THE IMPACT OF ONGOING MONETIZATION TOOLS ON THE SUSTAINABILITY OF ONLINE FREE-TO-PLAY GAME SERVICES

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ABSTRACT

In the current online game market, freely accessible products struggle to attract, keep and monetize users. This paper creates and applies a new framework to measure the impact of monetization tools on performance indicators for sustainability in online Free Play game services.

The center of the study is a 9-month-old active video game case. Monetization Tools and Performance Indicators that represent a game's sustainability are defined and clustered. The game data is used to find correlations between the Tools and the Indicators by conducting a Linear Regression and ultimately finding out how game companies can predict sustainability through changes in monetization tools.

The outcome is that Monetization Tools can have a substantial impact on the average revenue made by paying users. Especially In-Game events that offer exclusive, time-limited content have a significant effect on the sustainable growth of game service.

Monetization Tools can also have a non-monetary positive or negative effect on a game service's ongoing success. The resulting change in player retention and the number of first-time purchases can boost or damage a game's long-term success, making this paper's findings interesting for practical implementation.

Keywords: Game Monetization, Free to Play, Game as a Service, Monetization Tools, Game Sustainability

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Alexander Erlebach

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CHAPTER 1
INTRODUCTION

The game industry is constantly growing and has been described as "recession-proof" (Dillon & Cohen, 2013), which is also showing in recent times during the COVID-19 crisis. It is one of the few markets that benefited from the pandemic because of the high demand for home entertainment due to social distancing. Reports say that in 2020 the market generated 159 Billion Dollars and is expected to grow to 200 Billion in 2023, making it one of the fastest-growing media markets. Global player numbers have increased over a third in the last five years to 2.7 billion in 2020. Numbers are expected to surpass 3 billion players in 2023, partly due to the significant growth in Asia and Africa (Newzoo, 2021).

The industry is continuously evolving, pushed by developing technology and changing customer needs, which fundamentally shifted its revenue structure. In 2018, more than 80% of the revenue digital games made was due to free-to-play games (Lake Washington Institute of Technology, 2019). Game titles are increasingly seen as a service rather than a single transaction which impacts the business model and monetization structure.

1.1 Problem Statement

The main problems on the business side for gaming companies are strongly connected to the current dominant way of how value is added to products. Online games with a Free-To-Play business model do not require an upfront payment, making them easily accessible and dependent on the customer's optional purchases (Alha, Koskinen, Paavilainen, Hamari, & Kinnunen, 2014).

Many online Free-to-Play games have one of two issues that hinders them from becoming financially successful. One is the lack of retention, which means that they cannot attract and keep enough players and not scale their business. The other is that they are unable to monetize their existing users enough. According to the game business intelligence provider delta DNA, free-to-play mobile games should have at least 10% of the players that start the game playing after seven days, with 10% of those spending money. The lifetime value should be over 1$ for each customer on average. Shockingly, only 16% of games achieve all relevant measures (Cormack, 2018).

A big challenge for game companies is finding the right balance between providing a rewarding game experience and incorporating monetization in the gameplay loop, so include optional payment into the repetitive activities that the player is doing throughout playing the game. Targeting high spenders with aggressive monetization is beneficial turnover-wise (Yang, Yang, Huang, Chen, & Liu, 2018). However, it can lead to players losing interest once they feel that success can be directly bought with money (Flunger, Mladenow, & Strauss, 2017).

A superordinate problem for companies is the lack of rich player data. Basic sales and critical milestones of players reaching a certain point in the gameplay are readily available. However, qualitative data on player behavior and cross-connections with performance indicators require effort and resources. Therefore, in many game projects, it is not clear how different monetization elements impact the revenue and player experience. Without monitoring and interpreting the game data, it is not possible to make well-founded decisions.

Retention, micro-transactions, and the psychological aspect of selling digital goods, like ethnical and gambling related issues, are dealt with in recent academic literature**.** However, the concrete issue of creating ongoing monetization over the lifetime of a game product has not been picked out as a central theme and will be the focus of this paper. Since optional purchases require player motivation and involvement, getting a return on investment takes time and effort to make the sold content appealing. Selling the same products over the lifetime of a game will lead to fatigue since the player will lose the need or interest in these products.

Creating new effective content that can be monetized is challenging since there are many options, and it requires resources. New or updated content, graphics or digital goods all cost money and need time to be implemented. Wrong decisions can negatively impact the economic game performance, for example, by giving too high discounts, flooding the in-game economy with digital goods, and negative added value in the long term. Discounts and bundling of items has been found to come with a negative consequence and therefore have to be used with care (Stanev, 2020). Game production is expensive and risky, and significantly smaller new companies have a lack of liquidity and no data of previous titles (Sotamaa & Svelch, 2021). This means they have to obtain the information during live operation, with limited resources and scarce research data publicly available. This paper aims to define and categorize Monetization Tools and elaborate on how they can impact the sustainability of a game service to contribute to solving the issue of successfully creating ongoing monetization.

1.2 Research Objective and Research Questions

This research builds upon the issue of creating sustainable monetization over a game project's lifetime. The aim is to explore the connection between Ongoing Monetization Tools and the Performance Indicators of an online game service by measuring possible dependencies.

Research Question 1: How do the Monetization Tools impact the Active Revenue per Paying User (ARPPU)

Research Question 2: How do the Monetization Tools impact Player Retention?

Research Question 3: How do the Monetization Tools impact the amount of New Paying Users (NPU)?

Research Question 4: How do the Monetization Tools affect Daily Active Users (DAU)?

1.3 Scope of the Study

The goal is to determine how monetization tools can impact performance indicators by analyzing a single operating Free to play online game service. Monetization tools will be defined in the Literature Review and adapted for the specific practical case. By looking at a single case, the aspiration is to understand the relation between monetization tools in greater detail. An exploratory Regression Analysis will be conducted to find possible connections and create a system to predict the influence of changes in monetization on the sustainable performance of the game service.

1.4 Significance of the Study

The study aims to provide practical insight into game service monetization and the economic effects to understand better the market, customers, and possible impact of proven and innovative monetization tools. Due to the access to rich data of operating live game services, the immediate consequences of applied theoretical knowledge can be interpreted.

Since every game product is different and there are many individual performance impacting parameters that are not the focus of this research, the outcome means to be an adaptable framework rather than a complete industry overview.

The academic knowledge on ongoing monetization is currently minimal and this paper aims to contribute a deep inside into a test case to demystify Ongoing Monetization Tools and their impact on a game's performance over its lifetime.

The findings on how to impact your service by modifying your monetization tools can also be relevant for other industry especially related ones that use a free access business model like Software Monetization and Web monetization.

1.5 Definition of Terms

Online Game: A video game that requires an internet connection to be played

Mobile Game: A video game that is playable on a smartphone or tablet.

ARPPU: Average Revenue per Paying Player. A performance indicator that shows how much money is made by a single paying player.

DAU: Daily Active Users. A Performance Indicator that describes how many individual players logged in to the game on a given day.

Retention: A measurement of how long users stay with a game service. "x" Day Retention is measured by how many % of users log in again "x" days after their first login.

Monetization: The act of creating money from an asset, in this context, a game service that is given away for free.

Monetization Tool: A group of similar implements to generate money from users.

Virtual Goods: Purchasable products that only exist and only bare value in the context of a virtual game world.

Microtransaction: A small purchase of virtual goods. Mostly under 10$

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CHAPTER 2
LITERATURE REVIEW

This paper aims to analyze game monetization tools to improve a game's lifetime value sustainably. Game Monetization describes the process of creating Revenue with a game product. At its core, games deliver entertainment to the customer, who, in exchange, pay for it (Fields, 2014). Although correct, this simple definition does not explain the process sufficiently since, over the last two decades, how video games generate Revenue has fundamentally changed (Davidovici-Nora, 2014). To grasp this matter, we will first look at the standard business models of the gaming industry.

2.1 Business Models in the Gaming Industry

2.1.1 Pay to Play (P2P)

After PC games shifted from being experimental programs in mainframe laboratories or Computer Science collages to a real business, they were sold in a standard retail model. Customers buy a physical data storage device like a floppy disc, CD, or DVD, which contains an executable program that launches the game. After fast-speed internet connections became more broadly available in households, digital distribution became more popular. Consumers simply purchase the game online and download the required data right away, making the distribution very quick and convenient. Popular distribution platforms are, for example, Steam for computer or Play station and Xbox store for Console (Fields, 2014). This model is holding firm until today and is responsible for around 50% of the created Revenue from PC games (OC&C Strategy Consultants, 2020). Companies develop a game, ship it, and if everything goes well, they are making a profit by high enough to cover the cost and kickstart the next project. Since there are no high follow-up costs after the game is developed and the first copy cost of digital goods is high, but scaling numbers and distribution are cheap compared to physical goods, the process also fits nicely into the value chain of a classic offline game product. When online games came up, suddenly, there were running costs for servers and maintenance which have to be covered.

Online games are video games that require and utilize the internet and therefore require data storage which comes with extra cost (Dillon & Cohen, 2013).

After the first attempts, companies charging customers prices up to 12 USD per hour of playtime could not attract enough users. Games like Meridian 59, Ultima Online, and later World of Warcraft (WoW) came up with another model. They are charging a monthly fee for unlimited access (Fields, 2014). As technology evolves, server space and play devices become cheaper and make online games financially feasible. Mandatory subscriptions have become more popular to compensate for the extra cost on the user's side. This model dominates the western PC games market until 2009. WoW still operates the same way today, though, since this method has some significant downsides. Due to the high cost for purchasing and running the game, players demand a high-quality product and level of service, which leads to increased development costs and, therefore, significant risks for the developing party. Another issue is that it is not easy pulling users away from a game they are invested in. As the number of games increases, so does the number of failing titles, leading to many publishers shifting their business strategies (Fields, 2014).

2.1.2 Free to Play (F2P)

Free to Play means that an online game product is provided with no upfront cost. The monetization occurs with the optional purchase of virtual items called microtransactions. The player is offered additional functions and services that are meant to improve the game and player experience. (Flunger et al., 2017)

The roots of this business model are claimed to be in the software industry. A typical example would be an anti-virus software where a primary or content-reduced version of the tool is offered for free. However, for better coverage or unlimited usage, the premium version must be purchased (Flunger et al., 2017). It got first adapted in the Chinese and South Korean market (Fields, 2014).

The main economic reason for using a Free to play model besides the low entry barrier is the flexible price point, which allows monetizing on players with different willingness to pay and the low access barrier. Also, due to adding value over time, game elements and economic measures can be tweaked based on experiences in the live operation (Alha et al., 2014). Another efficient bonus of the free to play business model is that illegal game copies are canceled. The called software pirating, one of the biggest problems of the pay to play business model, is not eradicated. However, a lesser issue since the game is freely available and data is stored on a server (Cai, Chen, & Leung, 2014).

In 2020, games with the free to play business model were responsible for over 90% of mobile game revenue and 50% PC revenue. The console market is still mainly monetizing with the classic P2P model, but additional in-game purchases are often added to the top and represent 16% of the console games sales (OC&C Strategy Consultants, 2020).

