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Can Process Mining Detect Video Game Addiction Through Player's Character Class Behavior?

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Abstract. For more than fifteen years, we have witnessed the effervescence of video games, first considered by a handful of scholars this hobby knew how to penetrate most homes. Video games are no longer necessarily considered a simple hobby, players have been able to take advantage of this enthusiasm to make a business, the birth of e-sport, community channels, and various monetized videos are proof of this. However, the news shows us that for some people video games can become a real addiction and bring with it its share of the problem.

Since video games are by nature computer programs, we may wonder if it is not possible to retrieve information about their users in real-time to detect any addictive behavior and thus protect the player. In this paper, we will use process mining techniques to analyze player logs to try to find a behavioral pattern of addiction.

Keywords: Addiction · Video Games · Process Mining

1 Introduction

A video game is usually defined as an electronic game with a user interface allowing a playful human interaction by generating visual feedback [1]. The video game player has devices to act on the game and perceive the consequences of his actions in a virtual environment. According to this definition of a video game, its history can begin around 1950 with OXO (1952), Tennis for Two (1958), or Spacewar! (1962), which is the most commonly accepted date. Pong (1972), is the first game whose gameplay is catchy and addictive enough to make it a known success with a public audience.

There are many benefits that video game players get from engaging in their chosen activity. These can be educational, social, and/or therapeutic [2]. However, excessive use can pose a health threat to some people (basically young people but addicts can be found in all categories of people). The most important risk concerns networked games and in particular multiplayer role-playing games. Detecting these addictions can be a real challenge to help addicts as soon as possible. Besides traditional techniques used by health professionals (time consumed playing for instance), we investigate the possibility to use user logs to identify addiction by looking at the player's character behavior. In network games, players are often playing a character belonging to a specific class, like

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Knight, Mage, Hunter, Druid, Warrior, etc. The player activities are completely different as each class has different objectives in the group (kill enemies, collect treasures, treat injuries, and so on). This means that each class will have a specific behavior and that we have to study each class separately from the other.

We believe that we should be able to detect an addict's behavior by looking at the activity logs of a user belonging to a specific class. Thus, our main research question is the following: "**RQ: Can we identify a video game addiction from activity logs?"**. This research question is decomposed into two other questions:

- RQ1: "Does it exists tools to detect addiction to video games?" and
- RQ2: "Can process mining help to identify addiction in class logs?"

Section 2 will give some background works on video-games addiction and process mining. Section 3 shows an experiment to try to demonstrate that it is possible to make a correlation between addicted players and their logs. We conclude in Sect. 4.

2 Background

This section will give some insights into the two domains studied in this work: video game addiction and process mining.

2.1 Video Game Addiction

Historically, the term addiction only involved addictions to toxic substances (drugs) but today we can mention addictions such as sexual addiction, compulsive shopping, gambling, and so on. Among these new addictions, we find the addiction to video games, officially an addiction since June 18, 2018, when the World Health Organization (WHO) listed this addiction as a disease just like addictions to drugs, tobacco, or alcohol. The WHO gives us the following definition of a video games addiction: *"Gaming disorder is characterized by a pattern of persistent or recurrent gaming behavior ('digital gaming' or 'video-gaming'), which may be online (i.e., over the internet) or offline"*[1] It also gives details about the characteristics of this addiction, like an impaired control over gaming, an increasing priority given to gaming to the extent that gaming takes precedence over other life interests and daily activities, and the continuation or escalation of gaming despite the occurrence of negative consequences.

Currently, the majority of the literature works in the field of video game addiction is Asian and deals mainly with adolescents. Yet the popularity of video games continues to grow (especially online video games). According to [3], the increase in this popularity has consequences on the population as it also develops an addiction. The particularity of this pathology is that it is difficult to diagnose because in normal times the gaming activity is not problematic. In addition, the use of video games may in some cases have beneficial effects, which is seen as inconceivable for "traditional" addictions such as

[1] WHO Definition of Gaming disorder: https://icd.who.int/browse11/l-m/en#/http%253a%252f%252fid.who.int%252ficd%252fentity%252f1448597234.

cocaine or alcohol (even if there are studies that show that marijuana can help people reduce nausea and vomiting during chemotherapy, improve appetite in people with HIV/AIDS, and reduce chronic pain and muscle spasms [4, 5]).

