



Microtransactions in the Company's and the Player's Perspective: A Manual and Automatic Analysis

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Abstract. Microtransactions dominate today's video game industry and will continue to do so for the foreseeable future, despite all the controversy it brings. To approach this problem, we created a survey, shared it on several gaming forums (a total of 1661 answers were obtained), then we designed a theoretical model and based on that, an automatic analysis was performed to understand what microtransactions are adequate to certain types of videogames. In parallel, we also performed a manual analysis that helped us gain insights into player preferences. Through the manual analysis we can conclude that players show a greater tendency to spend on microtransactions in mobile games. On average, respondents spend more on microtransactions than on purchasing videogames per month; with this, we can understand why the market of microtransactions has been growing greatly in recent years. Players that have jobs spend more on time savers microtransactions, and this probably happens because of the lack of time these players have comparing to the rest and the fact that they have an income to spend. Players aged 25 and above have shown to be more inclined to spend money to remove advertisements from games; however, players under the age of 25 are more inclined to spend money on general microtransactions in contrast to their older counterparts. It is also noticeable the negative sentiment towards players that spend money on advantageous items.

Keywords: Microtransactions · Video games · Pay-to-play · Free-to-play · Gaming platforms · Cosmetics · Neural network

1 Introduction

The digital and online world, and technology in general, have changed the face of many industries in recent years – including education, the finance industry and how commerce takes place [14–18]. Leisure activities have also been transformed. The first video game was created in the mid-1900s, but it was not until the 1970s, when Atari got involved with arcade games, that the video game industry increased significantly; but only in the 1980s video games became a popular hobby. At the beginning, publishers adopted a very basic approach to make profit out of their video games, in which they would sell the entire game, at full price, to a customer (pay-to-play (P2P) concept). Although this concept seems appropriate to make a profit, the excess of video games as well as the diverse preferences of the market motivated publishers to try a different approach, and they soon began to sell partial content instead of the entire version of the game. This approach would make the base game more accessible, or even make the game free, while all additional content or extensions would be charged through microtransactions (games that can be played for free are called Free-to-play (F2P)).

There is not a specific definition for microtransactions that perfectly encapsulates and represents the term. In general, a microtransaction is anything you pay extra in a video game, outside of the initial purchase. The purchases may unlock specific features or content. Microtransactions that unlock new content are more commonly known as DLC (Downloadable Content) and provide new ways to experience an already existing game through new extensive storylines, levels, challenges, game modes, etc., in order to expand the game's life span. Microtransactions that unlock specific features are more focused on consumable and cosmetic items. A cosmetic item is simply for aesthetic purposes and will only change the appearance of a character, weapon or any other item of a game. Consumable microtransactions have different types that serve different purposes:

- Time savers, that can boost experience to level up or simply skip levels, for example, in puzzle games like Candy Crush Saga;
- Advantageous items, where you can purchase stronger weapons or useful items that give the player an edge against his/her opponents. Games with this type of microtransaction are often considered as Pay-to-Win (P2W), as you are almost required to spend money on the game to play it competitively and win;
- Loot boxes, where a player can receive a random item, based on a collection, of different qualities (or rareness);
- In-game virtual currency, which is the currency a game may have so players can purchase virtual items. In most cases, virtual currency can be earned by playing the game, although at a slow rate.

There is not a concrete definition of a microtransactions. Whether it is good or bad, there is always controversy [1]. However, we can find examples considered good and bad from which we can learn from.

The F2P game Warframe is one of the best examples of a microtransaction model that's considered good [2]. The developers interact often with the community discussing if the prices are fair, how much play time is needed to get certain items, and

when the community dislikes an update on the model an immediate response is given [3] and the revenue generated is then used to further develop updates, that are given for free, to offer players more content.

Examples of microtransaction models considered bad are everywhere, since this theme generates a lot of controversy. Star Wars Battlefront II is the most recent case. There were many aspects of the game that outraged players [4], many of which involved loot box microtransactions. A user estimated that, in order to unlock all the base content for the game, one would have to spend 4,500 h playing the game, or hand out \$2,100. This is certainly not a feature a player is expecting from a game that retails for \$60.