Game Design-wise, F2P games are built differently compared to P2P titles. The goal is not to deliver the best possible gameplay flow and pleasant experience for the customer but intentionally plant hurdles and difficulties to increase the need for the player to purchase premium goods to progress (Hamari, Hanner, & Koivisto, 2020). Designing monetization is a complex matter, and industry professionals with different skill sets are required to optimize it (Švelch & Van Roessel, 2019).

The selection of the business model is not always binding. Over time, combined models were created and successfully implied. There are even cases where the revenue model was changed mid-service (Luton, 2013). P2P and F2P can be therefore rather seen as superordinate categories which allow for evolution and innovation.

The trend clearly shows that upfront payment revenue models are becoming less prominent, and the industry is moving towards a more service-oriented approach (OC&C Strategy Consultants, 2020). The phrase Games as a Service is getting increasing attention over the last few years. At its core, it describes that games are offered on a continuing revenue base so either a subscription model or through voluntary monetization tools (Vaudour & Heinze, 2020). The critical aspect of this study is that the player perceives the product instead of as an evolving service. The game is changing and offering the user more exciting features over his playtime. The game can also become a part of the player's lifestyle by generating a social community. Socializing in-game can lead to a more profound game experience and give an extra incentive to keep playing (Eremeev, 2015). The general service approach increases the importance of the post-launch phase, which makes strategizing the ongoing monetization during live operations key.

2.2 Ongoing Game Service Monetization

Since game companies are increasingly shifting to service-centered business models, the generated Revenue per customer enormously varies. The player's decisions to buy virtual goods are directly impacting the generated Revenue. The dependency of player choices makes predicting Revenue very challenging. Analyzing player behavior and putting player feedback into consideration is one way to help to allocating a budget and optimizing the product. It is important to identify customers that are especially valuable for the product. Since the conversion rate from free to premium players usually is just between 1% and 5%, depending on the game, it is critical to identify the high-value customers to build a suiting monetization strategy (Flunger et al., 2017).

One key indicator for the success of a game service is the Customer Lifetime Value (CLV). It describes a company's profit made by one or more customers throughout their business relationship (Pfeifer, Haskins, & Conroy, 2005). Estimating how much value a customer is very hard and depends on many factors, but it can generate allows companies to allocate their budget accordingly and take measures to utilize the remaining potential (Burelli, 2019). Game companies are handling many repeated customers, which has to be considered when applying monetization tools. Therefore, an intense game launch or peak month seems less critical than a sustainable monetization over time.

2.2.1 Monetization Tools

1) Premium Currency

For games that allow transactions inside the game, it is common to follow a dual model with at least one currency freely obtainable in-game and one currency that can almost exclusively be bought with real money for premium purchases. It is also called soft and hard currency, and often exchanging the hard premium currency back into soft currency is possible but not the other way round (Alha et al., 2014). One reason why game companies add a premium currency is that players are more likely to purchase if the goods are psychologically far away from spending actual money (Tomić, 2018). Another benefit is that game companies can discount on selling a more significant amount of premium currency. These amounts are often not divisible by the item prices offered, leading to follow-up purchases to round the missing amount. (Hamari & Lehdonvirta, 2010). Premium currencies can be paired with other monetization tools since they work instead as a step in between than a tool itself.

2) Progression Improving Items

In this paper, items that improve Progression are defined as any purchase that helps players progress. Virtual items and bonuses can be purchased to increase the chance of succeeding in the game. Progression Improving Monetization tools can also be very aggressive and give the player an unfair advantage over non-paying players. In this case, they are often titled pay to win, which means that success can be purchased instead of achieved through gameplay (Zendle, Meyer, & Ballou, 2020). There is explicit criticism about this kind of aggressive monetization in the academic literature. Some claim that it shifts the success from being dependent on skill and time investment to the amount of money paid (Heimo, Harviainen, Kimppa, & Mäkilä, 2018) and leading to an unfair game experience for lower spending players (Alha et al., 2014). Despite the negative perception, many games utilize pay-to-win elements because they work economically. A certain percentage of players accept these methods to an extent where they are willing to purchase 6000$ a year to compete with the top players (Tregel, Schwab, Nguyen, Müller, & Göbel, 2020).

3) Cosmetic Items

Contrary to Progression improving Items, Cosmetic Items only have an aesthetic impact on the game and do not interfere with its gameplay (Zendle et al., 2020). They often come in the shape of skin or costume to alternate the look of a character in the example of Fortnite to League of Legends. Visual effects that can express a win, like explosions or special dances, are also a common sold feature. (Zendle et al., 2020) These items can be a way to individualize the player's character and work exceptionally well when they can be shown off to other players.

4) Loot Boxes/Gachas

Players can spend much money getting specific items and getting mostly side items that he does not need (Tomić, 2018). The adequate amount of money he spends on the desired item is therefore often higher. There is also a transparency component, similar to premium currency, since user loses easily focus on how much they effectively spend. On top of that, Loot Boxes are proven to have an addicting nature similar to gambling since the outcome has a luck component, and players go on after getting a bad result to make up for the loss.(Macey & Hamari, 2019)**.**

5) Advertisement

Advertising is a widespread tool for online monetization on websites, social media platforms, and also games. The game provider sells advertisement slots to third parties and gets paid when the ad clicks or leads to a purchase action. The placements can be very subtle, where they do not interfere with the gameplay and give small optional benefits, or more prominent where the user gets interrupted in the game flow to watch an AD. Some games even offer a paid option to deactivate ads. The money per click is relatively low, which is why this monetization method is especially popular with casual and social games that have a high user count (Terlutter & Capella, 2013). Some games make 75% of their total revenue with Ads. (Levy, 2016). Others do not have them in their game, to be seen as a game design decision based on the audience.

6) VIP Pass

The concept of VIP, Season, or Battle Passes was introduced in 2013 by the Valve Company and their Massive Online Battle Arena (MOBA) game Dota 2 Since then, many games have introduced forms of a VIP Pass as a periodical Virtual Purchase (Joseph, 2020). These digital passes come in many shapes but have two things in common. They are time-limited, so they only work for a defined period and give the player exclusive access to certain content or virtual goods. A prevalent version is the battle pass used in games like Fortnite by Epic Games or Rocket League, where all players get some free content by progressing when the pass is active but can multiply the rewards by purchasing the pass. This way, a feeling of achievement is created by progressing during a limited time rather than just making a direct purchase of a virtual good (Petrovskaya & Zendle, 2020). The overall value of virtual goods is also often very high compared to a direct purchase, making it subjectively cost-effective.

7) Additional Content

It is usual for game services to add new content and improvements to a game during live operations in patches. These changes do not necessarily have to be monetized and instead be a fix or life improvement (Lee, Jett, & Perti, 2015). In the context of monetization, additional content can be defined as either gated or free content. Gated content means that a payment is required to access the content. A widespread way is offering it as Downloadable Content (DLC). DLC refers to an additional purchase after the game is already playable. It is dominantly used for Pay to Play titles across platforms and a way for game companies to add monetizable elements to their successful game title without launching a completely new product (Lizardi, 2012). For Free to play game services, additional content can also mean adding more challenging content to increase the demand in microtransactions or add new ones. In this case, it can instead be seen as a revenue-driving factor and not a monetization tool itself. An increasingly popular way of adding monetizable content over a game's lifetime is in-game events.

8) In-Game Events

Game Events are often modeled after real-time events like Christmas or Valentine's Day since these events have the nature of attracting customers (Flunger et al., 2017). Events are also often customized to fit the style of the game but can also be entirely made up by the game (Hamari & Lehdonvirta, 2010).

In-Game Events are not a monetization tool itself but can be seen to create demand and engagement. The monetization comes with extra virtual item offers that fulfill these demands (Hamari & Lehdonvirta, 2010) Exclusivity and time limitations are significant selling factors for these goods (Flunger et al., 2017).

Events can also come with additional content, giving long-time players a new incentive to play and spend money. It was found out that players only stick to the game and be loyal as long as their expectations are met (Vaudour & Heinze, 2020). Events can be a tool to keep players engaged and meet their demands. In-game Events are expected to be an essential step in-game monetization. Even famous titans of the industry, with valuable intellectual property, like Grand Theft Auto, utilize events to increase profit by monetizing existing players (OC&C Strategy Consultants, 2020).

Since often the content has to be unlocked by putting a lot of effort and resources into the game and not just making a direct purchase, it creates a feeling of achievement. The challenge to obtain the goods that are gated by a high-level of another barrier can also give a feeling of Scarcity (Hamari & Lehdonvirta, 2010).

2.2.2 Perceived Value and Motivation

When talking about Monetization tools, it is essential first to understand why players willingly spend money for a free product. Games rely on player engagement to create revenue (Russi, 2021). In traditional business models, it is easy for the customer to put the price of a product to the expected value and make the decision to purchase. The customers' evaluation process for game services is much more abstract and less transparent due to complex structures and pricing models. Another critical element is that the sold content is split into many different segments, leading to variations in the customer patterns based on their purchase behavior. The total price each individual pays for the service varies enormously (Hamari et al., 2020).

A study on player behavior in Taiwan has found that two main player types are essential for monetization. The social and the aggressive gamer. Social gamers are more interested in non-functional cosmetic items that, for example, enhance the attractiveness of their fictional character and avoid competition. The aggressive gamer wants to defeat and wants to be superior to others, so they are more interested in goods that push their performance and gives them an advantage over others. These players were also the strongest payers, which makes them a significant group to focus on when strategizing monetization (Tseng, 2011). Other researchers also see competition between players as a critical motivation for purchases (Flunger et al., 2017). It could be projected that aggressive monetization tools that affect a player's performance have a strong impact on the competitiveness, which gives them high perceived value for these types of players. Offering items that aggressively interfere with the in-game success has to be done cautiously. Another study shows that aggressive monetization methods can negatively affect the perceived quality of a game service and create inequality between paying and free users (Alha et al., 2014).

Game companies use engagement optimizing measures to optimize game monetization. By using specifically designed algorithms, it is possible to provide specific monetization based on the user profile for each player (Russi, 2021). It was also found out that the feeling of being rewarded is a significant psychological factor for engagement, and wildly unexpected rewards are measured to be effective (Russi, 2021). Here, a link to loot boxes and randomized virtual content can be drawn.

The resulting challenge is to monetize hard enough, so the customer is motivated to purchase but not so hard that he leaves the game out of frustration. According to recent literature, there seems to be no straight formula to solve this complex issue, but knowing and clustering users is critical to plan monetization. This topic is very new and just became the center of recent academic papers (Dreier et al., 2017; Yang et al., 2018; Zendle et al., 2020). Analyzing the userbase requires a lot of rich data and a significant psychological component; it also varies based on the individual game, making it not easily adaptable. The literature emphasizes that the number of paying users and Average Revenue Per Paying User (ARPPU) can be an effective tool to predict the effectiveness of monetization on user groups to get new paying users and see how well they can be monetized (Yang et al., 2018).

