarly to Robocide, this allows us to categorize players based on how actively they take part in Agency activities and therefore Spymaster data should be very useful for this study.

4.3 Variables

The target of measuring is the effect of different factors on long-term use continuance. This makes long-term use continuance the dependent variable of the analysis. Following the hypothesis, early social feature engagement is the primary independent variable. In addition to social feature engagement, there are other independent variables that might explain long-term use continuance: early spending and early overall gameplay activity.

Regarding the independent variables, the focus is on early activity for two reasons. The first one is the direction of influence. By comparing early activity to longer term use continuance it is ensured that the alleged cause precedes the alleged effect. Second reason is related to usefulness for game developers. The sooner one can draw conclusions from data, the faster one can take action and make informed development decisions. So from the developer perspective, the ability to evaluate the long-term behavior based on seven days of data is much more valuable than data that has to be waited for 14, 30 or 90 days, even if it comes with a cost in accuracy. For the purpose of this study, early activity consists of the first seven days after launching the game app for the first time.

4.3.1 Long-term use continuance

Long-term use continuance is the dependent variable in the analysis. There are many ways to measure use continuance, often referred to as retention in the gaming industry. Retention data is used to gain insight on how well the game is retaining its players over time, and for calculating players' lifetime-value (LTV). Commonly retention is measured as a percentage of unchurned players at a certain point in time, such as 7, 30 or 90 days after launching the game app for the first time. A simple way is to sum up the count of distinct players that logged into the game exactly on their 7th, 30th or 90th day after launching the game app for the first time and divide that number by the count of all distinct players who launched the game app for the very first time at least 7, 30 or 90 days ago. However, if a player logged into the game on their 29th and 31st days, but not exactly on the 30th day, the player would be calculated as a churned played when analysing day 30 retention. As a player might not log into the game every single day, there is always an element of inaccuracy involved in measuring use continuance in this way.

In this study, a player is considered a retained player for a given seven day period, if they logged into the game on at least one day during the period. For example, when analyzing the amount of players who continued to play the game after 30 days, all players who logged into the game on any day between their 30th and 36th day will be marked as a player who is still playing the game. If a player has no logins between their 30th and 36th day, the player is marked as a player who is no longer playing the game during that period of time. If a player has no logins between their 30th and 36th day, but has logged into the game at least once between their 60th and 66th day, the player is marked as an active player for the period of days 60 to 66, but inactive for days 30 to 36.

Drawing a line between early, mid-term, and long-term use continuance can be tricky, as there is no established convention in the industry. Some games aim to be a service that retains and monetizes their players for years, while other games are focused on making the bulk of their profit in the first few weeks. Therefore, in case of some games, all the activity starting from day 30 could be considered long-term use continuance for their business case, while in other games it could still be seen as early gameplay. Because of this, the measurements will be taken from multiple periods of seven days, starting from days 14 and 30, and when available, days 60, 90 and 180. This way a distinction can be observed if the plausible effect of the independent variables increases or diminishes over time.

4.3.2 Social activity

In this study, social activity is the primary independent variable expected to have an impact on long term use continuance. The games that are analysed in this study have social features, where players interact with each other either directly or indirectly, and non-social features, where there is no interaction between players. In the case of these games, players are free to choose whether they engage with single player content or multiplayer content. All feature engagement is saved as log data in the analytics database as described in chapter 4.2. Therefore, measuring the ratio of social vs non-social feature usage allows us to describe with a single number, how actively a player engages with the social versus non-social content in the game. In this study all the various types of social features are collapsed into a single parameter instead of tracking each type of social feature independently. This allows us to focus more on the overall high level phenomenon of social activity rather than trying to pinpoint differences in impact of the various social features present in the games.

For the purposes of the social activity variable, the following gameplay events are categorized as social gameplay events in Robocide:

- creating an Arena level
- attacking the Arena levels built by other players

All the gameplay events related to engaging with the single player content in Starmap and Warp modes are categorized as non-social gameplay events. Gameplay events related to upgrading the playable robot characters are left out, because the characters are used in both single player and multiplayer modes and therefore cannot be attributed to one category or the other.

Spymaster has a wider selection of social features than Robocide. All the following gameplay actions are categorized as social gameplay events:

- placing defending agents and attacking enemy agents in Agency Battle mode
- requesting and providing help for captured agents
- requesting and donating agent cards from/to other players in your Agency

Sending messages in the Agency chat were not tracked with the analytics events so chat usage is not included in the social gameplay events. All the gameplay events related to the single player content in World Map mode are categorized as non-social gameplay events. Agent characters are used both in single player mode and multiplayer mode so therefore gameplay events related to unlocking and upgrading them are left out.

4.3.3 Spending

Spending money in a F2P game is observed to have a positive impact on player retention (Hanner & Zarnekow, 2015). Hamari (2011) argues that players have loss aversion: purchases made in a game cannot be transferred to other games so if a player stops playing the game they would "lose" the value of their purchases as well. This sunk cost fallacy then might keep some paying players in the game who might have switched to some other game had they not spent any money in it.

Measuring player spending is simple and straightforward. Whenever a player makes an in-app purchase (IAP), an event is sent to the database containing information about the player and the purchase - including the price in US dollars. The total amount of player spending from any time period can be calculated by summing up the prices of all the in-app purchases made during the given period of time.

4.3.4 Gameplay activity

A player who downloads a game, but uninstalls it after launching the game once and playing it for a minute or two, probably did not find the game very enjoyable. On the contrary, a player who spends a lot of time playing the game over multiple days and gameplay sessions probably found the game enjoyable. And as described in chapter 2.7, perceived enjoyment is connected to use continuance intention. Therefore, a player who plays more can be expected to continue playing the game over a longer period of time than a player who spends considerably less time in the game.

A simple way to measure gameplay activity on a player level is to count the distinct days when the player has opened and played the game. For example, if the interest is focused on the first week activity after the first day of activity, the count of active days cannot be more than seven days. Other common ways to measure gameplay activity is to count the number of gameplay sessions or measure the amount of time spent in the game. Players who interact with the game multiple times a day or play for long sessions can be considered more engaged players. There are many ways of defining a gameplay session, but in the data provided by PlayRaven a new gameplay session start is reported when the player opens the game for at least 5 seconds and there has been at least 30 minutes of gameplay inactivity before that. So a player who opens the app three times with a 15 minute break in between each session would be considered to have had only one gameplay session that day. The length of that session would be the total amount of time that the game app was open and on the foreground of the phone. A player who opens the app three times with a 60 minute break in between each session would be considered to have had three gameplay sessions that day.

In this study, count of distinct active days from the first seven days of playing after the first day of activity is the primary measure for gameplay activity. This means, that the variable for this can range from 0 to 7. For

Spymaster, session counts and total time spent in the game are also used, but for Robocide this data was not available.

4.4 Data processing

Only certain fields of data are required for the study so standard SQL queries were used to extract only the necessary data for further analysis. Over the years PlayRaven has had some changes in its data analytics systems so there were some differences in the database schemas between the games. Spymaster tables have some nested fields while the other games have a more traditional structure. Other than that there were no major differences between the datasets; all the games have tables grouped by event type and the structure of the events are similar as well.

Since the interest in player activity extends all the way to day 186 from launching the game for the first time, all the players who started to play less than 186 days ago need to be excluded. For example, all players who started to play the game five days from the date of analysis must be excluded since their behavior can only be observed up to their day five. However, for Spymaster there was no clean sample available beyond day 36 so for Spymaster data only the players who started to play the game at least 36 days from the date of analysis were included.

