ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Data Science and Marketing Analytics

The exploration of the motivations of problematic engaged viewers and engaged viewers in live streaming of games.

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Date final version: 29-04-2020

Abstract

Purposes The aim of this study is to identify problematic behavior among Twitch users. The central research question is: *'Which motives and types of engagement are associated with problematic use of Twitch viewers?'.* To answer the research question there are three sub categories analyzed: (1) to identify the types of engagement of Twitch viewers and to identify if one of the types is problematically engaged with Twitch; (2) to determine associations between motivations to use Twitch and the identified types of engagement; (3) to determine associations between behavioral engagement elements and the identified types of engagement.

Methods The sample of the study includes 329 respondents in an age range of (13 - 48) and 84.5% of the respondents is male. The data collection took place from September to October 2019. The data was collected through the use of an online questionnaire using different measurement scales to identify problematic use of Twitch, motivations to use Twitch and behavioral engagement elements for Twitch. The data was analyzed by simultaneously optimizing a Multiple Correspondence Analysis together with a K-means clustering analysis to identify the engagement types. A descriptive analysis is used to describe associations with the identified types of engagement and the behavioral engagement and motivations.

Results Based on the tuning the MCA K-means on the Silhouette width, three clusters were identified: non-engaged viewers (43.8%), engaged viewers (48%) and potentially problematic engaged viewers (8.2%). The clusters have been found stable and well separated based on a bootstrap with the Jaccard coefficient.

Conclusion Potentially problematic engaged tend to have stronger motivations to use Twitch. Differences in associations have been found for motivations between potentially problematic engaged viewers and other viewers. Problematic engaged viewers tend to have higher motivations towards entertainment, relax, companionship, distraction and escape in comparison to other viewers. There were no indications found that behavioral engagement elements are likely to differentiate potentially engaged viewers from engaged viewers.

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1 Introduction

Live streaming of video games has become popular over the last years. Since then Twitch has become the largest live streaming platform for video games and for hosting the gaming community (Hamilton, Garretson, & Kerne, 2014). Twitch has 15 million unique visitors daily and they spend on average 95 minutes watching live streams (Twitch, 2019). Other live streaming platforms such as Youtube Live are significantly smaller and the audience engages less hours in the platform (Perez, 2019). It has become an important leisure activity to quiet a lot of people.

Getting people 'hooked' to a channel might be the goal of every streamer, so they become regulars to their channel (Clark, 2017). These live streaming platforms, such as Twitch, have the aim to entertain their users daily as many hours as possible on their platform to be relevant for their adverts (Khan, 2020; Twitch, 2020). The platform and streamers learn about the preferences of their viewers to increase user time. Technologies become more advanced and more addictive and therefore increases the likelihood of harmful use (Alter, 2017).

In extreme cases people involving in live streams continuously and repeatedly could become compulsive with having negative consequences like having an addiction(Deleuze, Long, Liu, Maurage, & Billieux, 2018). In related fields such as binge-watching (want to watch one more video), gaming and social media use, there are concerns about the consequences on mental well-being of the users(Deleuze et al., 2018; Flayelle et al., 2019; Kuss & Griffiths, 2011). Therefore, this paper wants to contribute to the ethical side of the usage of Twitch.

1.1 Available literature

There have been researches to problematic use of Facebook (Andreassen, Torsheim, Brunborg, & Pallesen, 2012), Tinder (Orosz, Tóth-Király, Bőthe, & Melher, 2016), series watching (Orosz G, Bőthe B, & Tóth-Király I, 2016). These approaches have been based on problematic-like behaviors, but other papers criticize them for neglecting the uniqueness of the behavior (Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015; Flayelle et al., 2019; Kardefelt-Winther et al., 2017). They argue that researches mostly focus on the identification of potential similarities with other forms of addiction, thus cause potential overpathologization (= to overrepresent the activity as a disease) of non-harmful engaged activities.

According to Flayelle et al. (2019), including the unique motivations decrease the risk on potentially overpathologizing of normal behavior. Motivations have been found important predictor in earlier research when distinguishing healthy from problematic binge-watching behavior and as well from problematic gaming behavior (Deleuze et al., 2018; Flayelle et al., 2019). Therefore, this research takes live streaming motivations into account when distinguishing problematic behavior from (high) engagement. There has been studies about the motivations of consumption of live streaming. These studies found significant associations for motivations of the Twitch audience in connection to increased engagement in Twitch (Hilvert-Bruce, Neill, Sjöblom, & Hamari, 2018; Sjöblom & Hamari, 2017). Problematic involvement, such as addiction or obsessive use, has not been explored for viewers of Twitch. Therefore, research fields of other leisure activities such as gaming and watching tv will be used to identify problematic usage of Twitch.