2.2.3 Market Regulations

The games industry is self-regulated, but politicians start recognizing possible issues with transparency and unreasonable prices (Goodstein, 2021). Experts also claim that the games industry is very globalized, so centralized national approaches to regulate them are not practical. (Perks, 2021) There are some local measures, one especially drastically one was implemented in China where the playtime for underaged players was limited, and a curfew between 22:00 and 8:00 was implemented. The maximum amount of money spent was also regulated, which would be a significant factor in the context of this paper (Lehtimäki, 2021)

Since Free Play game monetization is a relatively new subject, the difference between theoretical regulations and how they are implemented in practice differ (Perks, 2021).

Especially Loot boxes are often under critique since they show similarities to gambling as laid out under section 2.2.1 Legally it is often a matter of details and definition which leaves them as a monetization option for games (Goodstein, 2021).

Pressure on game companies regarding limitations of monetization comes mainly from the media and users who speak up about unfair paywalls (Perks, 2021). This is connected to the under section 2.2.2 explained issue of aggressive monetization.

So although there are currently minimal regulations regarding game monetization, there are expected to be more in the future due to health and transparency concerns and which game companies must be aware of (Goodstein, 2021).

2.2.4 Defining performance indicators for Ongoing Monetization

This paper is dedicated to researching game companies having difficulties keeping up a game's success over its lifetime. This issue is strongly connected with sustainability. The term has to be defined in the context of a game service first to analyze how monetization tools impact it.

When looking at sustainability, the overall revenue is not the only indicator of success. As pointed out under if the game, for example, offers a pack with many permanent boosters at a 90% discount, the revenue will most likely be significant. However, it can lead to satiating the market and reducing the player's demand. The opportunity cost of selling the items at such a high discount is also very high. Another scenario would be that a game company offers mighty virtual objects that strongly impact the game balance. Some players might buy it, but it can scare off other users and decrease overall player numbers. Since these are just scenarios, this study tries to put data into them.

Researchers have found that non-monetary contributions can be significant as well, especially in social games. Trying to push monetization on these people can negatively impact them (Beltagui, Schmidt, Candi, & Roberts, 2019).

Although not directly pushing revenue, some performance indicators positively affect the long-term success of game services and are therefore essential when looking at sustainability. A big issue that game services have is that they are either not attracting enough players or monetizing existing users. The ambition is to include this knowledge in the selection of performance indicators.

To analyze how strong users are monetized, the Average Revenue per Paying User (ARPPU) will be examined. This performance indicator is created by taking the total revenue during a set time and divide it by the number of users who purchased anything in the same time frame (Fields, 2014).

Regarding attracting more paying users, there are two possibilities: monetizing existing players and acquiring new users. When having new users, it is essential to see how they stick to the game since we already pointed out that game services need time to monetize. In general, the stickiness of a game service is dependant on the gameplay itself (Skobeltcyn & Shen, 2018) so analyzing the influence of monetization tools is experimental. It will be looked at the 7 Day Retention, so how many % of players log in 7 days after their first launch of the game. The longer a player stays in the game, the happier they are and the more likely they will spend money (Luton, 2013).

For monetization tools, it is essential to see which ones are responsible for the most revenue and what makes players start to spend. First, purchase deals are a familiar concept, and after players get financially involved in in-game service, they are more likely to keep on spending (Luton, 2013).

It is also emphasized that the whole product life cycle has to be looked at to measure sustainability (Fiksel, McDaniel, & Spitzley, 1998). In the case of a game product, that would mean looking at the effect of monetization tools over time which is strongly connected with the customer lifetime value. The prediction of CLV is complex (Burelli, 2019).

The success of a Game Service can not be predicted solely by looking at the past created Revenue since video games have much individual cost, the required monthly and lifetime revenue required to make a profit.

The exploitable game design tries to generate short-term profits with aggressive monetization (Alha et al., 2014) danger of losing players. The danger of satiate the users with high sales and deals and eventually killing the demand

2.2.5 Positioning the game case for this study

The game service in this study is an online free-to-play game, so it requires an internet connection, and user data is stored on a server. It is also possible for users to compare their progress in-game. The game is available for mobile devices, smartphones and tablets, and in the PC web browser.

Since the gathered academic knowledge will be applied to an active game, it is vital to look at the established monetization tools of the game genre. The title most closely resembles an Idle or also called incremental game. These are a relatively new video game genre that probably goes back to the early 2000s. These games are designed in a way that the player can progress without interacting for a longer time to gather resources (Khaliq & Purkiss, 2015). This concept results in an interval gameplay-loop with comparatively few interactions interrupted by inactive periods.

Essential for the player motivation and monetization is that this game revolves around the meta gameplay and primarily uses the core gameplay to gate the content. Core gameplay mechanics refers to the activity that users repeatedly repeat to progress and achieve goals (Fullerton, Swain, & Hoffman, 2004). Metagame relates to the systems surrounding the core gameplay. They can affect it but do not take part in it. Typical examples are daily quests or the gathering of alternative resources to solve optional side quests with their separate Progression and economy (Costiuc, 2019). Due to the simplicity of the core game, the game of this case study mainly motivates and builds demand through progress, and the metagame is an essential part of keeping players engaged and entertained over a long time. Therefore, a big part of monetization is time vs. money to reduce the idle time and get to the rewards faster.

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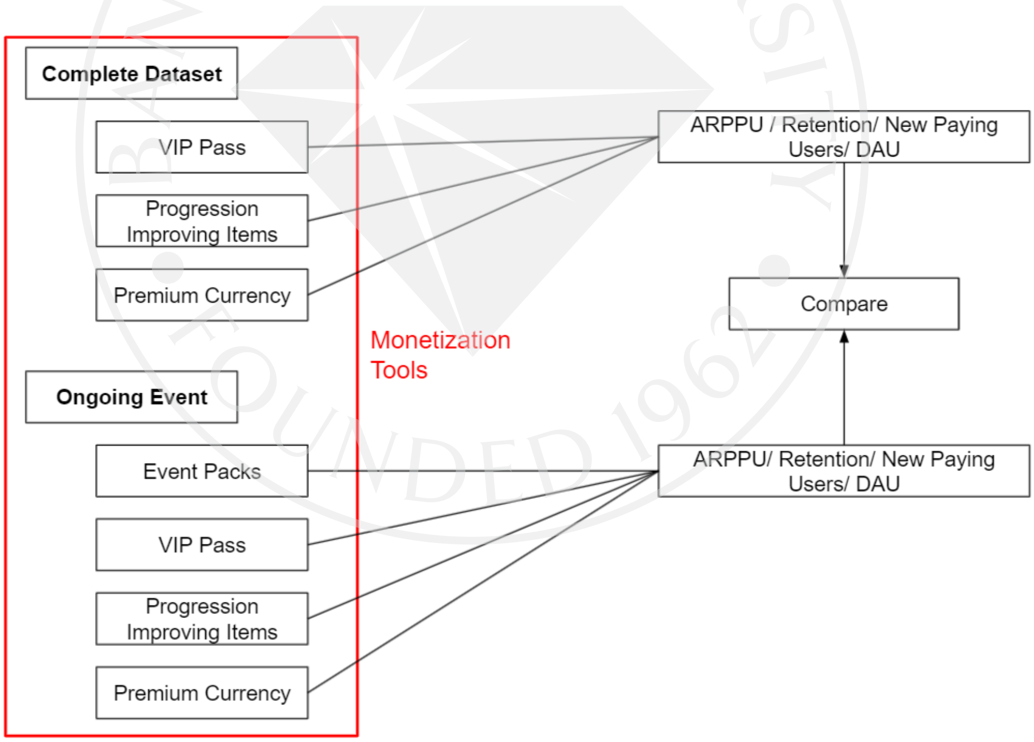
CHAPTER 3
RESEARCH DESIGN AND METHODOLOG

3.1 Research Framework

The possible effect of monetization tools on performance indicators will be analyzed with exploratory research of the game data. During the academic research, no literature was found that is already investigating ongoing monetization and, therefore, no suitable model to adapt. Game service products also tend to have very individual requirements (Burelli, 2019), so a customized model that fits the case study will be created.

Figure 3.1: Conceptual Model



The first step is to specify the relevant monetization tools as defined in section 2.2.1 and cluster them based on game specifics and academic knowledge. The variables are chosen to fit the individual characteristics of the game and are highlighted in red in Figure 3.1 Conceptual Model. Then, performance indicators will be defined to analyze the impact of the monetization tools on those. Two separate datasets will be used so the data for ongoing events can be singled out and compared with the complete dataset.

The Monetization Tools are expected to have an impact on the four Performance Indicators in both datasets, which will be verified with the exploratory Data Analysis.

The first monetization tool category in the conceptual model is Premium Currency Revenue. Although it was established under 2.2.1 that premium currency itself is no monetization tool, the items sold for premium currency in the game have specific characteristics. The in-game purchases available for Premium Currency are all cheaper than 10$. They include boosters that increase progress temporarily, loot boxes, and on-target sales to save time. Furthermore, during events, special event loot boxes are sold, containing items that are only useful during the event period. On average, players spend 2/3 of the Premium currency for progress boosting goods to increase in-game resource generation and 1/3 for event-related items. An essential attribute of things sold for premium currency is that there is no limit to the purchase and usually no discount, which sets them apart from the other groups.

The second monetization tool is Monthly VIP Pass Revenue. In the examined game case, the pass gives time-limited bonuses for 30 days and can be repurchased every month. The item has a sale that goes up to 80%, the benefits are also unique for the customer and can not be purchased in another way.

The third segment is the Revenue through selling Progression Improving items. Products in this category either permanently increase the player's performance like a multiplier on generated in-game revenue or are packs that are linked to the Progression in the game. These packs are a bundle of different performance-improving items, temporary and permanent, have a significant discount of up to 90% but are also limited to 1 purchase and are only available under a premise. This premise can be an in-game level requirement, or it must be the user's first purchase.

The last monetization tool segment is Event Pack Revenue. Events are expected to have a significant influence on the success of the product. Event Packs are time-limited offers that are distinguished by their connection to an ongoing event. They contain event-relevant items or currency that the user can utilize to access time-limited content combined with progress improving items. They are also given a visible sale, so they are sold for 30-65% under the value of the sum of included content if it would be purchased separately in the in-game shop. A separate dataset was created since the event-specific content is only sold during events, and including the remaining days would result in a lot of neutral values and dilute the dataset.

When determining how these tools impact the sustainable growth of the game service, performance indicators that are proven to represent ongoing success will be defined. The objective is to use the available data to describe what was defined as measurements of ongoing sustainable monetization in the literature review.

The effectiveness of user monetization will be represented by the Average Revenue per Paying User (ARPPU). Choosing an indicator that takes the user number into account helps to isolate and compare the quality of monetization. ARPPU is used over Average Revenue Per User (ARPU) since most users will never pay for the game, so it is expected to get a better result by only looking at paying players (Fields, 2014). If a substantial impact on ARPPU can be measured, it shows that the monetization tool benefits adding value through significant users groups.