The Diagnostic and Statistical Manual of Mental Disorders [6] worked on provisional criteria from studies on gambling addictions. The DSM-5 Checklist (DSM5) is an 11-item questionnaire that measures the degree (mild, moderate, severe) to which an individual meets diagnostic criteria for a substance use disorder.

There are currently several measurement tools to try and assess the intensity of addiction. However, these tools do not distinguish between game styles or the environment [7].

- The Internet Addiction Test (IAT) [8], in 1998, assess Internet addiction in general.
- The Problem Video game Playing (PVP) [9], in 2002, is based on several criteria of addiction defined by the DSM [6].
- The Game Addiction Scale (GAS) [10]: Created in 2009 with two versions of 7 and 21 items, also based on [6]. The objective here is to distinguish the playing time and the intensity of the addiction. However, the 21-item version has not been validated.
- The Questionnaire for Measuring Intensity of Addictive Behaviors (QMICA) [11], in 2010, aims at identifying the co-addictions (compensation of one addiction by another).
- The Internet Gaming Disorder (IDG) [12], in 2014, consists of 20 items distributed within the Griffiths model.

Currently, one of the most used models is the Griffiths one. Dr. Mark Griffiths [13, 14] has been working on substance-free addictions since 1987. He then began his research on gambling before turning to video games, putting in parallel dependent games and excessive games. This notion is important because excessive play may result in inordinate enthusiasm but it can remain an added value for the patient's life. On the other hand, a dependent game is not exciting and is harmful to the patient's life. He then concludes that two people can play a lot but without having the same result. To be able to distinguish between these two behaviors, Griffiths' model is based on 6 components found in behavioral addictions. The components of the model are Salience (the game becomes the main activity or you think about it even when you don't play), Tolerance (the gear system the more you play the more you have to play to be satisfied), Withdrawal symptoms (a psychological or physiological problem when you can't play), Changing mood (It is by playing that you manage to control your negative mood), Conflict (problem in personal relationships to keep a playtime, or deletion of other activity to keep the play time), Relapse (failure to stop the game or increase the playing time when a new extension arrives or when a new game is released).

Today we consider that the most addictive video games are the «Massively Multiplayer Online Role-Playing Games» (MMORPG) [15]. The reason for a massive addiction to this type of game is that we often get rewards (reward circuit) which cause a craving and a desire for «more and more» in the game. One can easily make the parallel with the winnings obtained in games to scratch or chance. In some countries such as Belgium, video games that offer random rewards (called loot boxes) for money have seen their «Pan European Game Information» (PEGI) ranking go from +13 years to +

18 years as if the game were a game of money. In addition, another factor to be taken into account in MMORPG-type video games is membership in a group/community/guild. Joining a group of players dependent on each other to progress in the virtual adventure gives a sense of social obligation to always play more. Finally, a well-known business model in the world of video games is Free to play (F2P), by which we mean a free game that has an internal store to the game to buy bonuses (experience boosts, cosmetics, extra characters, etc.). This internal store is the only source of revenue for the game publisher, but it remains very prolific. For example, the Fortnite game generated more than $300 million in 200 days after its launch on IOS [16].

2.2 Process Mining

In recent years, the sum of digital data continues to increase with more than 33 zettabytes in 2018 [17] and The 2020 Data Attack Surface Report estimates data stored in the cloud will reach 100 zettabytes by 2025 [12]. This increase is not going to stop, on the contrary. Faced with this, the computer sciences have matured in the exploitation of this data, thus creating many promising research frameworks. In this context, no company can ignore business intelligence (BI). BI is defined as a set of tasks such as the collection, storage, processing, processing, and operation of data to assist in decision-making. The objective is to better understand the activity and the sector in which we are located (for example a company). In other words, collecting data is nothing new for the IT sector, but it is so important that this collection is almost systematic and crucial. Controlling your data is then a real competitive advantage.

Process mining [18] is a mixture of Business Process Management (BPM) and Business Process Intelligence (BPI). BPM [19] is a process-oriented field, which provides a global view of business processes. Among other things, it allows us to see how these processes (and the business that composes them) interact with each other. BPI is a recent discipline that emerged thanks to the emergence of data but also and especially to their varieties [20]. According to [15] the BPI can be described as a set of forecasting, control, analysis, audit, and optimization tools serving business users but also IT services to manage the quality of the organization's processes.