1.2 The present study

This study tries to contribute to the ethical discussion of getting people hooked to their live streaming platform. The problem statement is as following:

How to identify problematic use of Twitch.

The focus of this research is to explore if there are differences in the behavioral characteristics and motivations to distinguish the problematic use from the normal engaged use for the viewers of gaming live streams. Reasons for excessive behavior could be different diseases such as impulse-control disorders, coping strategies, obsessive-compulsive disorders or it could be normal behavior (Kardefelt-Winther et al., 2017). These different diseases overlap in their symptoms and are not well distinguished from each other(Kardefelt-Winther et al., 2017). This research will not be focused on the distinction between diseases, but on the typology of problematic behavior and to separate it from normal behavior when people are interacting in gaming live streams. The unique motivations to use Twitch are included to understand if these differ between (high) engagement and problematic behavior.

1.3 Research questions

The research question for this study is as followed:

‘Which motives and types of engagement are associated with problematic use of Twitch viewers?’

To support the main research question the following sub research questions are created:

1. What subgroups of engagement of Twitch viewers can be segmented and which of these groups can be identified as problematic?
2. What behavioral engagement are associated with the identified subgroups of Twitch viewers?
3. What motivations are associated with the identified subgroups of Twitch viewers?

The research questions will be answered with help of literature research and quantitative research. A survey will be conducted based on criteria found in the literature review, these items will be presented in chapter 3 measurements.

1.4 Structure

The structure for the remaining part of this study is as followed. Chapter 2 explains the background of live streaming, engagement, behavioral addiction and how motivations connect to the types of engagement. Chapter 3 describes the indicators to distinguish problematic engaged viewing behavior from engaged viewing behavior, to identify the motivations of Twitch usage and to identify the behavioral engagement elements. Next to that, it will provide insides in the participants and the process of the data collection. Chapter 4 will explain the methodology of the data analysis. Chapter 5 will show the results of the data analysis. In chapter 6 the conclusion will be presented. Chapter 7 will present the discussion.

2 Background

This chapter describes what is live streaming, engagement, problematic behavior, and motivations. Next to that, the discussion on normal and problematic behavior will be described as well.

2.1 Live streaming

Live streaming of games should be seen in a broad context. Video games has been seen differently from television or movies in research (Dovey & Kennedy, 2006). However, through the development of live streaming of games they grow closer towards each other (Johnson & Woodcock, 2018).

Live streaming gives the opportunity to create user-based content by broadcasting a stream where other viewers can see streamers perform (Bründl & Hess, 2016). Gamers are often the live streamers, within their live streams they can show their gaming techniques and unique personalities(Hamilton et al., 2014). The streamers often have a webcam and can broadcast their own screen and stream it directly. The platform integrates a chat box with these live video's. Other gamers can view and communicate with the streamer and other viewers simultaneously (Hamilton et al., 2014). As a consequence of live streaming people can engage with the game not only through playing but also as a spectator (Johnson & Woodcock, 2019).

Previous research explored behavioral engagement of viewers with Twitch streamers (Hilvert-Bruce et al., 2018; Sjöblom & Hamari, 2017). These studies have shown that behavioral engagement in live streaming can be done with spending time in streams, chatting, donating, cheering and subscribing to channels. The main difference between donations and subscriptions is donations give only financial support to the streamer but give no extra benefits in the platform for the donator. Sometimes there are shout outs to the donators in the video. A subscription is a monthly financial support that also could give you a badge and additional emoticons to that specific stream(Hilvert-Bruce et al., 2018).

2.2 Engagement

In this study the engagement construct will be explored to identify when someone is (highly) engaged with live streaming. Video game live streams can be categorized as a passive leisure activity. Leisure activities are generally engaged in for comparable reasons (Flayelle et al., 2019). Schaufeli (2017) defines general engagement as *'positive, fulfilling state of mind that is associated with performing daily activities of any sort and is characterized by vigor, dedication and absorption '(*p. 11*)*. These constructs are explained as followed:

Vigor - Vigor is the physical-energetic engagement element. Meaning, that someone has high degrees of energy and high mental flexibility while engaging in an activity and the will to devote time and energy in the activity (Schaufeli, 2017).