For a sustainable game service, it is essential that players stick with the game. This stickiness will be measured with the 7-day retention value. Analyzing the possible impact of monetization tools on the percentage of players that log in again after seven days can give us information on which monetization has to be invested in to increase the number of players staying with the game.

Looking at the connection of monetization tools and New Paying Users is expected to be beneficial to understand the reasoning behind first purchases. If a group of monetization tools turns out to have a positive impact, it could be helpful for game companies to invest in those stronger.

The last performance indicator will be the Daily Active Users (DAU). A connection between user numbers and monetization tools was not found in the existing literature. Exploring a possible connection is expected to help understand the impact of monetization tools on sustainability better, which is why it is included in this research.

The model variables are customized for this case study. For other products, the monetization tools and performance indicators could be different. The game in this case study, for example, does not offer purely cosmetic items. All purchases have an impact on the gameplay. There is also no in-game advertisement.

3.2 Data Collection and Preprocessing

The first set of data, used to analyze the game's monetization tools, is gathered by a Business Intelligence (BI) tool. The software is integrated into the game's backend and can access user data. This way, the player's actions like purchases are tracked. The data is visualized in a browser application and exported as a CSV file to preprocess for further use. The data goes back to the launch of the game in September 2020. It includes over one million registered users at the point of access in June 2021. The data is captured in daily intervals and resets at midnight Coordinated Universal Time (UTC). This data includes the daily generated Revenue, the amount of new paying users (first-time purchases), and the Daily Active Users (amount of individual logins every day). The daily revenue numbers are accumulated from every purchase made, making it possible to allocate the income to the generating source.

In preparation for further analysis, the revenue will be clustered by monetization tools. All purchases are assigned to the four monetization tool categories: Monthly VIP Pass, Premium Currency, Progression Improving Items, and Event Packs. The sum of all monetization tools represents 100% of the total revenue.

This data gives an overview of the accumulated results based on time but misses the connection to individual users. It shows how much Revenue was made and how many users were active but not the cross-connection on how long an individual user is playing on average and how much Revenue was generated based on the number of spending players. This information will be taken from a data export from the distributor, allowing seeing the player retention and Average Revenue per Paying User (ARPPU). The data is taken daily as well, which makes the two sources comparable.

The demographic data is taken from the same source but is very limited. There are no indications about the age of the players. Regarding the location of access, 2/3 of the data is undefined. From the remaining third, the top 5 most popular countries by number are the USA with 19%, the Philippines with 9%, Brazil with 5%, Germany with 5%, and Mexico with 4%. It is also known that 52% of the users access the game via mobile devices and 48% via PC browser. For this study, the demographic data will not be included in the analysis process further.

The raw dataset consists of one entry for each variable on one day with a total of 267. To improve the informative value of the dataset, values that are not comparable or unusual shall be taken out. This means all data of the independent variables have no value. These can be spotted directly and are expected when either the product is not placed in the shop due to mistakes or production delay or is not captured by the BI tool. Such a technical failure has to be taken into account. External events, which are unconnected to the independent variables, can also influence the dataset and show extreme high or low readings, which is why outliers will be removed from the dataset. The first and third Quartile of the variables is taken to get the Inter Quartile Range, which is the two. Then the Upper Bound is created by adding 1.5 times the Inter Quartile Range to the third Quartile, the Lower Bound gets created by deducting 1.5 times the Inner Quartile Range from the first Quartile. All values that are higher than the Upper Bound or lower then the lower bound are removed (Hawkins, 1980). In the case of this product, the outliers could be explained by unusual conditions like the launch of the game, holidays that result in an overly high engagement, or special sales programs from the distributor, so filtering them out is expected to give a dataset that is more focused on the impact of the independent variables itself. After the removal, the complete dataset contains 154 entries. To extract the data, days that show Revenue via Event Packs are marked with a one and the remaining days with a 0 to quantify and filter out the data. The dataset of only event days includes 118 readings.

A revenue export of the top 100 spending users will be used to analyze the role of monetization tools on the top spenders. Same as the BI tool data, it is taken directly from the game's backend. The data includes nine months from October 2020 to June 2021.

3.3 Data Analysis

The game's current status will be described by looking at the trend of the under section 0 defined Monetization Tools and Performance Indicators over time. For this purpose, the complete raw dataset has to be used to make the total amounts comparable. The data is gathered in monthly intervals. Revenues and the number of New Paying Users get accumulated to show a monthly total. Daily Active Users, Average Revenue per Paying Player, and 7 Day Retention will be taken.

In the literature review under section 2.2.2, In-Game Events can create demand and engagement for a game service and, therefore, can significantly impact the product. To apply that knowledge to the test case, the total average values of the monetization tools and performance indicators, defined in 3.1, will be compared. The complete preprocessed dataset will be used with an indicator for 1 for event and 0 for no event to compare them. It has to be taken into account that the dataset without outliers only contains 36 samples.

It was also established that Monetization Tools could be strategized explicitly towards different paying user types. Comparing the data export of the top 100 paying users to the total revenue shares will be done to find out which Monetization tools are more effective on high-paying users.

A Linear Regression (LR) analysis will be conducted to explore the impact of monetization tools on the selected performance impacting dependent variables in the complete and the only event dataset. (Montgomery, Peck, & Vining, 2021) Linear Regression was found to be an effective tool to be used in a video game-related context (Luton, 2013) to predict the impact on the game when spending resources on a particular monetization tool.

The linear regression is always conducted with the two prepared datasets separately for each independent variable. The first is the "complete dataset," with a sample size of 154. The monetization tools which build the three independent variables are the Revenue from monthly VIP passes, Revenue from selling premium currency, and Revenue from selling Progression Improving items. The second dataset, "only event," includes only days with an active event, so it is smaller with 118 samples. It also includes "revenue from selling event packs" as a fourth independent variable. The monetization tools will be put into relation with four different performance indicators separately as the dependent variable.

A significance level of 5% is chosen for the linear regression, so variables with a significance (p-value) higher than 0.05 will be excluded (Hair, Black, Babin, & Anderson, 2009).

3.4 Conclusion

The relation between the defined Monetization Tools and the performance indicators will be analyzed in four ways:

3.3.1 Displaying the monthly development throughout the game's live operation.

3.3.2 Comparing the days with events with the days without events.

3.3.3 Looking at the top 500 paying users.

3.3.4 Conducting a total of 8 Linear Regressions. Four with the only event dataset, the Monetization Tools as the independent variables and performance indicators separately as dependent variables. Another four with the same principle but with the complete dataset and excluding Event Packs.

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CHAPTER 4

FINDINGS

4.1 Overview of Data Analysis

This section describes the process of applying the conceptual model to the data in order to explore knowledge towards the research questions.

4.1.1 Dataset Analysis

The monthly revenue of the under section figure 4.1 defined Monetization Tools will be displayed over time to evaluate trends in the game's performance throughout the live operation.

Figure 4.1: Monthly revenue by Monetization Tool

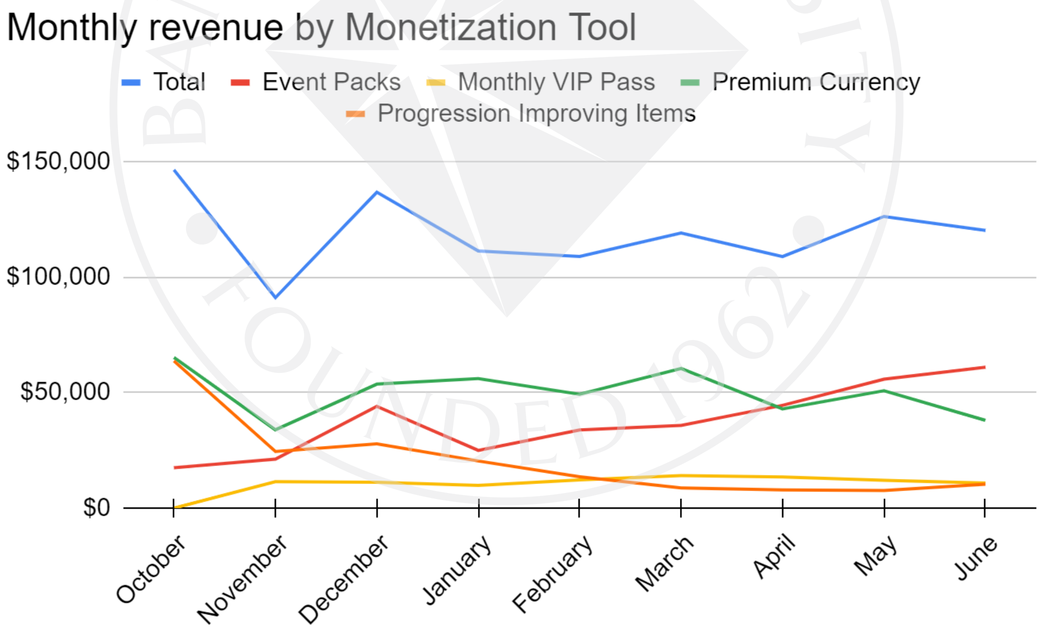

Figure 4.1 monthly revenue by Monetization tool shows the total revenue generated by the game every month as the blue line. The Monetizations tools are the four lines on the bottom of the chart, which, added up, resemble the total revenue. This means that the variations in the Monetization tool resemble the constellation of the total revenue. The total revenue in October starts very high. Since the game was commercially launched end of September, the hype around a newly released game is

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likely to be the reason for that since it is a common factor (Sotamaa & Svelch, 2021). In the first month, the most revenue comes from selling Premium Currency and Progression Improving Items. The VIP Pass was not available on launch, the events were quite small which was a possible reason for the low contribution.

In November, the overall revenue broke down to an all-time low. A decrease of revenue after the launch hype is over is not unusual, but this situation fits the describes issue of ongoing monetization in the Problem Statement. If the game service can not attract, entertain and monetize users over a long time, it will struggle to stay in business.

In December the revenue went up again. The most significant change seen in the monetization tools is the revenue of Event Packs which more than doubled compared to the past month. The data shows that the days with the highest revenue were during the In-Game Christmas event. The event's popularity coincides with the under section 2.2.1 established knowledge that events modeled after major spending holidays in real life can be transferred to games. The Event Pack revenue shows a strong peak over the holidays. After that, it establishes to be the second biggest Monetization Tool and the only one that increases every month.

Over the next month, the revenue due to the Monthly VIP Pass establishes a relatively low but steady level. The revenue due to Progression Improving Item started very high but decreased over the first half-year by factor 8.

When comparing the green line of Premium Currency revenue with the blue line for the Total revenue, it is uncanny how much they resemble. Except for the prominent holiday peak, they almost align, showing that the money spent for Premium Currency and the Total revenue seem dependant.

Overall, it shows that different monetization tools can impact how long the game is live. In the next step, the defined Performance Indicators relation over time will be analyzed.