In process mining, the process search is based on the analysis of event logs. The objective is then to analyze them to extract new business processes that would not have been prescribed but used since defined via the collected data. Once identified, they can be monitored and/or optimized. There are several types of objectives in process mining: process discovery, conformance checking, enhancement, and recommendation. Following [15], the main advantages of these techniques are objectivity (we discover the real processes because they are based on event logs), compliance (between the formalized process and the actual process), speed, the predictions and simulations, and the transparency (just like objectivity, processes being extracted directly from logs it is possible to go into detail of a process knowing who did what, when and how). There are a lot of tools that offer process mining techniques [21, 22].

3 Experiment

To answer our research questions, we made an experiment (a method of data collection designed to test hypotheses under controlled conditions, to eliminate threats to internal validity [23]) with players of a video game classified as highly addicting, an MMORPG[2] called World Of Warcraft (WoW) which is one of the most played MMORPG in the world (millions of players, distributed in 244 countries and territories).

The process used in this experiment was as follows (Fig. 1).

- Our first step was to define a survey that will allow us to define if the person was addicted or not. Then we selected a specific group in the game and submitted the survey to our players.
- The second step was to collect the logs of these players to use in process mining tools.
- We were then able to make a cross-analysis to see if predictions about addiction via the recovered logs were possible.

Fig. 1. Method used

3.1 Survey

We used the method preconized in [24] for the survey part. The process is composed of several steps (Fig. 2) that we detail in this section.

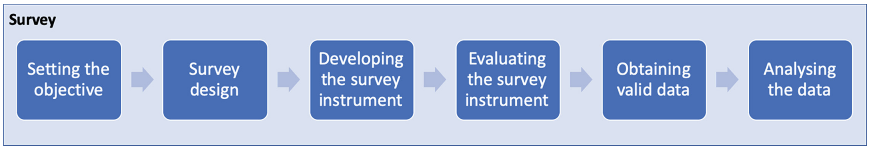


Fig. 2. Survey Process

Setting the Objective. Our goal is to be able to identify addicts and non-addict people in a specific group population of WoW players.

Survey Design. We ask for information at one fixed point in time, which means that our survey is *cross-sectional*, it gives a snapshot of the problem. The survey is a self-administered questionnaire where each participant is reached personally to increase the answering rate.

[2] MMORPG: Massively Multiplayer Online Role-Playing Game.

Developing the Survey Instrument. We identified the questions following several categories. The first one allows defining the respondent characteristics. The others are defined to identify the possible player addiction. The Griffiths model [13] is the most widespread model to wonder about the addiction of someone and we based our questionnaire on its 6 categories, as shown in Fig. 3.

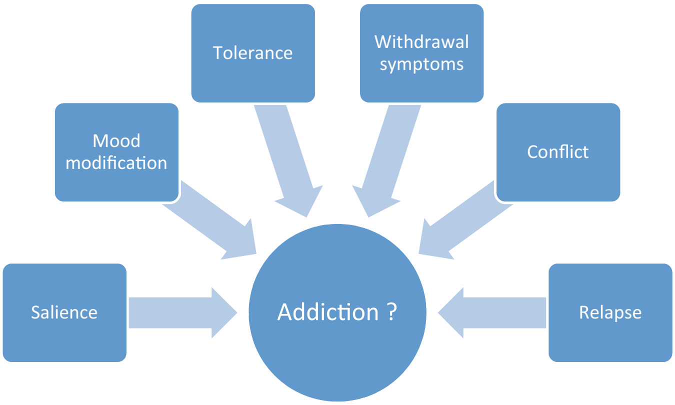


Fig. 3. Griffiths model elements (based on [13])

- *Respondent characteristics.* It is always useful to identify some characteristics of the respondent to be able to link answers to some profile.

  a. Gender (Male / Female)
  b. Age
  c. Pseudonym in the video game

- *Salience.* We wonder here about the importance of the playing activity compared to other usual ones in the person's mind.

  a. long sessions of games often interfere with sleep
  b. I usually think about my next game session when I do not play
  c. I think the game has become the most time-consuming activity in my life

- *Mood modification.* We report if the mood of a person changes when playing.

  a. I never play games to feel better
  b. I play to help me deal with any negative feelings I may have
  c. I play to forget everything that bothers me.