With these described cases we can affirm that not every model is successful, and we try to understand, from a set of defined variables, which of those are important and have a good impact on the success of a microtransactions model. Based on this set of variables, we also propose a theoretical model that suggests the best microtransaction model to be used in a hypothetical video game. This model would have a positive effect on players and help support the development/maintenance costs of the game. These ideas, however, are in the company's perspective and it is also important to understand what influences players to spend money on microtransactions, such as financial status, time that they spend playing or social aspects (pressure from other people or friends).

We can describe our main research questions as follows:

- Company perspective:
 - What variables are important to the success of a microtransactions model?
- Player perspective:
 - What influences or not the player to spend money on microtransactions?
 - How does a microtransactions model affect the sentiment of a player towards the game or other players?

2 Literature Review

Videogame microtransactions is a highly controversial topic that has been studied by many authors. By analyzing some of the works, we can conclude that:

1. Mobile games rely heavily on microtransactions because it is not possible for them to have the same price as PC games [5].
2. In multiplayer games, players want to be distinguished from others and so the additional content (microtransactions) that allows that is more easily accepted [8].
3. F2P games with microtransactions have much less problems related to piracy compared to P2P games [9].
4. Many players only accept cosmetic microtransactions as they don't create imbalance in the game [5, 6].
5. P2W microtransactions are especially unpopular in the gaming community. However, opinions on microtransactions that allow users to progress or get some items faster than a player that did not buy them are mixed. Some authors [5] state that these are accepted by the gaming community while others [6] declare that these have the same negative reaction as P2W microtransactions.

6. DLCs are a great source of extra income because developers can reuse the already created assets of the original game. In this way it is possible to charge almost the same amounts as for the original game and without requiring nearly as much work [10].
7. F2P games are accompanied by less negative publicity in case of lower quality content than P2P games [5], meaning that there's a lower probability that players are turned away from the game.
8. In general, the gaming community does not like it when premium games add microtransactions [5]. They feel like paying the full price for the game should be enough and that publishers are being greedy.
9. In-game currencies are used to create confusion and dematerialize payments [11]. In the end, most of the time users don't have a clear idea of the cost of the microtransaction that they want to purchase, this only making the said decision much easier.
10. Despite the negative attitude towards some microtransactions, players "become tempted to spend money on microtransactions themselves if they are confronted with other players who use them" [6].
11. Loot boxes have been considered a form of gambling, and it can lead to players overspending money because of an addiction to gambling [7, 12]. Some countries have already deemed these types of microtransactions as illegal [13].

3 Methodology

As observed in the previous section, the reviewed articles have a greater focus on the player's point of view, however, these lack research on the company's perspective of what variables influence positively or negatively a microtransaction model. In order to cover this, to answer the main questions that were mentioned in the Introduction (Sect. 1) and to gather sufficient data, we ended up, with the use of the Google Forms platform, creating an online survey. The survey was distributed, in the first instance, among the authors' network, and after that it was published in several subreddits (Reddit) and Facebook groups related with gaming. We tried to reach groups of all gaming platforms (Console, PC, Mobile) to avoid gathering biased data. The survey was made available in two languages, Portuguese and English, and was divided in five main sections:

- **Personal Information** such as gender, age, country of residence and if the person is a student and/or has a job;
- **Gamer Information** such as the favourite gaming platform, average hours a week spent playing video games, how much money a year they spent on video games and favourite game genre;
- **Buying Microtransactions**; here we asked if the player spends money or not on microtransactions, which buying methods are preferred, what type of monetization that games follow is preferred (free-to-play, buy-to-play or pay-to-play). We also placed some questions regarding the types of microtransactions, other video game characteristics and gaming platforms.

- **Social Aspect of Microtransactions**; here we try to understand if friends and other players pressure them into the purchase of microtransactions.
- **Real World Cases**, in this section we gave some freedom to the survey taker to comment on actual models and on the future of microtransactions.

The survey was available for two weeks and in this time, we were able to obtain 1661 answers. As mentioned in the introduction, a set of variables that influence microtransactions models were defined; these are based on the questions in the section Gamer Information. The variables are comprised of the genres and platforms that are included in the following questions:

1. “What’s your favourite genre?”
2. “What’s your favourite gaming platform?”

A few examples of genres included are: MMORPG, Fighting and MOBA. The platforms are PC, console and mobile; added up there are 15 variables (12 genres and 3 platforms) in total. Other variables could have been used however these were the ones that seemed, intuitively, to show more potential in demonstrating correlations with each microtransaction type.