Figure 4.2: Monthly Performance Indicator Ratio from Nine-month Total

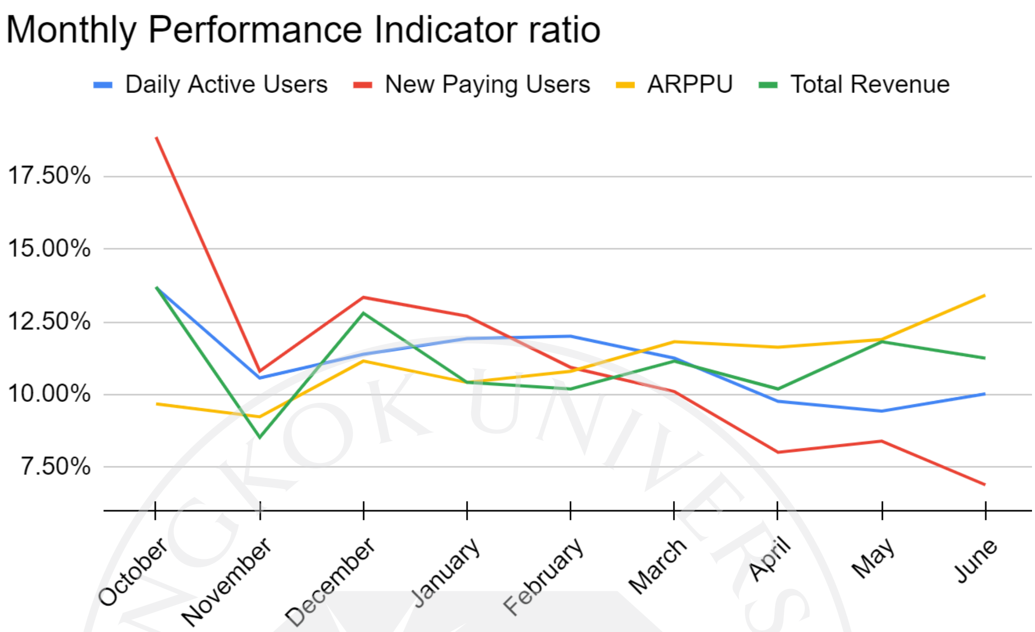


Figure 4.2 Monthly Performance Indicator ratio from nine-month total shows the evolution of the monthly average of Daily Active Users, New Paying Users, and ARPPU. The Total Revenue curve is also added in green as a reference. The data seen in Figure 4.2 Monthly Performance Indicator ratio from nine-month total is modified from the unlimited data to be comparable. The total amount for each Performance Indicator over the displayed nine-month was accumulated, and the percental share of each month is displayed separately in the chart.

As seen in the revenue over time, the first month shows solid numbers across the values except for ARPPU. The new paying users are very high around launch, which is logical since more new players overall. The number continuously decreases over time. The decreasing percentage shows a big challenge of ongoing monetization mentioned in the problem statement of section 1.1 The decrease in New Paying Users has to be compensated in order to keep up the revenue. The Daily Active Users show a peak initially, stayed relatively constant, and then moderately fall off after a half-year which looks generic.

The Average Revenue per Paying User is exciting in this context since it explains how the total revenue can keep up. It shows that the daily logins and new paying user numbers decrease significantly, and loyal users cover the difference by making repeated purchases, resulting from using the monetization tools effectively.

The revenue over time showed that the Event Pack as a Monetization Tool contributes enormously to the product's overall revenue. In the literature review, it was laid out that In-Game Events can work as an engagement and demand boosting mechanism. The effectiveness of Event Monetization for the case study will be analyzed by comparing the data during days with and without events.

Figure 4.3: Average Daily Revenue displayed by Monetization Tool

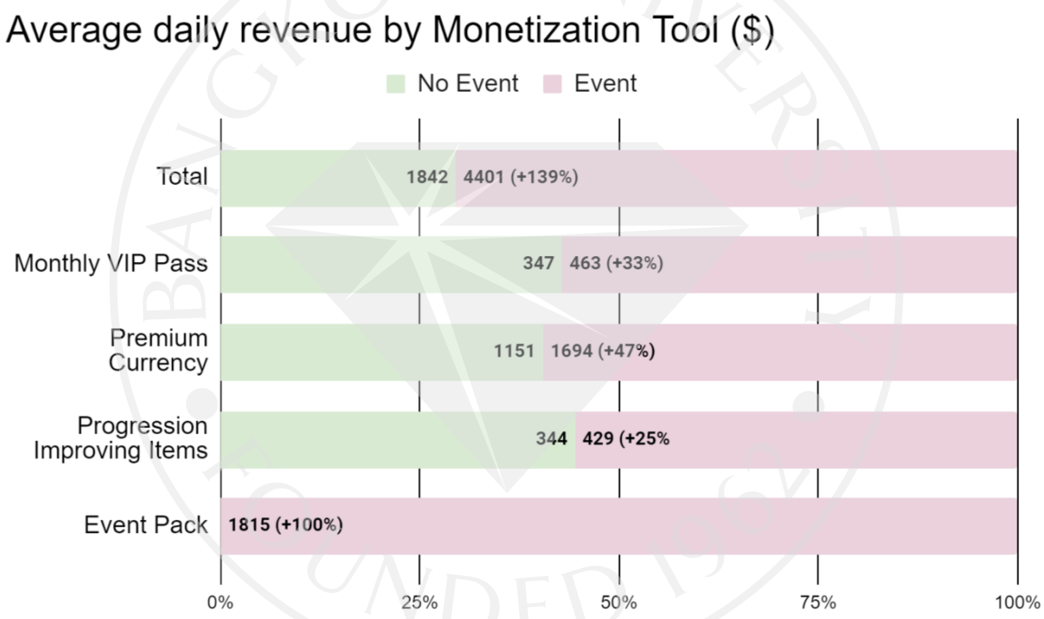


Figure 4.3: Average Daily Revenue displayed by Monetization Tool shows the average daily revenue split by the defined Monetization Tools. The total revenue is 139% higher when an In-game Event is happening, which is a significant difference. The extra offered Event Packs already generate as much revenue as made on a non-event day in total. Event Packs are only sold during events, so 100% of their revenue is created during these. They are responsible for 41% of the average total revenue during Events which is the highest share before Premium Currency with 38%.

When looking at the Monetization Tools sold in both periods, it shows that they all increase during events. The highest increase can be seen on sold Premium Currency with almost 50% more. Revenue from VIP Passes increased by a third and Progression Improving Items by a fourth, which is the lowest increase which means they seem more independent from events.

The issue with looking at the pure revenue is that it does not consider the opportunity costs. Periodically hosted events may reduce the potential revenue generated between them since players. As established in section 2.2.1, Event Packs also work with a high sale percentage which is a potential impacting factor for the sold amount of this Monetization Tool category. The other three categories are independent of this and therefore show an apparent pushing effect of Events on the willingness of users to purchase virtual goods.

Figure 4.4: Average daily value by Performance Indicator

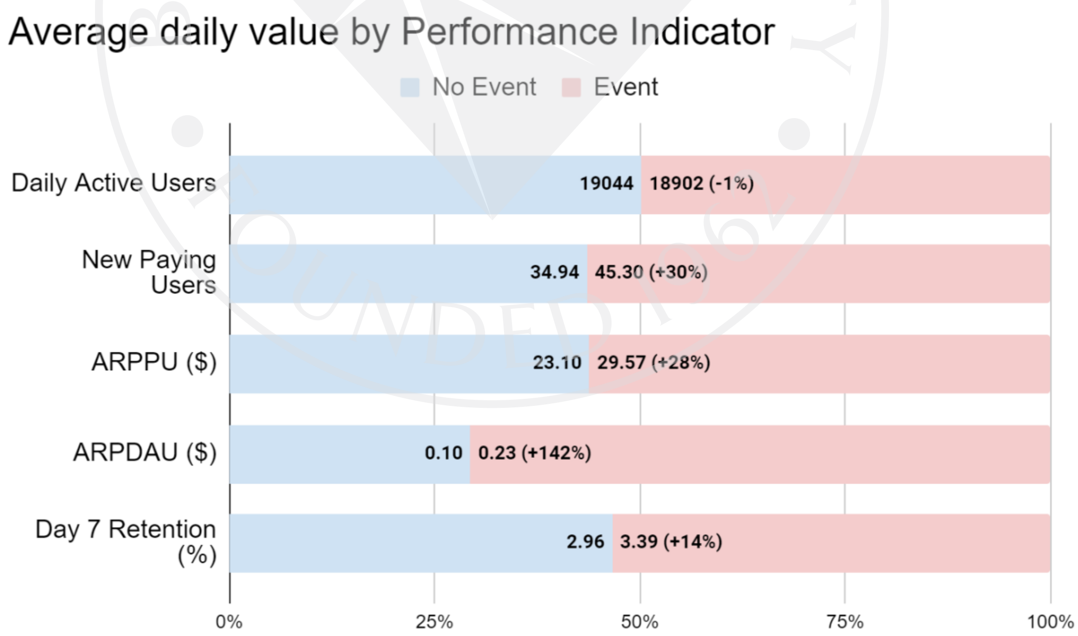


Figure 4.4 Average daily value by Performance Indicator visualizes the difference of user-centered values on days with and without an event. The first important finding is that the average Daily Active User is the only negative figure and

not strongly impacted by Events which suggests that Events do not promote daily individual logins.

When looking at New Paying Users, Events attract first-time purchases since the value increased by almost a third. As pointed out in section 2.2.1, new Paying Players are essential for a game's success since they can grow with the game service and help to generate ongoing revenue.

The Day 7 Retention is slightly higher on event days. Due to the slight difference and low sample size, this is a positive and not expressive change.

The substantial increase in revenue can not be explained with more users due to the steady DAU. The Average Revenue per Paying User increased by 30% on the event, so there was more money per paying user. The increased amount of Average Revenue per Daily Active Users (ARPDAU) of 142% indicates a mix of New Paying Users and repeating customers purchasing virtual goods rather than few high profile users.

Overall it can be said that In-Game events have a significant impact on the success of the game. It has to be taken into account, though, that Events need resources to be produced. Coding new features, creating graphics, and maintaining events are expensive, and we are only looking at the revenue, not the pure earning.

The revenue of the top 100 paying users for each monetization tool is related to the revenue of all users. This way, monetization tools that primarily work towards higher or lower spending users are singled out.