- *Tolerance.* This is more about the time spent in the game and if this one increase.

a. I significantly increased play time during the last year
b. I have to spend more and more time playing
c. I often think that a full day is not enough to do everything I need to do in the game

- *Withdrawal symptoms.* These are the mood symptoms that declare themselves when the person is not able to play as usual.

a. When I don't play, I feel more irritable
b. I feel sad if I am not able to play
c. I tend to become anxious if I can't play for any reason

- *Conflict.* We refer here to all possible conflicts, either with other people but also with other activities, or even inside the person's mind if they realize they might have a problem.

a. I lost interest in other hobbies because of my game
b. I lied to my family members because of the amount of time I spend playing
c. I think my game has jeopardized my relationship with my partner
d. I know that my main daily activity (work, education, responsibilities at home, etc.) has not been negatively affected by my game.
e. I believe my game harms important areas of my life.

- *Relapse.* When a person has realized he's an addict, succeeds to escape this addiction but comes back to it again.

a. I would like to reduce my playing time, but it is difficult
b. I don't think I could stop playing
c. I often try to play less, but I see I can't

The interviewees were able to answer on a Likert scale with the following values: Strongly disagree, Disagree, no opinion, Agree, Strongly agree.

Evaluating the Survey Instrument. We checked if the questions were understandable by asking some other people what they were understanding exactly. We made several testing to check the effectiveness of the follow-up procedures, and the reliability and validity of the questionnaire.

Obtaining Valid Data. On World of Warcraft, players are organized in guilds. Guilds participate in various events available in the game. These events require 40 players. So the logs that we were able to retrieve were flagged under the name of a specific guild (player group). We choose a specific guild called Inglorious, composed of 49 persons with a middle age of 31. Each of them was personally reached out and asked to fill out the form, and 43 accepted to do it.

Analyzing the Data. Once the questionnaire has been filled, we gave a ponderation to each of the answers as follows: Strongly agree *5, Agree *4, No opinion *3, Disagree

*2, and Strongly disagree *1. As a result, people having a score superior to 60 will be considered addicts, which was the case for 15 respondents. These results were communicated to the players who (quite honestly) validated the founding. This analysis answers the first research question.

3.2 Process Mining

We followed the first steps of the PM2 methodology [25] as shown below (Fig. 4).

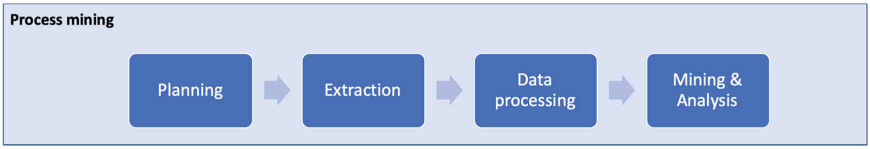


Fig. 4. Process mining methodology

Planning. The objective is to discover process models in the WoW game, to be able to compare the behaviors of addicts or non-addict people.

Extraction. There is a website[3] that provides a tool to record the logs of a WoW group to analyze the actions done by each player. Via this site, it is possible to analyze all the uploader data for a group, and offers different player-by-player metrics (who did the most damage, the most care, which skill was executed, and so on). The real objective of this site is to offer metrics on who does better and thus offer competition between players. We downloaded one complete month of data for the chosen guild whose members answered our survey.

Data Processing. The obtained CSV files only give two columns: the timestamp and a text chain (Fig. 5). This text chain follows several patterns (Fig. 6) that can be defined as follows: P1 (Name - Skill - Target – Amount), P2 (Name - Class - Skill – Target), P3 (Name - Win - Bonus - Source – Skill), P4 (Name - Swings-At – Target). We decomposed each of these text chains to create several useful columns.

[3] https://www.warcraftlogs.com/.

1	Time	Event
2	00:00:03	Stalfos Charge étourdissante Géant de lave 2 Immune
3	00:00:03	Stalfos casts Charge on Géant de lave 2
4	00:00:04	Stalfos gains 15 Rage from Stalfos's Charge
5	00:00:04	Stalfos's Posture de combat fades from Stalfos
6	00:00:04	Stalfos gains Posture berserker from Stalfos
7	00:00:04	Stalfos casts Posture berserker
8	00:00:04	Stalfos swings at Géant de lave 2
9	00:00:04	Stalfos Melee Géant de lave 2 318 Glancing
10	00:00:06	Stalfos casts Tourbillon
11	00:00:06	Stalfos Tourbillon Géant de lave 2 *682*
12	00:00:06	Stalfos Tourbillon Géant de lave 1 *534*
13	00:00:07	Stalfos gains Rafale from Stalfos
14	00:00:07	Stalfos's Rafale is refreshed by Stalfos