The players who did not play the game long enough to unlock the social features during the first three days are excluded as well. The social features are not available from the very start of the game, so a player needs to advance in the game a little bit before these features become available. In Robocide and Spymaster, according to player data, the social features can easily be unlocked during the first day or two of playing. If checking whether a player unlocked the social features early enough or not is not conducted, one would observe no early social activity for players who unlocked the social features later and therefore were unable to generate any social feature related events. This might skew the data, so only the players who played the game at least until the point they unlocked the social features are included.

A SQL query was prepared to extract data according to the requirements listed above. The data was grouped by the unique player id so that one row of data described the properties of a single player. Since the two games observed had some slight differences in the data available also the final datasets of the two games ended up having small differences. The variables extracted and their definitions are listed in tables 1 and 2.

TABLE 1 Robocide dataset parameters

Parameter	Definition
uid	Unique player identifier.
early revenue USD	Total amount of USD revenue generated by the player during the first week of playing.
social events per non-social event	Amount of social gameplay events the player has generated during the first week of playing divided by other first week gameplay events. Measures the relative social activity of the player.
active days 1 to 7	Count of distinct calendar days the player has been active between days 1 to 7 (the day of launching the app for the first time is considered day 0).
is Android	Mobile device platform of the player (1 = Android, 0 = iOS)
active days 14 to 20	Binary value that indicates whether the player was active at all on any day between days 14 and 20.
active days 30 to 36	Binary value that indicates whether the player was active at all on any day between days 30 and 36.
active days 60 to 66	Binary value that indicates whether the player was active at all on any day between days 60 and 66.
active days 90 to 96	Binary value that indicates whether the player was active at all on any day between days 90 and 96.
active days 180 to 186	Binary value that indicates whether the player was active at all on any day between days 180 and 186.

TABLE 2 Spymaster dataset parameters

Parameter	Definition
uid	Unique player identifier.
early revenue USD	Total amount of revenue generated by the player during the first week of playing in US dollars.
social events per non-social event	Amount of social gameplay events the player has generated during the first week of playing divided by other first week gameplay events. Measures the relative social activity of the player.
session count	Amount of gameplay sessions player had during the first week of playing. A new session is considered to be started when the player opens the app after at least 30 minutes of inactivity.
session time minutes	Amount of time (in minutes) the player spent in the game during the first week of playing.
active days 1 to 7	Count of days the player has been active between the days 1 to 7 (the day of launching the app for the first time is considered day 0).
active days 14 to 20	Binary value that indicates whether the player was active at all on any day between days 14 and 20.
active days 30 to 36	Binary value that indicates whether the player was active at all on any day between days 30 and 36.

4.5 Data analysis

After filtering and processing the data into a format more suitable for analysis, the data of each game was analysed separately. Since the dependent variable was in binary form, logistic regression analysis was utilized instead of linear regression as it is the more suitable method for models with a binary dependant variable.

4.5.1 Robocide

Robocide data sample includes 43 795 players from United States with approximately 68% of players playing on an iOS device and 32% playing on an Android device.

'Social events per non-social event' variable ranged from 0 to 2.4 with mean of 0.09 and median of 0.04. This means that half of the players included in the sample triggered only one or less social events for each 25 non-social events between their day one and day seven after the first day of activity. Approximately 70% of the players triggered at least one social event during the period and approximately 5% of the players made at least one purchase. For legal reasons PlayRaven was unable to give their permission to describe the revenue numbers in detail, but revenue data is included in the regression models.

Count of active days between days 1 and 7 varies from 0 to 7 as was to be expected. Figure 17 describes how many distinct active days the players recorded after the day of launching the game app for the first time. Approximately 6% of the players included in the sample did not login a single time at least for a week, while more than 13% of players logged in every single day.

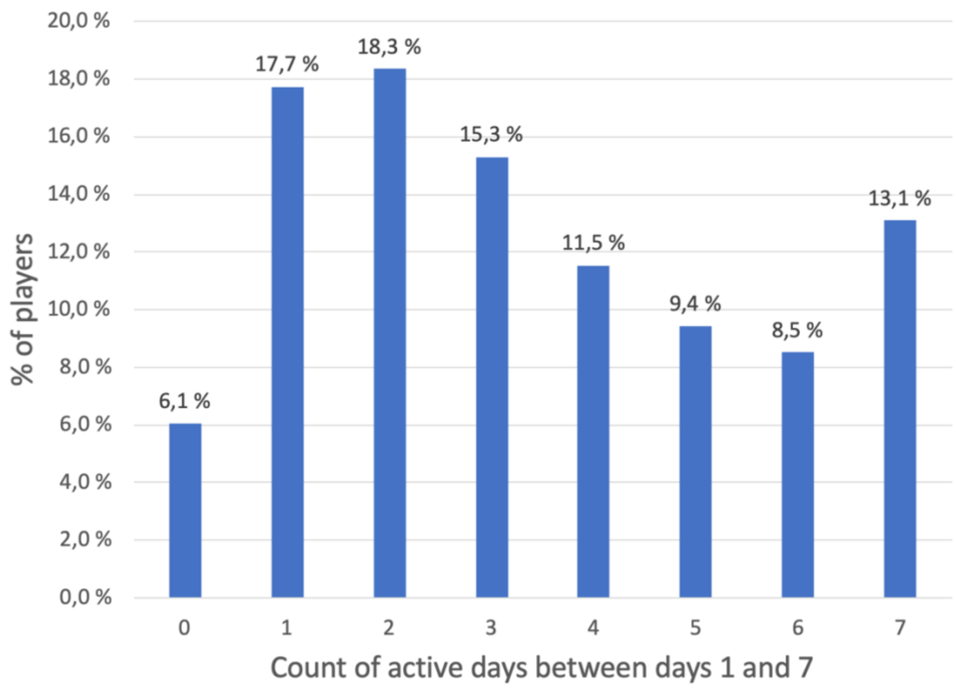

FIGURE 17 Distribution of the variable 'active days 1 to 7' (Robocide)

Count of retained players, i.e. players who logged in at least once during a given period of time, declines steeply over time. As described in figure 18, almost a quarter of the players logged in at least once between days 14 and 20, but less than one percent logged in between days 180 and 186. These numbers are not comparable to overall retention rate benchmarks that include all players, because the player sample used here only consists of players who played the game far enough to unlock the social features.