Figure 4.5: Monetization Tool Share on Total Revenue

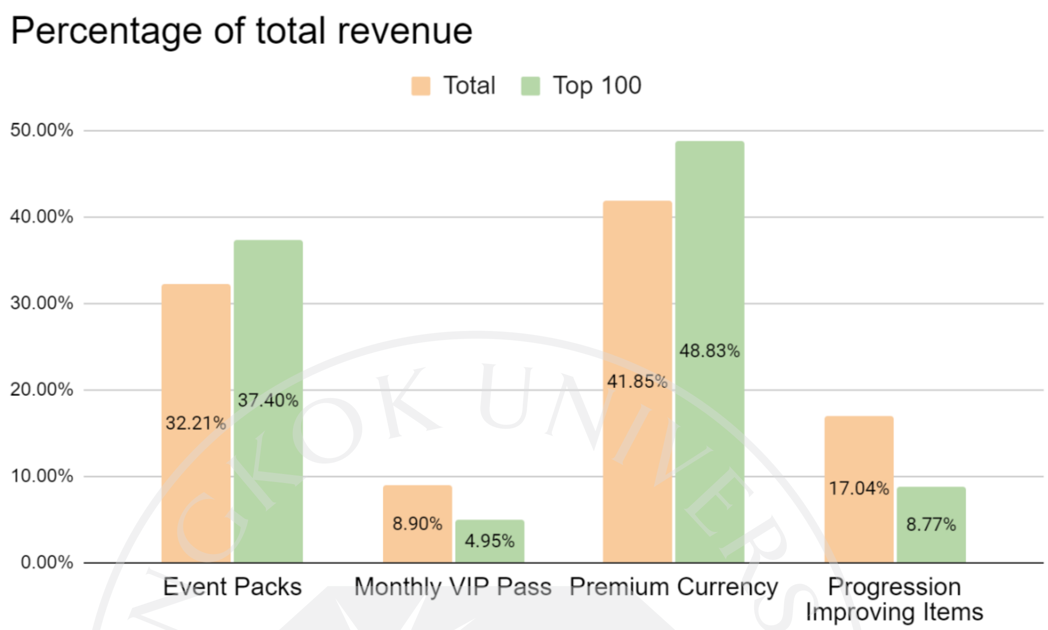


Figure 4.5 Monetization Tool Share on Total Revenue shows the share of each Monetization Tool on the overall revenue of the two groups separately. The top 100 users are accountable for almost 20% of the total revenue the game made in the analyzed time. With over 15 thousand total paying users, this is a significant share and shows how important this segment is. A single account of the top 100 spent on the game ranges from 1320$ to slightly over 6000$.

Both, Event Packs and sales of Premium Currency have an over 15% larger share each for the top 100 users. A reason could be that both categories offer usable items that are not permanent. These items give a temporary boost to the game but are consumed after, giving them significant demand. Event Packs are also offered at various price points, which can go as high as 80$, so they are already targeted to a high spending audience which seems to work. The data also shows that if multiple packs are offered, the most expensive one always generates the highest revenue.

The revenue portion of Monthly VIP Passes is 44% lower for the top spenders. This was expected since there is a maximum amount to be spent every month, so when the total player revenue increases, the monthly limited item share logically decreases.

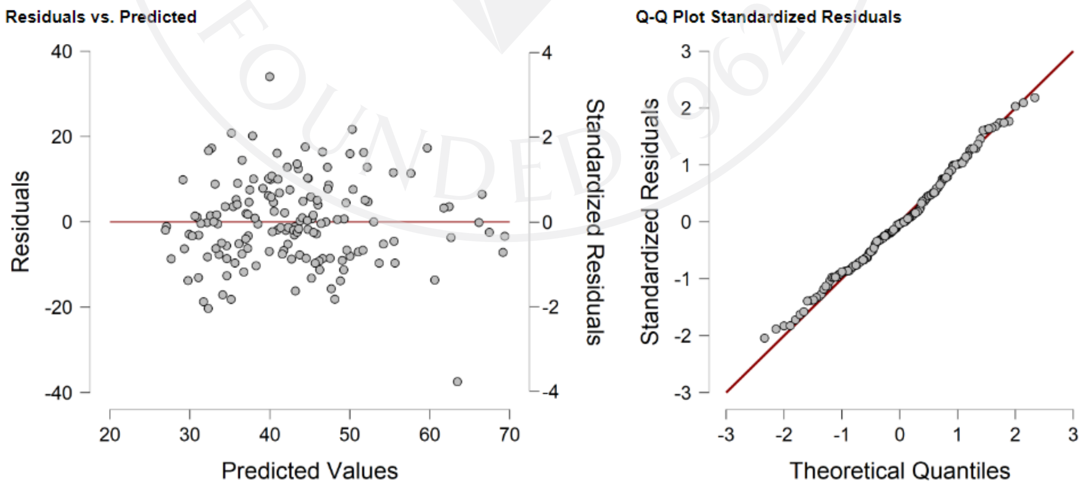
The ratio of Progression Improving Items shows the most significant difference. It is almost 50% lower for the top 100 payers. These items are not hard-limited like the VIP Pass but include permanent improvements which do not need to be repurchased like usable items. Progression Improving Items also include limited offers at a low price point designed to attract first and low spenders.

Working with the datasets shows that there are specific tendencies over the time of the service, between active event days and regular days, and in the purchase behavior of high spenders. These give essential knowledge about the Monetization Tools and the Performance indicators, and plausible reasoning.

4.1.2 Linear Regression

Analyzing the role of Monetization tools by comparing raw game data is limited. Potential other factors that are not included in the datasets can be the reason for differences. A Linear Regression is conducted to determine how far Monetization Tools impact Performance Indicators and how they correlate.

Figure 4.6: Residuals vs. Predicted Values and Standardized Residuals Example New Paying Users, Complete Dataset



All Linear Regression analyses are tested to prove the assumption that they are typically distributed, homoscedastic (have the same variance at every X), and independent (Seber & Lee, 2012). The complete datasets are typically distributed in the Q_Q plot of the standardized residuals, as seen in Figure 4.6 Residuals vs.

Predicted Values and Standardized Residuals Example New Paying Users, Complete Dataset. It lines up along the line and only falls out slightly towards the origin and the end. The Predicted Values vs. the Residuals are evenly distributed in a random pattern and therefore support homoscedasticity, which can also be seen in Figure 4.6 Residuals vs. Predicted Values and Standardized Residuals Example New Paying Users, Complete Dataset. Residuals show independence when the Durbin-Watson statistic is close to 2. The collinearity statistics indicate that the others do not linearly predict the predictor variables since the Variance Inflator Factors (VIF) for all lower than 5 indicates no significant multicollinearity (Montgomery et al., 2021).

One of the leading indicators for the quality of the Linear Regression Model will be the Adjusted R^2 since it also displays if a variable negatively impacts the model, and it is suggested by academic literature (Hair et al., 2009).

1) Monetization Tools on ARPPU

Two linear regression analyses with the defined monetization tools and the outcome, ARPPU, were conducted to predict the impact of monetization tools on the Revenue generated by spending users.

Table 4.1: Model Summary and Coefficients ARPPU, the Complete Dataset

Model Summary - ARPPU ($)

Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	F Change	df1	df2	p
H_0	0.624	0.389	0.385	4.451	0.389	96.703	1	152	< .001
H_1	0.629	0.396	0.383	4.456	0.007	0.830	2	150	0.438

Note. Null model includes Rev Premium Currency

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	18.560	1.030		18.014	< .001
	Rev Premium Currency	0.006	6.164e −4	0.624	9.834	< .001
H_1	(Intercept)	18.905	1.209		15.636	< .001
	Rev Monthly VIP Pass	−0.003	0.002	−0.087	−1.192	0.235
	Rev Premium Currency	0.006	6.899e −4	0.655	9.225	< .001
	Rev Progression Improving Items	0.001	0.001	0.051	0.773	0.441

As seen in Table 4.1 Model Summary and Coefficients ARPPU, the Complete Dataset, The Revenue through Monthly VIP Passes and Progression Improving Items do not significantly improve the model with less than 1%

contribution to the Adjusted R^2 and a significance of p=0.235 for Monthly VIP passes p=0.441 for Progression Improving Items. The p-values are higher than the defined 5% and therefore insignificant and will be taken out of the model. H_1 shows the complete model with three independent variables, and $H_{0\text{ is}}$ the improved model with only the Revenue of premium currency as the independent variable.

The Revenue with selling Premium Currency is a significant predictor for the dependent variable ARPPU. Adjusted R^2 shows that this variable explains 38.3% of the variance. The p-value is <0.01, so the null hypothesis can be rejected since there is a less than 1% probability that the improvements we are seeing with our one variable model are due to random chance alone.

The formula to predict the impact of monetization tools on ARPPU based on the linear regression is Y=18.560+0.006X, where Y is ARPPU and X the Revenue generated by selling premium currency.

Table 4.2: Model Summary and Coefficients ARPPU, Only Event Dataset

Model Summary - ARPPU ($) ▼

					Durbin-Watson		
Model	R	R²	Adjusted R²	RMSE	Autocorrelation	Statistic	p
H_0	0.763	0.582	0.571	3.544	−0.137	2.274	0.164
H_1	0.763	0.582	0.568	3.559	−0.133	2.266	0.178

Note. Null model includes Rev Event Packs, Rev Monthly VIP Pass, Rev Premium Currency

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	21.945	1.160		18.914	< .001
	Rev Event Packs	0.003	3.154e −4	0.610	8.757	< .001
	Rev Monthly VIP Pass	−0.005	0.002	−0.156	−2.385	0.019
	Rev Premium Currency	0.003	7.023e −4	0.294	4.025	< .001
H_1	(Intercept)	21.894	1.199		18.262	< .001
	Rev Event Packs	0.003	3.173e −4	0.610	8.697	< .001
	Rev Monthly VIP Pass	−0.005	0.002	−0.159	−2.352	0.020
	Rev Premium Currency	0.003	7.053e −4	0.294	4.010	< .001
	Rev Progression Improving Items	2.207e −4	0.001	0.011	0.182	0.856

Table 4.2 Model Summary and Coefficients ARPPU, Only Event Dataset shows the model for the only event dataset with all four independent variables as H_1 and the adjusted model as H_0.

The added independent variable Revenue through selling Event Packs shows a strong correlation with a Standardized Coefficient of 0.61. Premium Currency Revenue still shows significance and correlation, but with a Standardized Coefficient value of 0.294, it is more than 50% lower than the complete dataset.

The improved model with three independent variables shows through the Adjusted R² that 56,8% of the variance in ARPPU can be described through the model. It also shows that the overall model has a higher R², so it is overall stronger predicted by monetization tools.

Their Regression formula to predict the ARPPU with Monetization Tools during an event is:

$Y=21.894+0.003X_1-0.005X_2+0.003X_3$ Where Y is ARPPU X_1 The revenue through Event Packs, X_2 is the revenue generated by selling Monthly VIP passes X_3 the revenue made by selling premium currency.

Table 4.3: Model Summary ARPPU, Rev Event Pack as a Single Independent Variable, only Event Dataset

Model Summary - ARPPU ($) ▼

Model	R	R²	Adjusted R²	RMSE	Durbin-Watson Autocorrelation	Durbin-Watson Statistic	Durbin-Watson p
H_0	0.719	0.517	0.513	3.776	−0.114	2.226	0.226
H_1	0.763	0.582	0.568	3.559	−0.133	2.266	0.178

Note. Null model includes Rev Event Packs

Due to the significant correlation, a third Regression Analysis with only Event Pack Revenue as an independent variable was conducted on the only event dataset. As seen in the H_0 Model in table 4.3 shows the previous model in comparison, which is still better at predicting the change in ARPPU.