Dedication - Dedication is explained by the emotional engagement, characteristics are being heavily involved in the activity and having positive feelings such as inspiration, enthusiasm and significance (Schaufeli, 2017).

Absorption - Absorption is the cognitive engagement. It is characterized by an increase of concentration levels, a feeling of losing track of time and being consumed by the activity. It is difficult to disengage with the activity (Schaufeli, 2017).

According to Schaufeli (2017), the characteristics of high engagement are similar to being passionate. Vallerand et al. (2003; p. 757) defines passion as followed:

"a strong inclination toward an activity that people like, that they find important and in which they invest time and energy".

Vallerand et al. (2003) identifies a dual type of passion: harmonious passion and obsessive passion. Both types of passion are equally passionate (Vallerand, 2015). They argue that the dualistic concept is caused by how the activity is internalized into someone's identity. According to Ryan & Deci (2000), there are three basic psychological needs to be satisfied: autonomy (= the desire act in harmony with their identity), competence (= the desire to control the result) and relatedness (= the desire to be connected to significant others). These basic needs are related to engagement in activities (Schaufeli, 2017; Vallerand et al., 2003).

Vallerand et al. (2003) describes harmonious passion as a strong devotion to freely occupy themselves in an activity. So, the person is autonomous about engaging in the activity. Harmonious passion leads to positive emotions, an increase of concentration and flow (= a feeling of being in the zone having full involvement and enjoyment) during the activity. They don't have negative feelings when prevented from playing and feel in general positive in their life (Vallerand et al., 2003). People with an obsessive passion have strong desire to engage a significant time in the activity and they cannot stop doing the activity (Vallerand et al., 2003). The activity is actually controlling the person. Due to the loss of control the activity takes an excessive part of their identity and they have conflicts with other activities (Vallerand et al., 2003).

People who are harmonious passionate are not correlated with negative affect when they cannot engage in the activity (Vallerand, 2003). Next to that, harmonious players stop playing when they have other important things to do (Wang & Chu, 2007). According to Schaufeli (2017), engagement and harmonious passion overlap and would not predict problematic watching behavior.

2.3 Problematic engagement

The addiction literature and passion literature are used to understand problematic engagement. Marlatt, Baer, Donovan, & Kivlahan (1988, p.224) defines addictive behavior as followed:

"…a repetitive habit pattern that increases the risk of disease and/or associated personal and social problems. Addictive behaviours are often experienced subjectively as "loss of control" – the behaviour contrives to occur despite volitional attempts to abstain or moderate use. These habit patterns are typically characterized by immediate gratification (short-term reward), often coupled with delayed deleterious effects (long-term costs). Attempts to change an addictive behaviour (via treatment or selfinitiation) are typically marked with high relapse rates."

Griffiths bases his criteria on substance addictions and relates them to behavioral addictions. In earlier research Griffiths (1996) argues that there is never enough criteria to understand all cases of addictive behavior. Griffiths (2005) argue that most addictions consists of six core aspects namely: salience, mood modification, tolerance, withdrawal, conflict and relapse. Griffiths (2005) argues within this model that when the six criteria are met in any behavior this could be defined as an addiction.

Different addiction scales for leisure activities to describe excessive and compulsive use have been created based on Griffiths (2005) in the recent years, for problematic series watching (Orosz, Bőthe, & Tóth-Király, 2016), problematic usage of Tinder (Orosz, Tóth-Király, Bőthe, & Melher, 2016) and problematic use of Facebook (Andreassen, Torsheim, Brunborg, & Pallesen, 2012).

Distinguishing between addiction and engagement is still a highly debated discussion within behavioral addiction. Billieux et al. (2015) argue that daily activities are overpathologized, meaning that normal engagement is turned into behavioral addiction. They argue that a lot of behavioral addiction symptoms are assessed with proven substance addiction researches, however they neglect important mental processes that people endure when having dysfunctional behavior. According to Flayelle et al. (2019), including the uniqueness of the problematic behavior by including motivations will improve the distinction between highly engaged viewers and problematic engaged viewers.