4 Theoretical Model

With the variables that were defined in the section above, we propose a theoretical model that describes an ideal microtransaction model; this is a model that is, in theory, more successful in terms of the company’s perspective and its results try to not disrupt the will to play that players have - in other words, it doesn’t make players quit or feel that it jeopardizes their game.

To develop this theoretical model, we started with an abstraction; that is, from the set of variables that describe some of the properties of the game, the model will tell what kind of microtransactions should be present. We can observe a representation in Fig. 1. On the left, it’s possible to observe the set of variables, which are the model input. In the middle box there’s our proposed theoretical model, and in the right results a value that represents the affinity the set of variables has with a type of microtransaction, from the types of microtransactions that were discussed in the Introduction (Sect. 1).

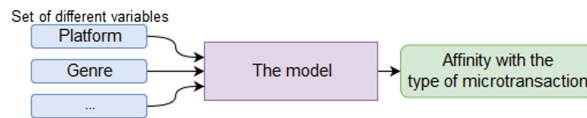


Fig. 1. The abstraction of the proposed theoretical model.

We define our theoretical model (middle box) as a function that calculates the affinity value for each type of microtransaction

$$F(x; \theta) : R^d \rightarrow R \quad (1)$$

Here, function 1 is parameterized by θ , which can be represented as a matrix of parameters, these are inferred during data analysis, d is the total number of variables. The output is a real numeric value belonging to a $]0, 1[$ interval; the closer this number to 1 the higher the affinity will be. This function has to be able to extract nonlinear relations.

Since we defined our theoretical model as a function we can also find the maximum values of it; this corresponds to finding the variables (game characteristics) that would theoretically have more success in each type of microtransaction.

$$x = x - \lambda \nabla J(\theta) \quad (2)$$

Equation 2 defines an iterative process, since manual analysis is impracticable due to the function being multidimensional, to find which variables x could give us the maximum affinity value related to each type of microtransactions. Where λ is the chosen learning rate constant value, $J(\theta)$ is the loss function of Eq. 1, which represents the error of our theoretical model; lastly $\nabla J(\theta)$ corresponds to the gradients - these basically show us how to modify the values of our variables x so that we can find a local or optimal maximum of $F(x; \theta)$.

Now, the crucial part is to find the parameters θ and b for Eq. 1, and for that we propose an approach using artificial intelligence, more precisely, a machine learning algorithm that will leverage the data gathered in the survey to approximate a function.

5 Discussion on the Fieldwork

We opted to divide the analysis of the data in two parts:

- The manual analysis that gets conclusions directly from the survey;
- The automatic analysis in which the theoretical model is applied.

We decided to introduce the last one, due to the impracticality that it is to manually find relations with such a great amount of variables that can influence the affinity result; this is because there's the need to consider the combinations of all the different variables (32768 combinations) and also some relationships have been shown to be non-linear or non-trivial. Finally, we compared these results with the conclusions from the other works presented in the Literature Review.

5.1 Manual Analysis

To give some context on the results we will present later on, basic statistics about the survey takers are shown in the following statements, these are **direct results** from the survey:

- A total of 1661 answers were obtained;
- 91.1% of the survey takers are male;
- 75.6% of the survey takers are between 18–34 years old;
- 52.2% of the survey takers are from the U.S.A., 8.3% are from Canada and 5.7% are from the U.K.; we had answers from 66 different countries;
- 71.4% of the survey takers have full-time or part-time jobs;
- 57.7% of the survey takers prefer credit card as a payment method followed by e-wallet (e.g. PayPal) with 30.3%.

More importantly:

- Only 2.7% of the survey takers spend less than 1 h per week playing video games;
- 86.5% of the survey takers have bought microtransactions and the main reasons for the remaining 13.5% who haven't, were because they're too expensive (54.5%) and, specifically talking about advantageous/time saving microtransactions, because they don't want to make their gameplay easier by taking shortcuts (44.6%). We also gave freedom to the survey taker to give other answers and we noticed quite a few of them said they don't want to support the practice of microtransactions;
- 38% would rather buy microtransactions in F2P games than P2P, because they didn't have to pay for the game, while 43.5% of them are indifferent;
- 36.6% would be more inclined to buy microtransactions in mobile games rather than with consoles (5.7%) or PCs (16.2%).
- Players don't like and even hate players that spend money on P2W microtransactions;
- In general, players don't feel pressured by their friends to spend money on microtransactions; however they do feel inclined to buy cosmetics when they run into strangers that bought them (38.3%).