2) Monetization Tools on 7 Day Retention:

The two Linear Regressions executed to explore the impact of monetization tools on the 7 Day Retention prove the assumption that the data is usually distributed, Homoscedastic (have the same variance at every X) and Independent.

Table 4.4: Model Summary and Coefficients Day 7 Retention, the Complete Dataset

Model Summary - Day 7 Retention

					Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	Autocorrelation	Statistic	p
H_0	0.592	0.351	0.342	1.133	−0.069	2.083	0.623
H_1	0.599	0.359	0.346	1.129	−0.081	2.098	0.603

Note. Null model includes Rev Premium Currency, Rev Progression Improving Items

Coefficients

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized	t	p	Tolerance	VIF
H_0	(Intercept)	2.669	0.284		9.403	< .001		
	Rev Premium Currency	−4.417e −4	1.588e −4	−0.185	−2.782	0.006	0.976	1.024
	Rev Progression Improving Items	0.003	3.587e −4	0.592	8.914	< .001	0.976	1.024
H_1	(Intercept)	2.502	0.306		8.165	< .001		
	Rev Monthly VIP Pass	8.901e −4	6.244e −4	0.108	1.426	0.156	0.749	1.334
	Rev Premium Currency	−5.476e −4	1.748e −4	−0.229	−3.132	0.002	0.800	1.250
	Rev Progression Improving Items	0.003	3.695e −4	0.567	8.293	< .001	0.914	1.094

Model H_1 in table 4.4 Model Summary and Coefficients Day 7 Retention, the Complete Dataset shows the initial model with three independent variables. For the complete dataset, the Revenue Monthly VIP Pass does not meet the significance level of 5% with a p=0.156 and does not contribute much to the model, so, therefore, it will be removed. The linear regression was redone, as can be seen in H_0. The correlation of Revenue Premium Currency is negative and low with a Standardized Coefficient of -0.185, which means that purchased premium currency slightly reduces the 7 Day retention statistically but is very low. The model's total effect on the Day 7 Retention is moderate with an adjusted R^2 that explains 34.2% of the variance on the 7 Day retention.

The Regression formula is $Y=2.502+0.00044X_{1+}0.003X_2$ where Y is the 7 Day Retention and X_1 revenue Premium Currency and X_2 Revenue Progression Improving Items.

Table 4.5: Model Summary and Coefficients Day 7 Retention, Only Event Dataset

Model Summary - Day 7 Retention

					Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	Autocorrelation	Statistic	p
H_0	0.637	0.406	0.396	1.097	−0.181	2.299	0.106
H_1	0.642	0.412	0.391	1.101	−0.178	2.286	0.146

Note. Null model includes Rev Premium Currency, Rev Progression Improving Items

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	3.271	0.344		9.520	< .001
	Rev Premium Currency	−7.011e −4	1.812e −4	−0.280	−3.869	< .001
	Rev Progression Improving Items	0.003	3.628e −4	0.605	8.361	< .001
H_1	(Intercept)	3.176	0.371		8.565	< .001
	Rev Event Packs	7.208e −5	9.812e −5	0.061	0.735	0.464
	Rev Monthly VIP Pass	4.545e −4	6.291e −4	0.058	0.722	0.472
	Rev Premium Currency	−8.259e −4	2.181e −4	−0.330	−3.786	< .001
	Rev Progression Improving Items	0.003	3.752e −4	0.588	7.868	< .001

When looking at the Only Event dataset, the added independent variable Revenue Event Packs and Revenue Monthly VIP Pass show almost no correlation and a high p, so they will not be considered when predicting the 7 Day Retention. The null hypothesis can be rejected for the other two independent variables since their p-value is >0.001. Revenue Premium Currency has a moderately low negative correlation with the dependant variable. The Revenue from Progression Improving Items has the highest impact on the 7 Day Retention with a Standardized Coefficient of 0.605. In total, the Model can statistically predict 39.6% as seen in the Adjusted R^2.

The Regression formula is $Y=3.271-0.0007X_1+0.003X_2$. Y is the 7 Day Retention. X_1 Revenue Premium Currency and X_2 Revenue Progression Improving Items.

3) Monetization Tools on New Paying Users:

The tests performed on the Linear Regression with Monetization Tools as the independent and New Paying Users as the dependant variable shows that the data is typically distributed, homoscedastic, and Independent for both datasets.

Table 4.6: Model Summary and Coefficients New Paying User, the Complete Dataset

Model Summary - New Paying User

					Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	Autocorrelation	Statistic	p
H_0	0.000	0.000	0.000	13.461	0.309	1.360	< .001
H_1	0.675	0.456	0.445	10.031	−0.056	2.112	0.541

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	42.877	1.085		39.528	< .001
H_1	(Intercept)	14.296	2.722		5.252	< .001
	Rev Monthly VIP Pass	0.020	0.006	0.252	3.620	< .001
	Rev Premium Currency	0.008	0.002	0.367	5.443	< .001
	Rev Progression Improving Items	0.016	0.003	0.309	4.896	< .001

All dependent variables have a high significance for the Complete Dataset with a p-value lower than 1%. The correlation with the dependent variable is relatively low, with Revenue Premium Currency having the highest Standardized Coefficient of 0.367 followed by Revenue Progression with 0.309 and Revenue Monthly VIP Pass with 0.252. The Adjusted R^2 of the model with three independent variables show that they explain 44.5% of the variance in the dependent variable.

The Regression Formula is $Y=14.296+0.020X_1+0.008X_2+0.016X_3$. Y describes the New Paying Users, X_1 the Revenue Monthly VIP Pass, X_2 Revenue Premium Currency, and X_3 Revenue Progression Improving Items.

Table 4.7: Model Summary and Coefficients New Paying User, Only Event Dataset

Model Summary - New Paying User ▼

					Durbin-Watson		
Model	R	R²	Adjusted R²	RMSE	Autocorrelation	Statistic	p
H_0	0.638	0.407	0.391	10.300	−0.040	2.079	0.742
H_1	0.638	0.407	0.386	10.344	−0.041	2.081	0.741

Note. Null model includes Rev Monthly VIP Pass, Rev Premium Currency, Rev Progression Improving Items

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	17.188	3.468		4.956	< .001
	Rev Monthly VIP Pass	0.019	0.006	0.259	3.240	0.002
	Rev Premium Currency	0.007	0.002	0.317	4.077	< .001
	Rev Progression Improving Items	0.016	0.004	0.333	4.453	< .001
H_1	(Intercept)	17.205	3.484		4.938	< .001
	Rev Monthly VIP Pass	0.019	0.006	0.258	3.215	0.002
	Rev Premium Currency	0.007	0.002	0.310	3.546	< .001
	Rev Progression Improving Items	0.016	0.004	0.332	4.418	< .001
	Rev Event Packs	1.590e −4	9.221e −4	0.014	0.172	0.863

As seen in table 4.7: Model Summary and Coefficients New Paying User, Only Event Dataset, the Only Event dataset H_1 shows a very low correlation of the added independent variable Revenue Event Pack with the dependent variable and a p-value of 0.863, which is much higher than the defined significance level of 5%. It does not contribute to the model and will be removed. The other variables show significance.

Rerunning the Linear Regression with three independent variables leads to 40,7% of the variance being explained by them and a similar distribution compared to the complete dataset.

The resulting Regression Formular is $Y=17.188+0.019X_1+0.007X_2+0.016X_3$ with Y as the New Paying Players, X_1 representing Revenue Monthly VIP Pass, X_2 Revenue Premium Currency, and X_3 Revenue Progression Improving Items.

4) Daily Active Users (DAU):

The data shows a less typical distribution of the residuals regarding the independence and homoscedasticity but is sufficient for this exploratory model. The Independent for both datasets is given.

Table 4.8: Model Summary and Coefficients DAU, the Complete Dataset

Model Summary - Daily Active Users

Model	R	R^2	Adjusted R^2	RMSE	Durbin-Watson Autocorrelation	Durbin-Watson Statistic	Durbin-Watson p
H_0	0.393	0.155	0.143	2003.082	−0.114	2.227	0.163
H_1	0.394	0.155	0.138	2009.092	−0.119	2.236	0.166

Note. Null model includes Rev Premium Currency, Rev Progression Improving Items

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	16500.394	501.909		32.875	< .001
	Rev Premium Currency	1.034	0.281	0.279	3.685	< .001
	Rev Progression Improving Items	1.989	0.634	0.238	3.137	0.002
H_1	(Intercept)	16565.902	545.201		30.385	< .001
	Rev Monthly VIP Pass	−0.348	1.111	−0.027	−0.313	0.755
	Rev Premium Currency	1.076	0.311	0.290	3.458	< .001
	Rev Progression Improving Items	2.041	0.658	0.244	3.105	0.002

Revenue Monthly VIP Pass is insignificant as a variable to predict DAU due to its high p-value and a very minimal negative correlation, as seen in the H_1 model in table 4.8 Model Summary and Coefficients DAU, the Complete Dataset the variable was removed, and the Linear Regression retook with the remaining two independent variables that significantly improve the model. The model only explains 14.3% of the variance of Daily Active Users with the Adjusted R^2

The Regression formula is $Y=16500.394+1.034X_1+1.989X_2$, where Y is DAU, X_1 Revenue Premium Currency, and X_2 Revenue Progression Improving Items. The low impact of the Monetization Tools as independent variables on the DAU as the dependant variable shown in the Model suggests that there is a very low correlation and, therefore, no significant linear dependency.

Table 4.9: Model Summary and Coefficients DAU, Only Event Dataset

Model Summary - Daily Active Users

					Durbin-Watson		
Model	R	R²	Adjusted R²	RMSE	Autocorrelation	Statistic	p
H_0	0.463	0.215	0.194	1927.586	0.065	1.870	0.455
H_1	0.464	0.216	0.188	1934.980	0.069	1.862	0.383

Note. Null model includes Rev Event Packs, Rev Premium Currency, Rev Progression Improving Items

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	16231.943	604.010		26.874	< .001
	Rev Event Packs	−0.485	0.172	−0.270	−2.827	0.006
	Rev Premium Currency	1.572	0.365	0.412	4.311	< .001
	Rev Progression Improving Items	2.068	0.639	0.271	3.235	0.002
H_1	(Intercept)	16145.542	651.820		24.770	< .001
	Rev Event Packs	−0.488	0.172	−0.272	−2.830	0.006
	Rev Monthly VIP Pass	0.399	1.106	0.033	0.361	0.719
	Rev Premium Currency	1.531	0.383	0.401	3.993	< .001
	Rev Progression Improving Items	2.013	0.659	0.264	3.052	0.003

For the Only Event dataset, Revenue from selling Monthly VIP Passes was insignificant as well, judging by the high p-value of 0.719 and will be taken out of the model. The adapted model with three variables shows a low impact on the dependant variable with an R² of 21,5%.