Deleuze et al. (2018) argues that engagement and addiction are related, however can be separated from each other. Both highly engaged and addictive gamers correlate with the symptoms of internet gaming disorder (Deleuze et al., 2018; Przybylski, Weinstein, & Murayama, 2017). The differences between highly engaged gamers and problematic engaged gamers are reduction of control and depression symptoms. These are associated to problematic engagement (Deleuze et al., 2018). This is also in line with the identification of obsessive passion of Vallerand et al. (2003). They feel a negative affect and decreasing levels of concentration when prevented from doing the activity. There are multiple researches that concluded that obsessive passion is associated with problematic behavior in video gaming (Wang & Chu, 2007;Stoeber, Harvey, Ward, & Childs, 2011).

2.4 Taking motivations into account

Taking motivations into account for Twitch usage is an important step to explore if the behavior is normal or problematic. Vallerand (2015) argues that key underlying aspects of passion are motivations. Flayelle et al. (2019) argues that motivations support the distinction between problematic behavior and (high) engaged behavior when researching problematic leisure behaviors. According to Flayelle et al. (2019), the need for information and entertainment are predictors for (high) engagement. Padhy et al. (2015) argues exploration or understanding something new also contribute to well-being. Flayelle et al. (2019) argues when people satisfy the need for entertainment it increases their well-being and they have positive emotional experiences. Also, motivations for personal enrichment, containing the learning aspect and to rise to their full potential, are positively associated with engagement (Flayelle et al., 2019).

According to Hamilton et al. (2014), there are two main reasons why people are engaging in live streams: the content of broadcaster/channel and the interaction with the community within. Hu, Zhang, & Wang (2017) specifies it further to a personal identification with the broadcaster, a group identification creating together a co-experience or a fandom culture(=where viewers see their broadcaster as their idol). They argue that viewers of the gaming live streams that are associated with group identification are also fans of the games, which tends to increase group communication and group engagement with in the live stream.

The motivations found to increase behavioral engagement levels of Twitch viewers significantly were social(Hilvert-Bruce et al., 2018), enjoyment, relieving stress, escaping the real-world and gaining knowledge (Sjöblom & Hamari, 2017).

Increasing time spent on channels are correlated with social interactions(Hilvert-Bruce et al., 2018). Motivations to donate and subscribe to specific broadcasters are associated with the sense of community and social interaction (Hilvert-Bruce et al., 2018). This is in line with Sjöblom & Hamari (2017), they argued that the audience want to share their experiences and want to have deeper connection with the community and satisfy these needs by subscribing.

Social motivations are complex and can serve for (high) engagement and problematic engagement. In the research of Hilvert-Bruce et al. (2019), there are correlations found between people with less social interactions offline and an increase in their time on Twitch. According to Flayelle et al. (2019), this could potentially be harmful as loneliness is correlated with problematic behavior. However, social interaction motivations and making online friends are potentially linked to positive engagement as

Twitch viewers can talk about their hobby, such as football players like to talk about football (Charlton, 2002).

Tension release have been found associated with problematic binge watching. However, there is a distinction between mental disorders and temporary motivations to deal with personal problems, because temporal coping can also be beneficial (Flayelle et al., 2019).

2.5 Conclusion

To measure engagement it is important that highly engaged viewers that have control over the activity are also included in the definition of engagement. Therefore, engagement will follow the definition of harmonious passion of Vallerand (2003). Someone is engaged when a viewer is passionate about an activity they have the free will and desire to engage and the person is autonomous about engaging in the activity.

Although, Griffith (2005) is criticized for overpathologizing normal behaviors it is still often used in the literature for identifying problematic behaviors that are related to gaming live streaming such as Facebook, gaming and Tinder. Due to difficulties with distinguishing problematic engaged viewers and engaged viewers the obsessive passion of the Passion Scale of Vallerand (2003) is also used as it is known for the dual construct of engaged viewers behavior and problematic viewers behavior.

To measure the unique aspects of live streaming, the following motivations are used: tension release, social enrichment, personal enhancement, information and entertainment. These motivations fit with the unique characteristics of using Twitch and are also found important to separate problematic engagement from normal (high) engagement. The assessing criteria for input in the data collection will be discussed in the next chapter.

3 Measurements

This chapter continues with the operationalization of the concepts of motivations, problematic behavior and engagement. Next to that, the participants and procedure of the data collection is explained.

3.1 Engagement

In the previous chapter we have seen that passion is divided in two types: harmonious passion and obsessive passion. In the following subsections the measurement of these will be discussed.