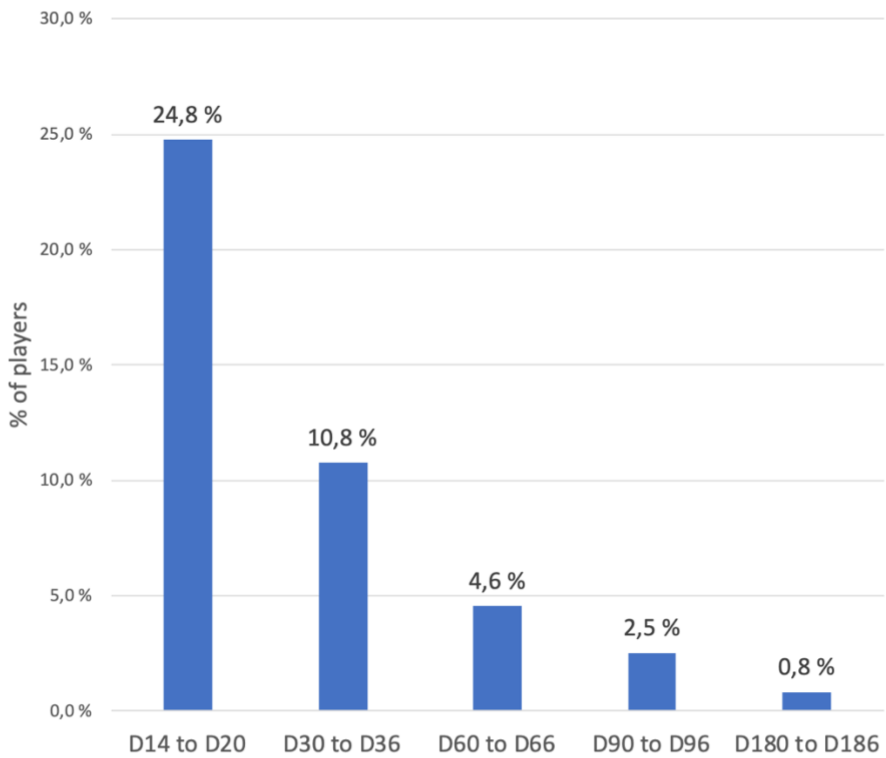

FIGURE 18 Percentage of Robocide players who logged in at least once during a given period of time

To study the effect of the independent variables on the dependent variables, five different logistic regression models were created in R - one for each active days binary variable: 'active days 14 to 20', 'active days 30 to 36', 'active days 60 to 66', 'active days 90 to 96', and 'active days 180 to 186'. Rest of the variables, 'early revenue USD', 'social events per non-social event', 'active days 1 to 7' and 'is Android', were used as independent variables.

Since 'uid' is a mere identifier instead of a descriptive data point it was not included in the model. Instead of using the plain value of 'early revenue USD' a log10 transformation of the value was used instead because the effects of relative changes in revenue rather than absolute are more important: an increase in a player's revenue from $1000 to $1100 is expected to be less impactful than from $10 to $110.

4.5.2 Spymaster

In case of Spymaster there were more parameters to analyse as both session counts and session times were available, but there was not enough clean data to analyse days 60 or onwards, so the observable period of time was limited to day 30 to 36. The Spymaster player sample consists of 1058 players from Australia, Canada and Netherlands. All the users were playing on an Android device because the game was not available on iOS devices.

'Social events per non-social event' ranged from 0 to 3.4 with mean of 0.25 and median of 0.11. This means that half of the players triggered at least one social per 10 non-social events while an average player triggered one social event for each four non-social events. Approximately 80% of the players triggered at least one social event, which is 10 percent points more than in Robocide. Less than 3% of players made at least one purchase, which is roughly two percent points less than in Robocide. Again, more detailed description of revenue is not possible for legal reasons.

Average session time in minutes from the seven day period was 209 minutes or roughly three and a half hours while median was 108 minutes, a bit less than two hours. Having a small amount of extremely highly engaged players registering very long session time totals is not uncommon in mobile games and Spymaster does not seem to be an exception: the highest session time total was more than 2040 minutes, which translates to almost five hours of daily session time when distributed evenly across the seven day period. These extremes explain why the mean differs so much from the median. Mean of session count was 16 and median was 9 sessions. These numbers translate to an average session length of about 13 minutes.

Figure 19 describes how many distinct active days the players recorded after the day of launching the game app for the first time in Spymaster. Approximately 10% of the players included in the sample did not login a single time at least for a week, while more than 23% of players logged in every single day. This is

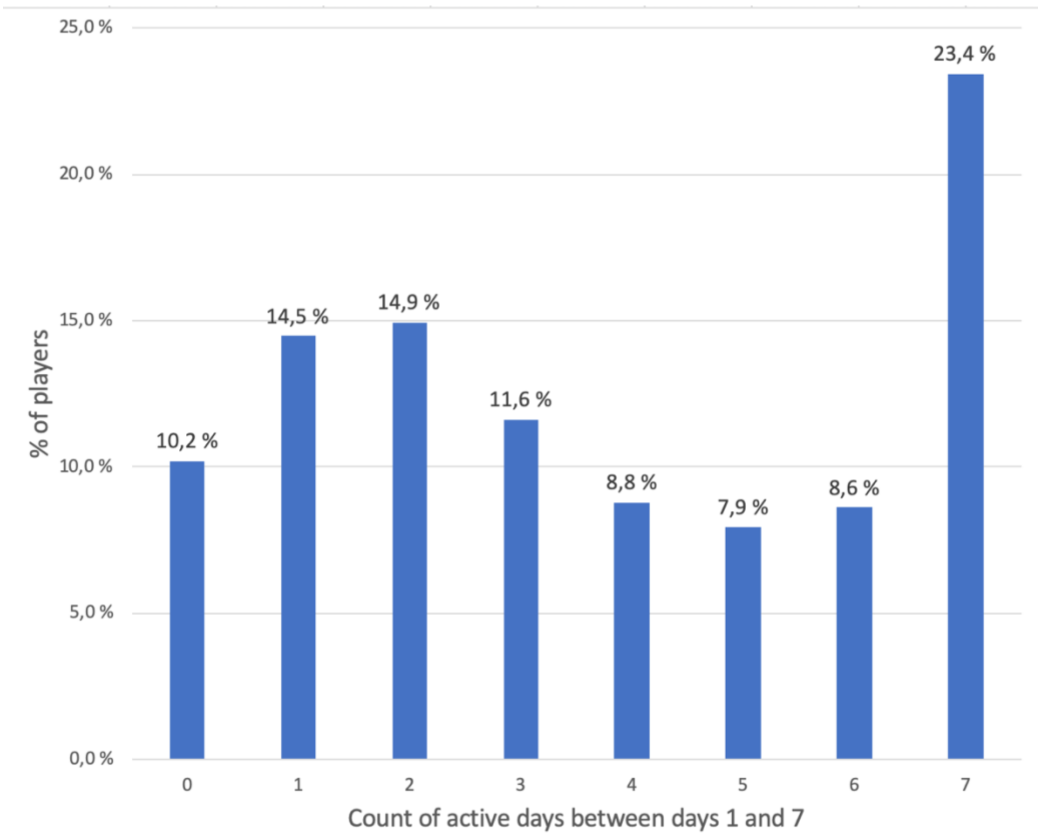

FIGURE 19 Distribution of the variable 'active days 1 to 7' (Spymaster)

Count of retained players declines over time in Spymaster as well, but the decline is not quite as steep as in Robocide. As indicated by figure 20, more than 29% of players logged in at least once between days 14 and 20 and almost 18% between days 30 and 36. In Robocide the decline was from about 25% to less than 11%.