Fig. 5. Log sample from Warcraftlog

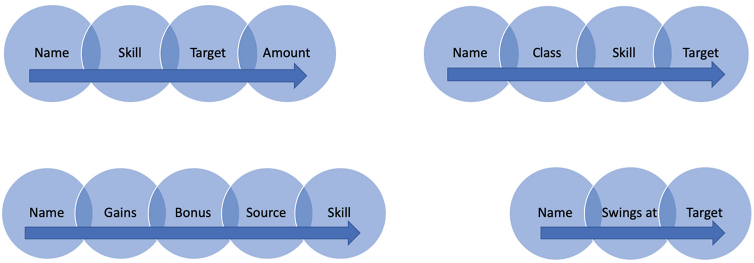


Fig. 6. Logs patterns

Another problem had to be solved in the logs export. We can export the logs of a fight (a fight is a very current event and does not represent much at the scale of the game session). To have a sufficiently consistent measurement we had to export a large number of CSV files to have the equivalent of a game time in hours. For example, extracting a player's logs for a game time of 2h23 on 16 October 2019 requires 98 CSV files. We then had to merge all the CSV files into a single file.

Mining and Analysis. We used Disco to discover the generic process model of the game players. However this was not significant as, in WoW, each player is a member of a specific class and we know that the player's role behavior is strongly dependent on this class. We then decided to analyze each class behavior separately and discovered the corresponding process models. This gives some insights into the real sequences between the various possible activities of each class member, which can help players to adapt their behavior when sharing a session with other people.

3.3 Cross Analysis

In this part, we tried to identify some relationship between the results of the survey and the process models obtained in the logs.

Let's take the example of the Warrior class. We had 6 players playing this role in our dataset. We used process mining techniques to identify the behavior of the class and the behavior of each of these 6 persons for all the quests. We then compared the models and the questionnaire results. Figure 7 shows the behavior obtained for the most addicted player in the group.

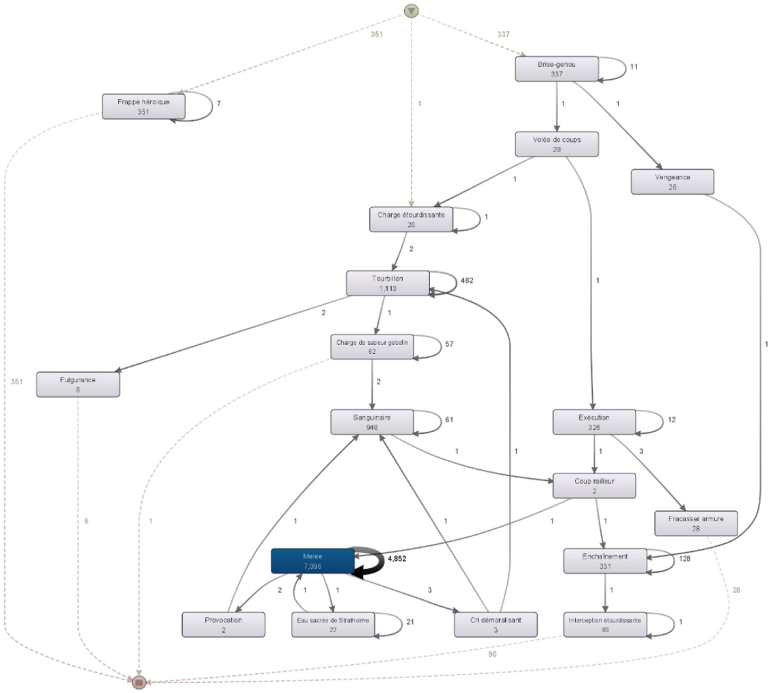
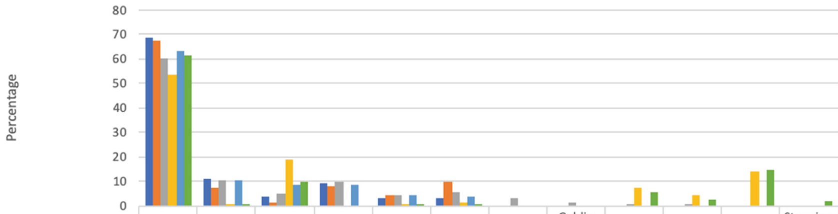


Fig. 7. Most addict player's behavior (Player 1)

However, when looking at the generic warrior discovered process model or all the behaviors of the class players, no conclusion can be made. The behaviors are quite different from one player to the other and we found that addict players don't play in the same way as the other addicts. The same conclusion can be drawn with all the different classes of the game.