3.1.1 Level of engagement

To measure engagement of Twitch it has to reflect the elements of passion of Vallerand et al. (2003). Therefore, items have been included to measure the level of engagement with Twitch, because the dual structure of being harmonious passionate has been supported in different fields with the condition that someone is identified as passionate (Vallerand, 2015). Passion is characterized to have a strong desire to use Twitch and to have Twitch as a part of their identity. They love to spend time on Twitch and to put energy into Twitch on a regular basis.

5-items of the Passion Scale are used to reflect passion. The wording 'this activity' of each item has been replaced by 'Twitch'. To be identified as passionate these criteria are summed and the sum has to be on or above the midpoint (Vallerand, 2015). Usually, the Passion Scale is answered on a 7-point Likert scale, however respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree. Due to the consistency needed for the statistical analysis.

3.1.2 Harmonious engagement

To measure (high) engagement the construct of harmonious passion is used (Vallerand et al., 2003). Harmonious passion is characterized by free will. It interacts harmoniously with other important activities and activities that are part of themselves (Vallerand et al., 2003). Harmonious passion is not related to the loss of control as it is a choice of free will and they are autonomous about the time they spend on the activity.

To assess (high) engagement 6-items reflecting harmonious passion of the Passion Scale are used (Vallerand et al., 2003). Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

The wording 'this activity' of each item has been replaced by 'Twitch'. Three items have been modified based on the recommendations of test subjects that use Twitch (e.g. 'Watching Twitch is in harmony with other things that are part of me' and 'Watching Twitch is in harmony with the other activities in my life'). The word 'harmony' confused them about the meaning of the sentence, this has been replaced by the word 'balance'. Next to that, the question 'Watching Twitch is the only thing that really turns me on'. The test subjects were confused by the words 'turns me on' and interpret the meaning differently than it was intended. Therefore, it has been changed to 'excites me'.

3.1.3 Obsessive engagement

For every harmonious criteria there is also a opposite criteria created to measure obsessive engagement (Vallerand et al., 2003). These are based on the loss of control, the activity controlling them and the conflict with other activities and themselves.

To assess obsessive passion 6-items of the Passion Scale are taken (Vallerand et al., 2003). The wording 'this activity' of each item has been replaced by 'Twitch'. Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.2 Problematic behavior

The criteria to assess problematic behavior need to make a clear distinction with engaged behavior. Therefore, Bergen Social Media Addiction Scale(BSMAS; Andreassen, Pallesen, & Griffiths, 2017) is used because the scale reflects the criteria of Griffiths (2005) and was validated in a large sample about social media (Bányai et al., 2017). In this study the overall accuracy of predicting problematic behavior performed well (Bányai et al., 2017). In the next subparagraphs will be explained how problematic viewers behavior is measured.

3.2.1 Salience

Under salience is understood that an activity becomes the person's most important activity in their life. The activity takes over most of their thinking, feelings and behavior(Griffiths, 1996). If they are not doing the activity they think about the next time they are going to do it (Griffiths, 1996). Indicating criteria is a high frequency, doing the activity at least once a day and thinking about the next time doing it (Griffiths, 1996). Thinking about your hobby is also connected with social talk about the hobby with friends but also with high achievers that want to improve by thinking about tactics (Ko, 2014).

Salience is measured by the frequency of thinking about Twitch or planning to how they are going to use it during the last year (BSMAS; Andreassen, Pallesen, & Griffiths, 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.2.2 Mood modification

Mood modification applies to the changes in the state of mind by doing the activity (Griffiths, 1996). Symptoms for behavioral addictions are having a buzz when engaging in the activity (=also called euphoria criterium) or to make themselves feel better by escaping from negative feelings such as depression or guilt(Griffiths, 1996). In research of gaming the criteria of euphoria does not distinguish behavioral addiction well (Charlton, 2002). Excitement is part of positive emotions that reflect engaging behavior (Schaufeli, 2017; Deleuze et al., 2018). Also, Flayelle et al. (2019) argues that regulating their mood by binge-watching is an important predictor for problematic behavior.