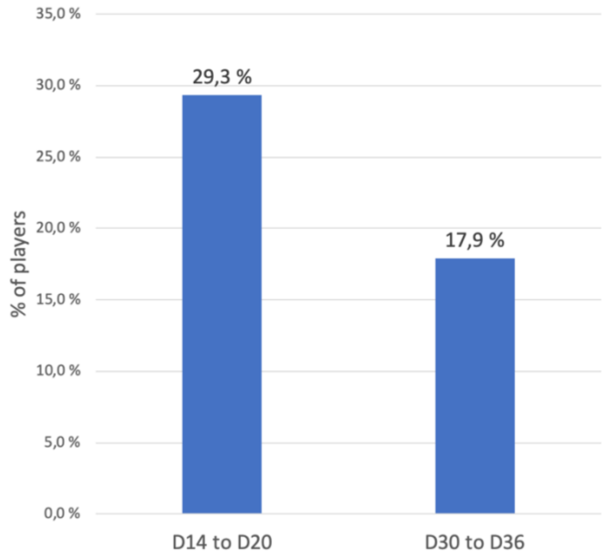

FIGURE 20 Percentage of Spymaster players who logged in at least once during a given period of time

As was done for Robocide data, a logistic regression model was created in R for each available time period: days 14 to 20 and 30 to 36. Spymaster was only released on Android so there was no need for a device platform variable. Again, revenue was transformed into log10 as was done for Robocide data. Similar transformation was done to 'session time minutes' parameter for the same reasons: in our case relative changes are more important than absolute changes.

5 RESULTS

This chapter describes the results of the logistic regression models. The results from performing logistic regression analysis on data from two different free-to-play mobile games were found to be mixed.

5.1 Robocide

The relative amount of engagement with social features had no statistically significant impact on the dependent variable in any of the Robocide regression models as the measured p-values exceeded 0.05. However, count of distinct active days between days 1 to 7 (‘active days 1 to 7’) and log10 of early revenue (‘early revenue USD’) did show sufficiently high p-values in models of all time periods. Device platform (‘is Android’) failed to have statistical significance in any of the models.

The coefficient estimates and odds ratios of each model are presented in table 3. The odds ratio of ‘active days 1 to 7’ declines from 1.69 down to 1.43 over time while the odds ratios of revenue remains fairly stable, fluctuating between 1.17 and 1.23 without a clear pattern. This means that an extra day of activity between days 1 and 7 gives the player 1.69 times, or 69%, higher odds of being active in the game between days 14 and 20. Increasing the spending by a tenfold only increases the odds by 1.2 times, i.e. 20%, for the same time period. Starting from the model of days 14 to 20, odds ratio of early active days falls from 1.69 to 1.56 for days 30 to 36, to 1.50 for days 60 to 66, to 1.45 for days 90 to 96, and to 1.43 for days 180 to 186. Therefore, even though the positive effect on odds diminishes down to 1.43 by days 180 to 186, it remains higher than the effect of early revenue. P-values of ‘social events per non-social event’ and device platform suggest that they have no statistically significant impact on the dependent variable in any of the models.

TABLE 3 Robocide regression models (n= 43 795)

Model	Independent variable	Coefficient estimate		Odds ratio
Days 14 to 20	social events per nonsocial event	0.059		1.06
	early revenue USD log10	0.186	***	1.20
	active days 1 to 7	0.525	***	1.69
	is Android	-0.022		0.98
Days 30 to 36	social events per nonsocial event	-0.075		0.93
	early revenue USD log10	0.207	***	1.23
	active days 1 to 7	0.444	***	1.56
	is Android	0.053		1.05
Days 60 to 66	social events per nonsocial event	0.149		1.16
	early revenue USD log10	0.161	***	1.17
	active days 1 to 7	0.404	***	1.50
	is Android	-0.039		0.96
Days 90 to 96	social events per nonsocial event	0.153		1.17
	early revenue USD log10	0.162	**	1.18
	active days 1 to 7	0.373	***	1.45
	is Android	-0.117		0.89
Days 180 to 186	social events per nonsocial event	-0.419		0.66
	early revenue USD log10	0.203	*	1.22
	active days 1 to 7	0.356	***	1.43
	is Android	-0.028		0.97

(*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$)

5.2 Spymaster

With Spymaster data the impact of social feature engagement was found to be statistically significant. Even though the time range of Spymaster data didn't allow analysis for other periods than days 14 to 20 and days 30 to 36 the impact was significant in both models. Interestingly the early revenue turned out to be the only variable to have no statistically significant impact on the dependent variable.

The coefficient estimates and odds ratios of Spymaster models are presented in table 4. Odds of a player playing the game between days 14 to 20 are 2.40 times higher when the amount of relative social feature engagement increases by one unit. In other words, a player who performs two social gameplay actions for each non-social gameplay action during their first week of playing was 2.40 times more likely to be still playing the game between 14 to 20 days since starting to play compared to a player who only performed one social action per each non-social action if the other variables remain the same. Similarly, a player who played the game on for example five days during their first week was twice as likely to be playing the game between days 14 and 20 compared to a player who only played on four days. Both of these effects diminish slightly when moving on to days 30 to 36: odds ratio of social feature engagement drops from 2.40 to 2.19 while odds ratio of early active days drops from 2.00 to 1.85.

TABLE 4 Spymaster regression models (n=1058)

Model	Variable	Coefficient estimate		Odds ratio
Days 14 to 20	social events per non social event	0.875	***	2.40
	early revenue USD log10	-0.044		0.96
	active days d1 to d7	0.694	***	2.00
	session count	0.031	***	1.03
	session time minutes log10	-1.402	***	0.25
Days 30 to 36	social events per non social event	0.783	***	2.19
	early revenue USD log10	0.249		1.28
	active days d1 to d7	0.617	***	1.85
	session count	0.019	*	1.02
	session time minutes log10	-0.871	**	0.42

(*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$)

The effect of session count was positive, but very small compared to social feature engagement and count of early active days. Interestingly log10 transformed session time showed a strong negative effect. The model suggests that when a players total amount of time spent in the game between days 1 and 7 increases by a tenfold they are four times less likely to play the game between days 14 to 20 and about 2.4 times less likely to play the game between days 30 and 36.

6 DISCUSSION

This chapter the research questions are answered and the results of the study discussed and interpreted in more detail.

6.1 Social feature engagement and long-term use continuance

The purpose of this study is to find out whether social feature engagement is actually connected to long-term player retention as the gossip in the F2P mobile game industry suggests or whether there are some other more relevant factors behind the retention. Two research questions were formulated:

1) How is engaging with social features related to long-term use continuance in free-to-play mobile games?
2) How does engaging with social features compare to other factors that might affect the long-term use continuance?

After analysing actual player behavior from analytics event data of two different F2P mobile games, arguments can be found both for and against the connection of social feature engagement and retention.

The data is showing mixed results. In Robocide the effect of social feature engagement was not statistically significant at all, therefore suggesting that there might be no connection between social feature engagement and long-term retention. However, in Spymaster the social feature engagement was found to be statistically significant and it also had a bigger impact on odd increase than any other variable in either of the games, suggesting that at least under certain conditions there seems to be a clear connection between social feature engagement and retention. Connection to long-term retention still remains somewhat speculative because there was no clean data sample available for time ranges beyond days 30 and 36 which within the industry can arguably be considered to be a mid-term period instead of long-term depending on the nature of the game.

The differences in results of Robocide and Spymaster data could be caused by various things. Comparing games in a detailed manner is difficult because they can be very different in terms of feature composition and audience. Robocide and Spymaster differ in core gameplay mechanics, monetisation mechanics, social features, they were live more than one year apart, and their audiences are likely to be different in many ways. All the gameplay mechanics and features form intricate systems that feed into and from to each other and these two games have very different feature sets. Therefore, it is not too surprising that when observing a single part of the system and trying to draw conclusions from the functionality or engagement with the given system one ends up with mixed results.