The Regression Formular is Y=16231.943-0.485X1+1.572X2+2.068X3. Y is the Daily Active Users, X1 the Revenue Event Packs, X2 Revenue Premium Currency, and X3 Revenue Progression Improving Items.

The Regression Analysis, therefore, supports the under 4.1.1 established insight that Events do not impact the number of DAU

4.2 Answers to Research Questions

Research Question 1: How do the Monetization Tools impact the Active Revenue per Paying User (ARPPU)

The literature review under section 2.2.2 found that the ARPPU can be a potent indicator of how strong a game monetizes its paying users. The game's live operations trends show that the daily logins and New Paying Player numbers dropped. The total revenue stayed at level, though, which can be explained by the constant raising ARPPU. The monetization is shifting to fewer people spending more for the game. The change in the Monetization Tool revenue shows that the revenue of Event Packs is rising in a similar manner which can be a sign that the two are connected. Event Packs have the highest correlation with an Adjusted R^2 of 51,7% when conducting the Linear Regression on ARPPU and using it as the independent variable. It can be seen that The Revenue Event Packs does an excellent job of predicting the change in ARPPU. The Revenue Premium Currency also displays a moderate correlation and contributes positively to the model. Revenue Monthly VIP Pass has minimal impact on the model but shows a negative correlation. Since the impact is small, it has to be looked into further, but it could mean that selling VIP Passes reduces the average revenue made by paying users. Another insight to support this theory is that the percentual revenue generated by selling VIP passes is 44% lower for the top 100 spending players.

Overall, Event Packs and Premium Currency positively affect ARPPU, where Monthly VIP Pass has a slight negative effect.

Research Question 2: How do the Monetization Tools impact Player Retention?

The pure data analysis could only show that ongoing events affect the 7 Day Retention. The Linear Regression showed that the sold Premium Currency and Progression Improving Items contributed to predicting the change in 7 Day Retention by 40%. The Revenue of Progression Improving Items shows a solid positive correlation, concluding that spending money on those virtual goods positively affects how long players stick to the game. It was indicated in section 2.2.1 that Progression improving Items have a good value and help players advance in the game, which can be a reason for that. It shows that a relation between Monetization Tools and Retention can be measured but only explains a small part of the variance. The impact of both Event Packs and the Monthly VIP Pass were unsignificant and, therefore not contribute to predicting the retention.

Research Question 3: How do the Monetization Tools impact the amount of New Paying Users

The display of NPU over the game live operation, as seen in Figure 4.1 Monthly revenue by Monetization Tool, shows a steady decrease that does not explicitly depend on any Monetization Tools. During the event, an increase of 30%

for New Paying Users was measured compared to days with no ongoing event. The increase was not due to Event Packs but rather the event as a demand-increasing measure for other monetization tools. The Linear Regression Analysis shows no significance or correlation with Event Pack Revenue but with the other three monetization tools. They all have a relatively low correlation but show significance which means that Monetization Tools have an impact on New paying Users, but no single tool is standing out, and overall it explains the variance in the dependant variable by 38.6%

Research Question 4: How do the Monetization Tools affect the amount of Daily Active Users (DAU)

Looking at the Daily Active Users over time, the curve in Figure 4.2 Monthly Performance Indicator ratio from nine-month total shows a natural trend that does not connect to Monetization Tools. When looking at the data of an active event, Daily Active Users were the only Performance Indicator that did not show an apparent increase. More users generally mean more revenue, but the direct effect of Monetization Tools on the user number could not be measured effectively with the set framework. The Linear Regressions Adjusted R^2 shows that Monetization Tools can explain less than 20% of the variation, and the individual correlation of the independent variables is very low.

Overall the DAU is very little impacted by Monetization Tools, so applying changes to those is expected to have a minor effect on the individual daily logins.

4.3 Conclusion

The conducted research found that Monetization Tools have the most substantial impact on ARPPU. Mainly Event Pack Revenue was found to increase the revenue attributed to paying users. In general, Events show to be a significant factor in ongoing monetization. This goes not only for the extra monetization tools that are exclusively available during these periods but also measured that the revenue of the remaining Monetization Tools is increased during the event period and the defined Performance Indicators. The only exception was the Daily Active Users, which hardly show any measured correlations with Ongoing Monetization.

Progression Improving Items do not show the most potent effect on overall revenue and ARPPU. However, they seem to be a tool to increase retention and also a tool to promote a first purchase which can make them valuable for sustainably growing a game service.

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CHAPTER 5
CONCLUSION AND DISCUSSION

The motivation to conduct academic research on ongoing monetization comes from the current issue in the industry to keep game services profitable over their lifetime. When visualizing the revenue of the test case over time, it can be seen that it dropped massively after the month of the launch. If the game would not have found a way to regain its relevance for the users and compensate for the loss in users, there is a big possibility that the project fails.

Measuring how events can massively improve a game's ongoing monetization in this context over time and by comparing the two datasets turned out very effective. The discovered peak over December, which has many significant holidays, showed the event's potential to increase monetization. However, the more critical information is that a product can establish a growing income stream through Events.

The chosen conceptual model succeeded in finding the impact of Monetization Tools on ARPPU. All chosen Data Analyzation tools contributed valuable insights to predict the effect of the defined Monetization Tools on the set Performance Indicator. The impact on Day 7 Retention and New Paying user was partly successful. The created models could partly explain the variance, but the data analysis over time did not show any significant results. Daily Active Users only have a minimal measurable correlation with the chosen framework, so the most valuable outcome is that the Monetization Tools do not directly impact the individual daily login numbers based on the available data and set operational structure.

A significant finding, which was aimed for when doing linear regression analysis and looking closer into correlations, was that items do not contribute to the revenue but can impact other factors that determine sustainability in Progression Improving items like the number of new first purchases or the user retention. It is also essential to see the negative impacts of Monetization Tools, which are even harder to single out since revenue is never negative. The Monthly VIP Pass is such a case since no significant positive impact on the Performance Indicators could be measured, and even negative correlations were found.

It was unexpected to see that Monetization Tools do not significantly impact daily Active Users. It was expected that the aggressiveness of monetization, so how strong they interfere with the game's balancing, has an impact on users that log in.

5.1 Practical Implication

As mentioned in the Research Framework of section 3.1, the created model has to be adapted for other game services due to many individual parameters. The way games monetize users is very diverse, and the impact of specific Monetization Tools varies. It was established, though, that there is a measurable impact of certain Monetization Tools on the Performance Indicators. Defining and analyzing the connections can help make decisions and prioritize development tasks.

The strong impact of Events on monetization is also an important finding. It shows that regularly added content that boosts demand and gives users a reason to play and spend money benefit sustainable growth for online game services.

The Regression formulas created out of the Linear Regression can also be a gadget to predict the outcome of a performance indicator based on changes in a Monetization Tool's revenue. If a game company is in a situation where the ARPPU is sinking, and they want to take measures to counteract that, they can calculate the impact on the ARPPU if they take measures to increase the Event Pack revenue.

The Regression Formular in this game's example comes out as $Y=21.894+0.003X_1-0.005X_2+0.003X_3$, Where Y is ARPPU X_1 The revenue through Event Packs, X_2 is the revenue generated by selling Monthly VIP passes X_3 the revenue made by selling premium currency. When putting in the overall average daily values, the ARPPU comes out as 30.24. If now a 50% higher Revenue for X_1, Event Pack Revenue, is assumed, the ARPPU increases to 32.96, a 9% increase. This is especially important if the company plans to create new content for a monetization tool and measure the possible impact on the sustainability of the game and if the investment is worth it.

It was also found out that specific Monetization Tools can hurt certain Performance Indicators, as seen in the impact of Monthly VIP Passes on ARPPU. Opportunity costs and negative consequences are very hard to see from pure revenue since it is always positive. For example, it was established that selling the Monthly VIP Pass might negatively contribute to sustainability.

5.2 Recommendations for the Game Owner

After analyzing the impact of the games Monetization Tools on Performance Indicators, putting the outcome into relation with the specifics of the game leads to concrete suggestions for the game owner.

The vital role of heavy spenders in the context of online free to play games was founded under section 2.2.4. The apparent impact on ARPPU and increasing share of the total revenue of Events and Event Packs suggests that they are crucial elements for ongoing player monetization. Especially for high spending users a big positive effect was found in the data. Allocating development resources to optimize event monetization further is therefore strongly recommended.

Progression Improving Items show a decreasing contribution to the total revenue, but other positive impacts on sustainability could be measured. They show a positive effect on New Paying Users and Player Retention, which are vital Performance indicators and therefore have an essential role in the monetization item portfolio.

Not all Monetization Tools showed a positive effect. The Monthly VIP Pass only had a neutral correlation to New Paying Users, a slight negative correlation with ARPPU, and showed otherwise no significance. The game owner should look into the tool and challenge its overall benefit. Investing in additional resources is not recommended.

5.3 Limitations

The most substantial restriction of this study is that it only looks at one single case. Although the findings can be transferred to other online game services, the individual nature of games require a redefinition of parameters and might vary.

The game in the center of the case study was also just nine months in business which gave many data, but a more extensive dataset could have been beneficial. Looking more into rich user data and demographics would also be helpful to have a better understanding of the customers' persona. The study also does not make a difference about the end device or genre. With a more extensive dataset, it would also be possible to increase the number of Monetization Tool segments, which are defined as independent variables in the Linear Regression Analysis.

This study mainly looked at revenues and user numbers of the game. Other external factors could not be taken into consideration. One example is marketing which is done by a third party that could not provide data. Marketing is a significant cost factor and is assumed to influence performance indicators, especially user-related ones like DAU intensely.

Except for the top spenders, it was worked with aggregated data and not individual player data, so it does not bear information about individual player behavior, which would have been a fascinating insight.

5.4 Future Research

Since the ongoing monetization of game services is a pretty new topic, game companies face many new issues every day. The amount of available literature is meager, so there is much room for research.

It was shown that different monetization tools have a different impact on the overall revenue based on the time and how long a game service is live. It would be interesting to explore a segmentation of ongoing monetization based on time and create phases that a game service goes through.

By looking at other games that have been around for longer, have other genres or end-devices, a more diverse understanding of ongoing monetization could be created

There is much information about customer behavior. It was established that this is a big part of monetization, so looking closer into user data and purchase patterns can help understand why customers purchase into ongoing monetization tools.

The effect of event parameters turns out to be an exciting topic, and see which kind of event has the most potential and how to optimize events can help optimize them. Since creating events and new monetization tools takes resources, it can also be interesting to define the Return on Investment.

A very effective way of finding out if a measure works in the game is A/B testing, where a control group gets the new measure implemented to compare the data with the remaining user base. This would be highly desirable for monetization tools since it can eliminate many external factors since both groups have the same circumstance.

The study showed the negative impacts of monetization tools like the Monthly VIP Pass on Performance indicators. It would be interesting to look into negative consequences like opportunity cost or in-game economy satiation in greater detail.

For Performance Indicators like Retention and DAU, it was found out that other factors have a more substantial impact on their variance. Finding and analyzing those could help create a more complete model to predict sustainable growth in better detail.

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