Mood modification is measured the frequency during the last year they used Twitch in order to forget about personal problems during the last year (BSMAS; Andreassen, Pallesen, & Griffiths, 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.2.3 Tolerance

Tolerance applies to need more time doing the activity to achieve the initial effects (Griffiths, 1996). Symptoms of tolerance are engaging longer in the activity than expected or not being able to stop when engaging in the activity (Petry et al., 2014). The tolerance criteria are more associated with engagement than addiction symptoms, because these criteria describe milder addiction symptoms

(Charlton & Danforth, 2007). When people are doing an activity already excessively, they are unable to increase the number of hours involved doing the activity, but they have diminished satisfaction when engaging in the activity (Ko, 2014). Someone who is engaged with an activity should not have a decreasing enjoyment, as they would optimize their well-being.

Tolerance is measured by the frequency of feeling the urge to use Twitch more and more during the last year (BSMAS; Andreassen, Pallesen, & Griffiths, 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.2.4 Withdrawal

Withdrawal is relevant when someone is prevented from doing the activity. Symptoms could be having psychological effects (such as irritation or moodiness) or having physiological effects (headaches, nausea or other stress-related effects) when prevented from playing (Griffiths, 1996). Griffiths et al. (2016) argues that withdrawal symptoms are best measured by blood-pressure measurements. You are able to measure craving symptoms or having the withdrawal symptoms including a period of time in self-reports. However, it is limited to the extent of predicting problematic behavior (Griffiths et al. 2016; Charlton, 2002).

Withdrawal is measured by the frequency of becoming restless or troubled if you are prohibited from using Twitch during the last year(BSMAS; Andreassen, Pallesen, & Griffiths, 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.2.5 Conflict

Conflict applies to lack of time for other activities or people causing conflict (Griffiths, 1996). Criteria should include that different aspects of life (family, education, work, health) are harmed significantly in the long-term (Kardefelt-Winther et al., 2017). Next to that, excessive use is less important than interference with important life tasks (Flayelle et al., 2019).

Conflict is measured by the frequency of conflict in their job/studies during the last year (BSMAS; Andreassen et al., 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.2.6 Relapse

Relapse applies to tendency returning back to excessive use of the activity when losing control (Griffiths, 1996). Reduction of control is an important predictor for problematic behavior and is not associated with normal (highly) engaged behavior (Deleuze et al., 2017; Flayelle et al., 2019; Vallerand et al., 2003).

Relapse is measured by the frequency of trying to cut down on the use of Twitch without success during the last year (BSMAS; Andreassen et al., 2017). Respondents answered this item on 5-point Likert scale ranging from (0) never to (4) very often.

3.3 Behavioral engagement

To measure behavioral engagement with Twitch, indicators have been taken from Hilvert-Bruce et al. (2018). Items included to measure behavioral engagement are: amount of hours watched, number of channels following, amount of viewers of favorite channel, time subscribed and donations (Hilvert-Bruce et al., 2018). The behavioral engagement elements have been measured with open questions.

3.4 Motivations

In the following sub paragraphs the measurements for the motivations are described. The motivations that will be discussed are information, entertainment, tension release, personal enhancement and social motivations.

3.4.1 Information motivations

The cognitive motivations are explained by seeking information and knowledge (West & Turner, 2010). Identified criteria for Twitch are learning about new games and strategies (Hilvert-Bruce et al., 2018; Sjöblom & Hamari, 2017). The learning aspect only has a small effect on the number of hours watched (Sjöblom & Hamari, 2017).

To assess information motivations 4-items of Hilvert-Bruce et al. (2018) are used. They adapted the items from Chang & Zhu (2011) changing the words ‘Social Networking Sites’ to ‘Twitch’. These items include both learning aspect for new games as learning about new strategies. Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.4.2 Entertainment motivations

The affective motivation is explained with the need for entertainment (West & Turner, 2010). Sjöblom & Hamari (2017) identifies the positive emotions that result from using Twitch. The entertainment motivations are associated with increasing hours of using Twitch (Sjöblom & Hamari, 2017).

Entertainment motivations are measured with four items from Sjöblom & Hamari (2017). These items were adapted by Sjöblom & Hamari (2017) and are taken Venkatesh (2000). Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.4.3 Personal enhancement motivations

Personal enhancement motivations is explained by increasing status or confidence (West & Turner, 2010). Sjöblom & Hamari (2017) specifies this to the recognition in the channel by for example having influence on the streamer and other viewers in the chat box. Personal enhancement motivations are correlated with decreasing number of hours watching live streams (Sjöblom & Hamari, 2017).