The most immediate explanation for different results is related to differences in the social features. Robocide and Spymaster have quite different sets of social features as described in chapters 4.2 and 4.3. It could be that the wider social feature set of Spymaster is enabling more meaningful social ties with its more synchronous player-to-player interaction, or it could be otherwise fundamentally different from the social feature set of Robocide. This might also be the reason why the social feature engagement did not have a statistically significant connection to retention in Robocide while it did have in Spymaster.

The social mechanics in Robocide revolve around the competitive player-versus-player Arena mechanic. Robocide does also have a guild mechanic in form of Alliances, but the options for interaction are very limited: there is no chat or other means of communication or playing together. The Alliance only sums up the Arena points of each Alliance member into a combined Alliance score, which is shown on the global Alliance leader board. Spymaster has much more diversity and depth in social features: in Agencies, the Spymaster equivalent for guilds, the players can chat with each other synchronously, gift in-game resources to other Agency members and help to release captured characters of other Agency members asynchronously, and take part in Agency Battles which utilise both asynchronous gameplay mechanics and synchronous in-game Agency chat for communication. In Robocide Arena the players are always playing alone as the gameplay consists of one player playing against an AI controlled opponent even if the opponent's defensive setup was formulated by another player. In Spymaster the Agency members are playing together on a shared map against another Agency. Collaborating, sharing information, and planning with other Agency members is beneficial. It seems clear, that the social mechanics in Spymaster allow for and encourage more interaction between players, and can therefore be argued to enable stronger social ties than the social mechanics in Robocide. This might explain, why social feature engagement was observed to have no impact on use continuance in Robocide while having a significant impact in Spymaster. Whether the effect is caused by simply having more opportunities for interaction, or influenced by the nature of the interaction (e.g. co-operative vs competitive interaction), or both, remains to be explored in future studies. In order to get a better insight, a higher granularity breakdown of the engagement with various different social features might be necessary, but in this study all the engagement with features related to player-to-player interaction were tracked into a single variable. Breaking down the social features could be done according to Ricchetti's (2012), Kuiper's (2018), or some other classification. In this study, a conscious decision was made to not break down the social features into subcategories in order to focus on the high level phenomenon of social interaction.

There might also be differences in the level of quality of execution of the features between the games. For example, if the players simply find the single player content more fun and engaging than the content where they interact with other players, it makes sense that engaging with the features they find less enjoyable is not going to make them stick longer with the game. If the social features in Spymaster create a more enjoyable gameplay experience than the social features in Robocide, it makes sense that social feature engagement was found to be relevant only in the Spymaster regression models. As demonstrated by van der Heijden (2004), in hedonic systems perceived enjoyment replaces perceived usefulness as a major factor affecting use continuance intention.

Unfortunately quantifying and tracking the amount of enjoyment or fun a player is having is not a straightforward task. Metrics such as count of sessions or sum of session times are sometimes suggested within the industry, but since players have varying amounts of time for mobile games in their disposal it is not trivial to make an argument that the session metrics would be good indicators for the perceived enjoyment or the experience of fun. Early engagement overall could still be argued to have some connection to the experience of fun. Building a habitual behavior takes at least a couple of weeks (Lally, Van Jaarsveld, Potts, & Wardle, 2010) and it also takes at least a week or two for the so called meta game loop, where the player starts to get more interested in longer term goals in the game rather than instant gratification and fun, to properly start rolling. So in the early parts of a game there should be less factors other than the experience of fun that could hypothetically drive player engagement. Therefore, an argument could be made that the count of active days from the first week could be a reasonable measure for the experience of fun since, unlike session related metrics, it is not affected that much by individual time restrictions for playing. Most likely there are still players who are only able to spend time with mobile games during the weekends than weekdays or the other way around. This creates some inaccuracy when using the count of distinct active days as a metric, but at least the method of counting distinct active days from the first week can still be seen as more robust than the method of relying on the session metrics. But even if one would establish that the count of distinct active days during the first week would be an acceptable metric for measuring the experience of fun, they would still have a hard time in determining how much the metric is driven by social feature engagement because the availability of the social features in the early stages of the game varies from game to game.

According to the developers of these two games, Robocide was originally designed to be primarily a single player game and all the social features were added much later in development. So the game was not designed from the very beginning to accommodate player to player interaction. Spymaster on the other hand was designed to be a social gameplay experience already in the first drafts of the game. This gives some, even if not necessarily conclusive, support for the argument that there might be qualitative differences between the games in their social features or how well they fit the overall gameplay loop.

So to answer the first question, the results of the data analysis suggest that in some cases social feature engagement can be a valid indicator of at least mid-term retention in some cases. However, it seems that a more detailed breakdown of different types of social features and engagement with them might be necessary in order to describe the relationship in more detail. Since it was not possible to get a clean sample of days beyond 36 for Spymaster, it is impossible to say with high confidence whether the effect would still be present for the longer term time periods. In case of Robocide social feature engagement was not showing any consistent pattern across the models or statistical significance, suggesting that at least under certain conditions early social feature engagement is not connected to long-term retention.

Revenue was found to be statistically significant factor only in Robocide data, where increasing the sum of early revenue by a tenfold improved the odds of retaining by 17% to 22% depending on the time period. Spending has been observed to have a positive impact on player retention (Hanner & Zarnekow, 2015). According to Hamari (2011) this might be caused by loss aversion: if a player stops playing the game they would "lose" the value of their purchases as well so they might be hesitant to start playing some other game instead. Based on this it seems peculiar that the early revenue did not seem to have any statistically significant impact on even shorter term retention in Spymaster. This might be caused by unrefined monetisation mechanics in Spymaster. Development of Spymaster was discontinued in soft launch and therefore the monetisation features were never developed or polished to the standards of a globally released product, leading to a very low overall amount of paying players and revenue. In case of Robocide, which was released globally and had more refined monetisation features, early revenue was one of the two metrics that had a statistically significant and positive impact on retention across all the models.

Count of distinct active days from the first week was the only metric that was found to be statistically significant and impactful across all the models in both games. In Robocide the improvement in odds of still being active in the game varied between 43% and 69% depending on the time period, which is higher than the 17% to 22% improvement caused by increasing the sum of early revenue by a tenfold. In Spymaster, increasing the count of early active days by one resulted in twofold increase in odds of being active in the games between days 14 to 20 while registering one more social feature action per non-social feature action resulted in 2.40 times higher odds. For days 30 to 36 the effect of early active days drops to 1.85 and the effect of social feature engagement drops to 2.19. So while the count of distinct active days from days 1 to 7 might have a more consistent effect on use continuance since it was present in all the models, the effect on social feature engagement can exceed that effect, but could be more dependent on the selection of social features and how they are implemented. It was already speculated that the count of distinct active days during the first week might be an indicator of experience of fun, but examining that in more detail goes beyond the scope and purpose of this study.

Session metrics were available only in Spymaster and both the session counts and sums of session times proved to be statistically significant. The effect of session count was slightly positive but effectively neglectful. Improving the count of sessions between days 1 and 7 did not have a relevant impact on use continuance in Spymaster. Interestingly, total session time showed a strong negative impact on use continuance. According to my personal experience as a game data analyst, session metrics are valued quite highly within the mobile game industry so these finding are somewhat surprising. The negative effect of session times could be related to highly engaged players burning themselves out in the game: excessively high session times within a relative short period of time could lead to digital "overdosing", after which the player starts to feel negatively towards the game (Schell, 2008; Kramarzewski & De Nucci, 2018). With excessively high session times a player could also play through most of the content in the game, ending up in a situation where there is not enough playable game content to keep the player entertained so the player stops playing the game for good. In Spymaster a player can only run a limited amount of missions at a time, but the mission timers can be skipped with in-game resources. Therefore, if the player keeps on buying these in-game resources with in-app purchases there is no mechanical restrictions on session lengths. The negative effect demonstrated by the session time gives some support to the speculation conducted earlier regarding the shortcomings of considering session metrics as indicators of the experience of fun.