In Table 1, we can observe that players do spend more money on microtransactions than buying video games.

Table 1. Comparison between money spent monthly on microtransactions and the purchase of video games.

	Microtransactions (\$)	Videogames (\$)
Worst case	18.16	12.78
Average	39.80	13.88
Best case	61.44	20.61

In Fig. 2, each graphic represents a different type of microtransaction and a histogram in which the scale goes from one to five (one represents that the player will quit because of the model and five represents that the player will buy microtransactions that are from the model). At first glance, it's noticeable how advantageous items are not accepted, as a great amount of people will quit because of those microtransactions or simply have negative sentiments towards them. In contrast, cosmetics are much more accepted compared to all the other types.

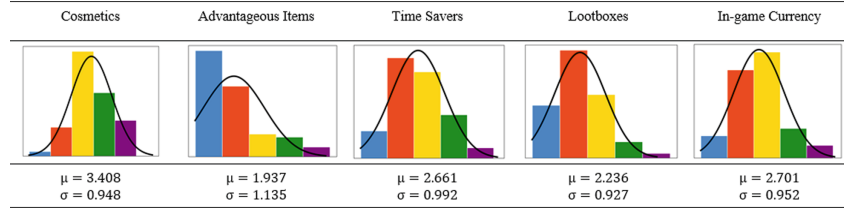


Fig. 2. Distribution of players' preferences regarding the types of microtransactions. The mean and standard deviation are presented below the graphics.

With the provided answers we were able to draw some conclusions and some possible deductions by crossing the given data from different questions; in other words, we can reach some certain indirect results by usually combining two specific questions from the survey. Next, a few examples of these **indirect results** are given:

- 73.4% that purchase microtransactions have a job (full-time or part-time);
- 79.6% that work would buy time savers and 74.4% like this type of microtransaction; we can deduce that people who work have less time to play, so they tend to buy this type of microtransaction;
- Adults (age 25+) are more likely to spend money to remove ads (49%) than younger people (ages 12–24), where only 35% would do so.

5.2 Automatic Analysis

Moved by the idea described in Sect. 4 of finding good microtransaction models and what variables influence them, we implemented the function 1 as a simple FeedForward Neural Network (NN) composed by 4 layers, an analytic representation of this is presented in Eq. 3, with the objective of predicting qualification (from 1 to 5, where 1 as the lesser and 5 as the higher affinity with the type of microtransaction), given the variables.

$$F(x; \theta, l) = \begin{cases} \sigma(\theta_l x + b_l), & \text{if } l = 0 \\ F(\gamma(\theta_l x + b_l), l - 1), & \text{otherwise} \end{cases} \quad (3)$$

This is a recursive function that calculates in each layer l , from a total of L layers, a linear combination $\theta_l x + b$ followed by a nonlinear function γ , this enables the function to extract nonlinear relations. In the last layer, which is the output layer $l = 0$, a sigmoid σ function is used to transform the values to the mentioned (Sect. 4) $]0, 1[$ interval.

After the definition of the NN, we proceeded to the training phase that corresponds to finding the parameters θ and b , for each layer, of Eq. 3 using the answers from our survey, and after this phase we have a nonlinear function that maps the variables to the qualifications of different types of microtransactions.

In Table 2, the F1 score and accuracy of the function were registered, and we also created two baseline models, the first one, “truly random” only returns with a

Table 2. Recorded results for the f1 scores followed by the accuracy scores in parenthesis performed on 431 samples, the remaining 1032 samples were used for the learning phase of the NN; it is also worth mentioning that we used the stratified strategy for the division of the test samples and the training samples.

	Cosmetic	Advantageous	Time savers	Loot boxes	In-game currency
Truly random	17.7% (20.6%)	15.8% (19.5%)	15.4% (18.4%)	16.3% (19.7%)	18.2% (20.4%)
Cumulative random	19.1% (28.7%)	21.6% (32.2%)	16.6% (25.5%)	17.9% (28.8%)	17.7% (30.2%)
Our function	29.7% (35.7%)	32.8% (36.2%)	27.7% (33.2%)	30.4% (36.7%)	30.7% (36.6%)

probability of 20% each type of qualification (1 to 5) and the second one “accumulative random” uses the number of occurrences to predict qualification. The f1 score metric should be given more importance due to the distribution of the data shown in Fig. 2. We can also see that our approximation function in general has a 10% better score than the baseline scores, which gives us the perception that there is some relation between the variables and the qualification of each type of microtransaction.