Personal enhancement motivations are measured with four items from Sjöblom & Hamari (2017). The items come from Hernandez, Montaner, Sese, & Urquizu (2011) and have been adjusted to Twitch viewers. Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.4.4 Social motivations

Social motivations are explained by enhancing connections (West & Turner, 2010). Twitch is used as a third place where communities are created and formed, therefore social motivations are important (Hamilton, 2014). Social motivations are split into separate motivations to use Twitch by the two studies that research behavioral engagement in Twitch (Sjöblom & Hamari, 2017; Hilvert-Bruce et al.,2019). Sjöblom & Hamari (2017) identified the importance of the motivations companionship (= to feel less lonely) and shared emotional connection (= to feel part of the Twitch community). Hilvert-Bruce et al. (2019) also includes the importance of friendship motivations such as the need for social interactions (= having meaningful online connections) and meeting new people. Social anxiety or social support did not significantly influence behavioral engagement, therefore these will be excluded from this research.

The social motivation measurement is divided into four categories: companionship, social interaction, community and meeting new people. Companionship is measured with 3-items and community is measured with 5-items. These items have been taken from Sjöblom & Hamari (2017). They took and modified the companionship items from Smock, Ellison, Lampe, & Wohn (2011) and the community items have been adjusted from Chavis, Lee, & Acosta (2008).

3-items measuring social interaction and 3-items measuring meeting new people have been taken from Hilvert-Bruce et al. (2018). This study took and modified the meeting new people items from Chang & Zhu (2011). Next to that, they took and modified the social interaction items to ‘Twitch’ from Chiu, Hsu, & Wang (2006). Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.4.5 Tension release

Tension release is described by escaping the real-world and diversion (West & Turner, 2010). Sjöblom & Hamari (2017) identifies relaxation, distraction and escapism as criteria for tension release. These criteria positively influence the number of hours live streaming, number of streamers watched and followed.

Tension release is measured with 9-items from Sjöblom & Hamari (2017). Three categories were measured that have been modified from Smock et al. (2011). The items were divided into following: 3-items assessing escapism, 3-items assessing distraction and 3-items assessing relaxation. Respondents answered each item on a 5-point scale ranging from (4) strongly agree to (0) strongly disagree.

3.5 Participants and procedure

The data was collected in a period of two weeks in September 2019 to October 2019. Participants were recruited online on Reddit for an online self-report questionnaire (Qualtrics). The target group follow live streaming about gaming at least once a week.

The online questionnaire started the guarantee that anonymity and confidentiality of their data and with their consent of participation. An incentive to participate was offered by taking part in a draw of two 50 USD gift cards to an online gaming store. The questionnaire takes 10 to 20 minutes to complete. Items within the categories have been randomized to avoid order effects and two attention checks have been included. To meet the target group a validation question have been inserted to be sure they were using Twitch at least 1 time a week. If they didn't meet the requirement they were directed to the end of the survey. After having answered Twitch consumption questions, participants completed the questionnaire in the following order: the Passion Scale, Twitch motivations, Bergen Social Media Addiction Scale and demographics. In total the questionnaire consists of 69-items of which 6 open questions.

The questionnaire first have been tested with three test subjects to make sure the understanding of questions is clear and no mistakes in grammar have been made.

There have been two attention checks included to confirm that respondents were reading the questions carefully. Also, quality screens are included to see that respondents spent an appropriate amount of time on the questionnaire and if they did not click through the questions as quick as possible.

580 participants qualified for the survey. Of the qualified participants 329 finished the survey and satisfy the attention checks.

4 Statistical analysis

This research focusses on the exploration between engaged Twitch viewers and problematic engaged Twitch viewers and to find associations between these types of viewers and motivations and behavioral engagement. Therefore, this chapter selects and describes the methodology for the data analysis. The analysis has been separated into two parts: the identification of types of engagement and measurement of associations.

4.1 Identifying types of engagement

First, the types of engagement need to be identified based on the data. Next, it will be assessed if one the types of engagement can be identified as problematic engagement with Twitch.

An unsupervised learning method will be used, because the research is an exploratory analysis and no dependent variable is included. To identify the types of engagement of the Twitch viewers a clustering method is needed. Clustering is used to find subgroups in the respondents and is often used in exploratory researches (James, Witten, Hastie, & Tibshirani, 2013).