Only Robocide was available on both iOS and Android platforms. The audience and their behavior tends to vary a little bit between the platforms at least in terms of monetisation, but in case of Robocide the platform did not have any statistically significant impact on use continuance.

To summarise, based on the data from the two games analysed it seems that at least under certain conditions early social feature engagement can have a significant positive impact on use continuance at least for the first month. When it comes to other early indicators than social feature engagement there are two major ones that also demonstrated an impact on use continuance: count of distinct active days from the first week, and sum of revenue from the first week. Count of distinct active days demonstrated a consistent effect across all the models in both games and therefore it was arguably the most relevant single factor having an effect on longer term use continuance. Whether it is an indicator of experience of fun or something else would be an interesting subject for further research. Revenue was the other impactful factor as was to be expected. The lack of effect in Spymaster is slightly surprising, but considering the unfinished nature of the monetisation features, understandable.

6.2 Reflecting against literature

In this study three metrics were found to be positively related to long-term use continuance: count of distinct active days from the first week, sum of revenue from the first week, and amount of social feature engagement in relation to engaging with non-social features.

6.2.1 Active days

As discussed earlier, count of distinct active days from the first week could be argued to be an indicator of experience of fun, because it happens too early to be considered habitual behavior or to be driven by longer term goals introduced by the F2P meta-game layer. If count of distinct active days can be seen as indicator of experience fun, then the result would be aligned with existing research. The positive impact of perceived enjoyment on use continuance intention has been observed at least in online games (Lee & Tsai, 2010), social virtual worlds (Barnes, 2011; Mäntymäki & Salo, 2011; Mäntymäki & Islam, 2013; Mäntymäki & Riemer, 2014), and mobile games (Liang & Yeh, 2011; Park et al., 2014).

6.2.2 Revenue

The positive effect of spending is aligned with findings of Hanner & Zarnekow (2015). In general spending is not addressed in IT continuance literature. The extended version of UTAUT (Venkatesh et al., 2012) does recognise price value as a factor that affects use continuance intention, but how directly that compares to player spending in F2P mobile games is debatable. Players who ended up spending in game probably were happy with the value proposition, but even the players who never spent anything might still find the initial value proposition (the game is free to download and play for free) good even if they are not willing or able to spend money in game. The mobile game market is full of games that are free to download and play so preferring one free game over the other free games can be argued to imply that the given game has a better price value even if no money was spent. Therefore, the perceived price value is something that is hard to measure with the given data.

6.2.3 Social feature engagement

As concluded in chapter 2.8, social factors have been observed to affect use continuance intention in two ways: through social influence (Hsu & Lu, 2004; Lee & Tsai, 2010), and by affecting the perceived enjoyment (Liang & Yeh, 2011; Lee & Tsai, 2010).

Social influence is a factor that the extended version of UTAUT (Venkatesh et al., 2012) recognises. As discussed earlier, the in-game community itself could be theorised to play the role of social influence: the more you engage with other players, the more impactful they become in affecting the player's intention towards continuing to play the game. However, this type of perceived social influence is hard to observe with the available data. If a player keeps playing the game because they think that their in-game social connections would approve such behavior, it could arguably manifest as increased relative social feature engagement as measured in this study. It would make sense that if there was social encouragement or pressure to play the game, it would be aimed at the parts of the game where the players interact with each other instead of playing solo.

Playing with and against other human players instead of computer controlled players has been observed to be more enjoyable (Weibel et al., 2008), and perceived enjoyment has been observed to have a positive effect on use continuance intention (Liang & Yeh, 2011; Lee & Tsai, 2010; Park et al., 2014). Arguably the social feature engagement parameter used in this study should capture this behavior quite well: if the social content is more enjoyable than the single player content, the player is more likely to engage with the social content, resulting in increased social feature engagement.

Whether the effect of social feature engagement and its impact on use continuance intention is more related to social influence or perceived enjoyment can only be speculated: player data logs only indicate what behavior has happened instead of how the behavior was motivated.

6.3 Reliability and generalizability

This study utilises analytics logs of actual players playing a commercial F2P mobile game to conduct logistic regression analysis to examine the effect of various player behavior metrics on use continuance. There were two mains reasons for utilising analytics logs. First of all, analytics logs are exact logs of actual players playing the game in their daily lives. This allows bypassing many problems related to certain other forms of data gathering, such as questionnaires or observing players in a controlled test environment. Questionnaires can suffer from various forms of biases such as response bias, participation bias, and low response rates. Observing players in a lab environment can be problematic since in a lab it is not possible to observe the players playing the game as they naturally would in their daily lives. Therefore, analytics logs can be argued to be a more reliable data source for the purposes of this study. Secondly, analytics logs are already utilised by majority of F2P game developers. Therefore, replicating this study should be fairly straightforward for any F2P game developer with analytics logs of their own games.

Accuracy of the data logs could be compromised by technical bugs in the game code, but the PlayRaven's analytics data has been successfully utilised for their day-to-day operations for years so the confidence on the accuracy of the data logs is high. Errors could also happen when formulating the SQL queries to extract the data from the analytics database. The logic and contents of the query are described in chapter 4. The author of this study has been working as a data analyst in the game industry for five years and is experienced in working with game analytics data. This helps in handling, analysing and interpreting the data, but the interpretations could include some related bias.

Even though analytics logs are a great way to track and analyse player behavior, player motivation behind the behavior is hard to examine with log data. Therefore, any player motivation related factors that might affect use continuance are unlikely to be covered with the data and analysis conducted in this study. Utilising other data gathering methods such as questionnaires might have helped to cover these player motivation aspects as well, but as demonstrated in chapter 6.2, analytics logs can be argued to cover two major factors present in literature: perceived enjoyment, and social influence.

Generalizability of this study is debatable. Every game is a unique environment of its own with its own distinct feature set. In multiplayer games also the other players one plays with varies from one game to another. For this reason, it is hard to make generalisable conclusions. However, even if the games have varying feature sets there might be certain shared qualities between games overall or certain types of games that could be recognised and analysed. The two games examined in this study are especially tricky to draw general conclusions from because they have a quite unique core gameplay mechanics and represent somewhat niche genres as well. Games with more traditional and widely used core gameplay mechanics would have been more useful cases for making general conclusions, but unfortunately such games were not available for analysis.

To avoid studying too specific and unique cases, a conscious decision was made to measure the social feature engagement with one variable only. Breaking down the social features of Robocide and Spymaster by utilising heuristics of e.g. Paavilainen et al. (2017) or Ricchetti (2012) would be possible, but it was decided to collapse all the social feature engagement into a single variable to focus on the high level phenomenon of social activity. This allowed to keep the focus and the scope of the study reasonable. The possible differences in impact between the various types of social features needs to be examined in future studies.