Disco software provides several metrics such as the occurrence of each event. We extracted these metrics to analyze them (Fig. 8). Let's consider the first Melee event. This event is the basic attack of the Warrior class and means that as long as the player is in range he will attack automatically. We note however that the distribution between automatic attacks and non-automatic events is different depending on the players. Indeed, player 1 and player 2 scores mean that they spent this percentage of time letting their character attack alone. Unfortunately, looking at these metrics doesn't allow us to identify a link with addiction: players 1, 3, or 5 are addict players in this group but some of their metrics are similar to the non-addict players 2, 4, or 6.



	Melee	Swirl	Heroic strike	Bloody	Executio n	Successio n	Shadow bolt	Goblin sapper charge	Revenge	Smash armor	Shield slam	Stunning winnowi ng
Player 1 (addict - 89)	68,82	10,79	3,4	9,19	3,16	3,21	0	0	0	0	0	0
Player 2	67,77	7,15	1,02	7,98	4,5	9,55	0	0	0	0	0	0
Player 3 (addict - 64)	60,22	10,38	4,67	9,48	4,09	5,53	2,86	1,46	0,35	0,08	0	0
Player 4	53,68	0,07	19,02	0	0,03	1,01	0	0	7,07	4,44	14,11	0
Player 5 (addict - 69)	63,51	10,61	8,71	8,26	4,06	3,42	0	0	0	0	0	0
Player 6	61,49	0,8	9,79	0	0,03	0,02	0	0	5,69	2,71	14,57	1,68

Fig. 8. Occurrence percentage of the most significant actions for the group players

Threat to Validity. [26] proposes five categories of validity. To minimize the impact of the validity threats that could affect our study, we present them with the corresponding mitigation actions in the following.

- **Descriptive validity** refers to the accuracy of the data. We unified the concepts used in the study and structured the information to be collected with a data extraction form to support a uniform recording of data.
- **Theoretical validity** depends on the ability to get the information that it is intended to capture. (1) We addressed a specific group in the game to be able to contact them personally to assuring the most honest responses for the survey. (2) We used WoW applications to extract the logs of interest.
- **Generalization validity** is concerned with the ability to generalize the results. This is where there is the most threat of validity as the logs were only taking into account the actions made for specific quests, not all the data from each player when he was playing the game (the tool used to record the logs had to be started by the player when a quest is launched to record its statistics, which he doesn't do if there is no quest on the run). Moreover, concentrating the dataset on only one group restricts the number of players in each class, which doesn't give enough data to use correctly process mining techniques.
- **Evaluative validity** is achieved when the conclusions are reasonable given the data. (1) Two researchers studied the results independently to identify potential analysis differences. (2) At least two researchers validated every conclusion.
- **Transparency validity** refers to the repeatability of the research protocol. The research process protocol is detailed enough to ensure it can be exhaustively repeated.

4 Conclusion

In this work-in-progress paper, we focused on the study of addiction in video games using process mining techniques as a detection tool. We studied and specified what is an addiction and more precisely what is a video game addiction. As explained, addictions without an active chemical substance are different from others based on a 100% behavioral addiction. We then analyzed event logs on a video game known as particularly addictive (WoW). With a questionnaire, on a set of forty people playing this game, we were able to identify people as addicts or not. After exporting and analyzing their logs we cross-checked these results with the questionnaire responses to identify whether one or more metrics would be viable to say whether a person is addicted or not.

Unfortunately, according to this analysis, no available metrics were relevant. The process model obtained for each player is quite different from the others and no specific deviation can be found. Some addict players have very high metrics, as not addict payers. Some addict players have low rates, as not addict players. It was then impossible to define a typical behavior pattern that would highlight the addiction of one player compared to another.

Based on this initial analysis, we will extend our data set by collecting more data on this game by contacting other players of other groups. Process mining uses statistical techniques, so it is necessary to work on a lot of data to have objective results. It may also be appropriate to move towards another analysis type. In this type of game we know that players try to reproduce a cycle of action that is as optimal as possible depending on their goal (e.g.: doing the most damage, giving the most care, and so on). A second hypothesis would be to identify the optimal process and measure the gap between this prescribed process and the player's behavior. We could see if the addict players manage to better respect the optimal path or not and thus can highlight one or more metrics to identify these players.

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