From this function we proceed to the next step, where we compute, in an iterative way, equation number 2 with the purpose of calculating a plausible local maximum that will tell us what kind of variables contribute for a better qualification of that type of microtransaction. The results are presented in Table 3, and for some cases it wasn’t possible to find a valid maximum; this is related with the lack of data for that type of qualification. In general, we agree with the results; for example, we can understand why “Console, PC, MOBA, Shooter, Sports” are extremely related with the qualification (5: “I would buy it”) for the type “cosmetics”; however, we are not sure why; for example, single player has a great influence on the qualification 5 for type “in-game currency”, and this could be associated with the error of our function, indeed. Therefore, it is worth mentioning we don’t produce a good approximation function as

Table 3. Results of what kind of variables X are more important to the different types of microtransaction model; the qualification (1) is associated with the idea of “will make me quit” and qualification (5) with the idea of “I would buy it”. This qualification is derived from the survey data.

	Qualitative 1 (will make me quit)	Qualitative 5 (I would buy it)
Cosmetic	Not found	Console, PC, MOBA, Shooter, Sports
Advantageous	MMORPG, Simulation, Single player, Strategy	Puzzle
Time savers	Single player, Strategy	Not found
Loot boxes	Console, Racing, Strategy	PC, Simulation, Sports
In-game currency	MMORPG	Cards, Single player

seen in 2; this could be related with the limited and incoherent data. A better neural network could also be used, but this was not the focus of the paper¹. Also, other variables can be used so that the function produces better predictions.

5.3 Results Comparison with the Literature Review

Through both analyses, we compared our results with some of the points drawn from the Literature Review (Sect. 2). Work [8] stated that players like to distinguish themselves from others, so content that provides that is more easily accepted; we can reinforce this statement since, through our automatic analysis, we observed that online games such as shooters and MOBAs are usually successful with these types of microtransactions. Other works [5, 6] also stated that players tend to accept more these types of microtransactions due to them not creating imbalance in the gameplay; we can support this through the results obtained by the manual analysis that can be observed in Fig. 2. Lastly, as mentioned in the paper [6], players do feel pressured or inclined to buy microtransactions when others do so; through the answers obtained in the survey we can conclude that players don't feel pressured by their friends but do feel inclined to buy cosmetics when strangers show them what they bought for themselves (38.3% of the players feel this).

6 Conclusions and Suggestions for Future Research

Since a lot of mistakes happened throughout the years regarding microtransactions (Battlefront II [4] for example), one of the main objectives of this paper was to find how companies could decide on a model of microtransactions for their hypothetical created video game. With the proposed abstraction in Fig. 1 an artificial intelligence based automatic procedure for analysing the data of the survey was developed. This made it possible to reach conclusions that otherwise, with only a manual analysis, it would not be possible to reach. Through the automatic procedure it was possible to correlate gaming platforms and video game genres with each type of the defined microtransactions. The consequent results were shown to be consistent, that is, the variables that influence the types of microtransactions appear to be plausible in Table 3, despite the metrics being poor; this is due to data limitations. Through the manual analysis we can conclude that players show a greater tendency to spend on microtransactions in mobile Games. On average, respondents spend more on microtransactions than on purchasing videogames per month; with this, we can understand why the market of microtransactions has been growing greatly in recent years. From the types of microtransactions, advantageous items and loot boxes are considered the least accepted types (loot boxes probably due to their gambling aspect, among other negative factors that can be pointed out), on the other hand - cosmetics are the most accepted as these don't create imbalances in the games - this can be seen in Fig. 2. Players that have jobs

¹ In some of the tests we pushed the neural network to 48% of accuracy (the F1 score was not implemented yet); this gives us an idea that there is space for improvement.

spend more on time Savers microtransactions; this probably happens because of the lack of time these players have comparing to the rest and the fact that they have an income to spend. Players aged 25 years old and above have shown to be more inclined to spend money to remove advertisements from games; however, players that are under the age of 25 are more inclined to spend money on general microtransactions in contrast to their older counterparts. It is also noticeable the negative sentiment towards players that spend money on advantageous items. For future work, more precisely in the manual analysis, we left a wide area to be explored. Also, with a bigger and more coherent data set the automatic analysis can show a significant improvement in results due to its consistence.

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