In this study, the chosen method of measuring ‘social’ might or might not be the best method of capturing and describing the phenomenon. One could argue that measuring the relative social feature engagement merely measures the personal gameplay preferences of a given player. Therefore, the connection between social feature engagement and long-term use continuance would only indicate that players who prefer social feature gameplay are a player-type that is more likely to retain than players who do not like to engage with social features. In such case, it might be more beneficial for a game publisher to focus on acquiring the right kind of players into their game rather than make the game more focused on social features and social gameplay.

One could also argue that one or both of the games analysed in this study attracts players with certain gameplay preferences. For example, the theme or genre of a game might be a factor that makes the game more attractive for certain types of players and therefore results in a biased pool of players, possibly weakening the generalizability of the study.

7 SUMMARY

The important question this study addresses is whether social engagement of players is connected to long-term use continuance intention in F2P mobile games. The F2P business model benefits from retaining the players over long periods of time in order to monetise them, so to a F2P mobile game developer all information that might be helpful in improving the retention is highly valuable. Within the mobile game industry it has been speculated, that engaging with other players in the game through various social gameplay features such as trading, co-operation and competition can be an important driver of engagement and retention in F2P mobile games. However, there is a clear gap in research regarding the connection between social feature engagement and player retention in the context of F2P mobile games. This study contributes to the discussion by utilising actual game analytics logs data from two commercial F2P mobile games and analysing the data with logistic regression analysis.

Research data was provided by PlayRaven, a Finnish F2P mobile game developer. These two games were ideal for the study as both of them allowed players either to engage with other players through social features or focus on the single player side of the game. This way a comparison can be conducted to examine whether the players who engage more with social features than single player features still kept playing the game after several weeks from the starting day. The applicable data was extracted from PlayRaven analytics database with SQL queries and logistic regression analysis was utilised in R to analyse the data. Various metrics were measured from the first week of gameplay of each applicable player including count of distinct active days, spending, social feature engagement, and session metrics. Then the data was analysed to determine how these variables affected whether the player was still playing the game after certain periods of time, starting from two to three weeks from the starting day all the way to six months from the starting day.

Results are mixed. In case of Robocide there was no statistically meaningful connection between the social feature engagement and use continuance on any measured time period. In Spymaster the connection between social feature engagement had a stronger positive effect on use continuance than all the other variables that were measured. In both games, count of active days during the first week was found to be connected to use continuance as well: in Robocide it was the most impactful single factor of the analysed variables and in Spymaster it was less impactful than social feature engagement. In Robocide, revenue generated during the first was also found to be impactful while in Spymaster there was no statistically meaningful connection between revenue and use continuance.

Overall, it seems that even though the results are mixed, at least in some cases social feature engagement can lead to higher player retention. In addition, there were no signs that engaging with the social features would have a negative impact on use continuance. While this might not confirm that F2P mobile game developers would be able to improve their retention metrics by focusing on social feature development, it seems that the chances for it should be better with a wide selection of social features that enables strong social ties.

There are various possible explanations for differences in results between the two games. First of all, the selection of social features varies: in Robocide the selection of social features is more limited and they more focused on competition while Spymaster has a wider selection of both co-operative and competitive mechanics and in-game chat. Therefore, it seems plausible that a game needs a certain amount or certain composition of social features before they enable forming of strong social ties and start having an impact on use continuance. In addition, there might be differences in quality of feature execution. Robocide was originally designed to be primarily a single player experience, while Spymaster was designed to be a social gameplay experience from the beginning. Therefore, it is possible that the social features of Robocide were of poorer quality than those of Spymaster, since the focus of the initial development was different. As concluded in chapter 2.8, social factors seem to impact via two mechanisms: social influence (Hsu & Lu, 2004; Lee & Tsai, 2010), and increased perceived enjoyment (Liang & Yeh, 2011; Lee & Tsai, 2010). Spymaster's feature set could therefore create a more enjoyable gameplay experience for the average, or it could be better for enabling more meaningful social ties, which then creates a certain social pressure to keep on playing the game, or both. It is also possible that the difference could be partially caused by differences in the audiences. For example, the theme of a game might draw in only certain types of players. If the player population happens to consist of players whose enjoyment is driven by other factors than interaction with other players, it makes sense that the social feature engagement would not affect use continuance in such games.

Plenty of questions are left to be studied in further research. A wider sample of games could be studied to examine the more precise conditions where the social features can have a positive impact on player retention. Further study is also needed to determine whether this effect is moderated by player preferences. Also a more detailed breakdown of different social features could be conducted to study the impact of individual social features instead of a composition of features. The role of player motivations could also be studied to examine whether the mechanism behind the positive impact on use continuance is related to social influence, increased enjoyment, or both. Any mobile game developer with event-based tracking systems could utilise similar methods as those used in this study to examine these topics and the impact of social features in their own portfolio of games.

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APPENDIX 1 ROBOCIDE REGRESSION MODELS

```
> # Creating and evaluating the model for days 14 to 20

> m14 <- glm(active_days_14_to_20 ~ early_revenue_USD + social_events_per_non
social_event + active_days_1_to_7 + isAndroid ,dataClean, family="binomial")

> summary(m14)

Call:

glm(formula = active_days_14_to_20 ~ early_revenue_USD + social_events_per_no
nsocial_event +

    active_days_1_to_7 + isAndroid, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-1.6649  -0.6061  -0.4676  -0.2813   2.5493

Coefficients:

                                   Estimate Std. Error z value Pr(>|z|)

(Intercept)                       -3.002049   0.042649 -70.389  < 2e-16 ***

early_revenue_USD                  0.185842   0.028707   6.474 9.57e-11 ***

social_events_per_nonsocial_event  0.059058   0.095368   0.619    0.536

active_days_1_to_7                 0.524984   0.006697  78.392  < 2e-16 ***

isAndroid                         -0.022027   0.027229  -0.809    0.419

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 49037  on 43794  degrees of freedom

Residual deviance: 39961  on 43790  degrees of freedom

AIC: 39971

Number of Fisher Scoring iterations: 5

> pR2(m14)

          llh       llhNull            G2      McFadden          r2ML
  r2CU

-1.998047e+04 -2.451838e+04  9.075822e+03  1.850820e-01  1.871707e-01  2.7785
86e-01
```

```
> # Creating and evaluating the model for days 30 to 36

> m30 <- glm(active_days_30_to_36 ~ early_revenue_USD + social_events_per_non
social_event + active_days_1_to_7 + isAndroid ,dataClean, family="binomial")

> summary(m30)

Call:

glm(formula = active_days_30_to_36 ~ early_revenue_USD + social_events_per_no
nsocial_event +

    active_days_1_to_7 + isAndroid, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-1.0977  -0.4655  -0.3037  -0.2381   2.8361

Coefficients:

                                   Estimate Std. Error z value Pr(>|z|)

(Intercept)                       -3.784933   0.055284 -68.463  < 2e-16 ***

early_revenue_USD                  0.206918   0.032076   6.451 1.11e-10 ***

social_events_per_nonsocial_event -0.074629   0.114062  -0.654    0.513

active_days_1_to_7                 0.442659   0.008686  50.964  < 2e-16 ***

isAndroid                          0.053393   0.035224   1.516    0.130

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 29903  on 43794  degrees of freedom

Residual deviance: 26283  on 43790  degrees of freedom

AIC: 26293

Number of Fisher Scoring iterations: 5

> pR2(m30)

          llh       llhNull            G2      McFadden          r2ML
  r2CU

-1.314146e+04 -1.495175e+04  3.620573e+03  1.210752e-01  7.934594e-02  1.6035
87e-01
```

```
> # Creating and evaluating the model for days 60 to 66

> m60 <- glm(active_days_60_to_66 ~ early_revenue_USD + social_events_per_non
social_event + active_days_1_to_7 + isAndroid ,dataClean, family="binomial")

> summary(m60)

Call:

glm(formula = active_days_60_to_66 ~ early_revenue_USD + social_events_per_no
nsocial_event +

    active_days_1_to_7 + isAndroid, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-0.7483  -0.3504  -0.2344  -0.1588   3.1074

Coefficients:

                                  Estimate Std. Error z value Pr(>|z|)

(Intercept)                       -4.61955    0.08052 -57.373  < 2e-16 ***

early_revenue_USD                  0.16089    0.04431   3.631 0.000282 ***

social_events_per_nonsocial_event  0.14946    0.15675   0.954 0.340321

active_days_1_to_7                 0.40419    0.01261  32.049  < 2e-16 ***

isAndroid                         -0.03943    0.05162  -0.764 0.444920

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 16216  on 43794  degrees of freedom

Residual deviance: 14773  on 43790  degrees of freedom

AIC: 14783

Number of Fisher Scoring iterations: 6

> pR2(m60)

          llh       llhNull            G2      McFadden          r2ML
  r2CU

-7.386423e+03 -8.108119e+03  1.443392e+03  8.900905e-02  3.242072e-02  1.0476
67e-01
```

```
> # Creating and evaluating the model for days 90 to 96

> m90 <- glm(active_days_90_to_96 ~ early_revenue_USD + social_events_per_non
social_event + active_days_1_to_7 + isAndroid ,dataClean, family="binomial")

> summary(m90)

Call:

glm(formula = active_days_90_to_96 ~ early_revenue_USD + social_events_per_no
nsocial_event +

    active_days_1_to_7 + isAndroid, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-0.5575  -0.2615  -0.1805  -0.1260   3.2714

Coefficients:

                                  Estimate Std. Error z value Pr(>|z|)

(Intercept)                       -5.06692    0.10447 -48.502  < 2e-16 ***

early_revenue_USD                  0.16205    0.05756   2.815  0.00487 **

social_events_per_nonsocial_event  0.15317    0.20562   0.745  0.45632

active_days_1_to_7                 0.37317    0.01643  22.716  < 2e-16 ***

isAndroid                         -0.11738    0.06898  -1.702  0.08879 .

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 10328.6  on 43794  degrees of freedom

Residual deviance:  9606.2  on 43790  degrees of freedom

AIC: 9616.2

Number of Fisher Scoring iterations: 7

> pR2(m90)

          llh       llhNull            G2      McFadden          r2ML
  r2CU

-4.803095e+03 -5.164288e+03  7.223858e+02  6.994051e-02  1.635942e-02  7.7867
77e-02
```

```
> # Creating and evaluating the model for days 180 to 186

> m180 <- glm(active_days_180_to_186 ~ early_revenue_USD + social_events_per_
nonsocial_event + active_days_1_to_7 + isAndroid ,dataClean, family="binomial
")

> summary(m180)

Call:

glm(formula = active_days_180_to_186 ~ early_revenue_USD + social_events_per_
nonsocial_event +

    active_days_1_to_7 + isAndroid, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-0.2979  -0.1503  -0.1053  -0.0848   3.5384

Coefficients:

                                  Estimate Std. Error z value Pr(>|z|)

(Intercept)                       -6.02727    0.17507 -34.427   <2e-16 ***

early_revenue_USD                  0.20271    0.09579   2.116   0.0343 *

social_events_per_nonsocial_event -0.41883    0.38043  -1.101   0.2709

active_days_1_to_7                 0.35552    0.02770  12.835   <2e-16 ***

isAndroid                         -0.02817    0.11567  -0.244   0.8076

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 4259.9  on 43794  degrees of freedom

Residual deviance: 4047.7  on 43790  degrees of freedom

AIC: 4057.7

Number of Fisher Scoring iterations: 8

> pR2(m180)

          llh       llhNull            G2      McFadden          r2ML
  r2CU

-2.023848e+03 -2.129962e+03  2.122265e+02  4.981931e-02  4.834183e-03  5.2155
07e-02
```

APPENDIX 2 SPYMASTER REGRESSION MODELS

```
> # Creating and evaluating the model for days 14 to 20
> m14 <- glm(active_days_d14_to_d20 ~ early_revenue_USD + session_count +
session_time_minutes + social_events_per_non_social_event +
active_days_d1_to_d7 ,dataClean, family="binomial")
> summary(m14)

Call:
glm(formula = active_days_d14_to_d20 ~ early_revenue_USD + session_count +
    session_time_minutes + social_events_per_non_social_event +
    active_days_d1_to_d7, family = "binomial", data = dataClean)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8699  -0.5654  -0.3047   0.6868   2.7989

Coefficients:
                                    Estimate Std. Error z value Pr(>|z|)
(Intercept)                        -1.882217   0.381681  -4.931 8.16e-07 ***
early_revenue_USD                  -0.044117   0.228013  -0.193 0.846579
session_count                       0.030553   0.007812   3.911 9.19e-05 ***
session_time_minutes               -1.402301   0.197547  -7.099 1.26e-12 ***
social_events_per_non_social_event  0.874523   0.236363   3.700 0.000216 ***
active_days_d1_to_d7                0.693629   0.068422  10.138  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1279.80  on 1057  degrees of freedom
Residual deviance:  855.56  on 1052  degrees of freedom
AIC: 867.56

Number of Fisher Scoring iterations: 5

> pR2(m14)
         llh      llhNull           G2     McFadden         r2ML         r2CU
-427.7824695 -639.9006382  424.2363375    0.3314861    0.3303362    0.4707683
```

```
> # Creating and evaluating the model for days 30 to 36

> m30 <- glm(active_days_d30_to_d36 ~ early_revenue_USD + session_count + ses
sion_time_minutes + social_events_per_non_social_event + active_days_d1_to_d7
 ,dataClean, family="binomial")

> summary(m30)

Call:

glm(formula = active_days_d30_to_d36 ~ early_revenue_USD + session_count +

    session_time_minutes + social_events_per_non_social_event +

    active_days_d1_to_d7, family = "binomial", data = dataClean)

Deviance Residuals:

    Min       1Q   Median       3Q      Max

-2.2672  -0.5180  -0.2609  -0.1791   2.9632

Coefficients:

                                    Estimate Std. Error z value Pr(>|z|)

(Intercept)                        -3.037556   0.513441  -5.916 3.30e-09 ***

early_revenue_USD                   0.249050   0.213725   1.165 0.243905

session_count                       0.018896   0.007682   2.460 0.013905 *

session_time_minutes               -0.870511   0.281212  -3.096 0.001964 **

social_events_per_non_social_event  0.783012   0.213674   3.665 0.000248 ***

active_days_d1_to_d7                0.617403   0.077922   7.923 2.31e-15 ***

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 993.09  on 1057  degrees of freedom

Residual deviance: 723.18  on 1052  degrees of freedom

AIC: 735.18

Number of Fisher Scoring iterations: 6

> pR2(m30)

         llh      llhNull           G2     McFadden         r2ML         r2CU


-361.5878924 -496.5441162  269.9124476    0.2717910    0.2251732    0.3698377
```