However, all clustering methods suffer from noise in the data (James et al., 2013). The dataset includes a high number of categorical variables and it is expected that not all variables are relevant for the distinction of engaged and problematic behavior(De Soete & Carroll, 1994). Therefore, a dimension reduction technique in combination with a clustering method is needed to overcome this problem. The goal is to identify well separated clusters with their own preferences while reducing the number of irrelevant variables with a dimension reduction technique.

4.1.1 Dimension reduction

Dimension reduction methods find patterns in the data and visualize them in a meaningful way. Several methods exists to reduce dimensionality, such as Principle Component Analysis (PCA) and Multiple Correspondence Analysis (MCA). In this case the MCA would be the best choice, because the variables used to identify the types of engagement are categorical variables, where the PCA needs continuous variables. Next to that, MCA does not assume linearity.

The Multiple Correspondence Analysis (MCA) is a widely used method to reduce the number of categorical variables in a large dataset by summarizing the information of the original dataset. MCA is often used to visualize social, marketing and psychology studies that contain many survey questions that have often discrete scales such as a Likert-scale (agree, neutral, disagree; Greenacre, 2010). The method is based on homogeneity, which measures to what degree variables have the same characteristics (Gifi, 1990). It searches for observations (=objects) that choose similar variable categories and create homogeneous groups(= observations in a group has similar characteristics;

Gifi,1990). The dataset is represented in a low-dimensional space, with a minimum number of dimensions(= axis) needed to explain the variability of the data set as much as possible (James et al., 2013).

4.1.2 Clustering

Clustering separates the observations in the dataset, it groups observations that have homogenous preferences and separates the observations when they have heterogenous preferences (James et al., 2013). The most known clustering methods are the K-means and the hierarchical clustering. The K-means needs a predetermined number of clusters to separate the respondents, where the hierarchical clustering does not need this and creates a visualization from where the number of clusters can be chosen from(James et al., 2013). However, it is not always clear how many clusters need to be chosen (James et al., 2013). The benefit of using K-means in comparison to other clustering methods is that the method is less effected by irrelevant variables and is more robust to outliers (Punj & Stewart, 1983).

To increase the robustness of the K-means and decrease the noise in the data, a tandem approach is an often used method (Arabie & Hubert, 1994). It sequentially combines a dimension reduction method with a clustering technique. This approach first reduces the dimensionality then uses these results in the clustering. However, there is a problem using the method this way because both methods use different criteria to optimize (De Soete & Carroll, 1994; Vichi & Kiers, 2001). People have different preferences and are assumed to be heterogeneous (Hwang, Montréal, Dillon, & Takane, 2006). MCA is a method to find homogeneous groups, however not to identify heterogeneous subgroups of individuals (Hwang et al., 2006). Doing the MCA before the clustering could distort and mask the cluster structure, because they optimize different elements (Green & Krieger, 1995; Vichi & Kiers, 2001). This could lead to irrelevant dimensions for clustering, because they do not reflect the original structure needed for clustering (De Soete & Carroll, 1994). Therefore, it is always important to check if the clusters make sense (De Soete & Carroll, 1994; Hennig, 2007).

Hwang et al. (2006) created an algorithm to optimize both K-means clustering and MCA. It uses Alternating Least Squares (ALS) to optimize one objective, where both MCA and K-means are optimized. This makes sure that the created dimensions also support the clustering method(Hwang et al., 2006). Also, the method allows to give more weight to the clustering or data reduction method (Hwang et al., 2006).

4.1.3 Conclusion

A K-means simultaneously with MCA is going to be used to segment the types of engagement among Twitch viewers. This method reduces the noise in the data and clusters the data, including the heterogenous preferences of the viewers. Next to that, due to the simultaneous optimization the structure needed for the clusters will not be masked.

In the next paragraph the methodology of the K-means in combination with MCA will be discussed in greater detail.

4.2 MCA K-means

The method of Hwang et al. (2006) optimizes the multiple correspondence analysis of (Gifi, 1990) together with K-means clustering algorithm. The method simultaneously reduces the dimension reduction as it creates clusters.

4.2.1 The notation

The dataset contains $1, \dots, n$ objects (individual observations/ responses) on j variables where each of the $J = 1, \dots, J$ variable takes on k_j different values (variable categories; Gifi, 1990).

An indicator matrix $\boldsymbol{G}_j$ is made representing the variable categories of each individual observation. It is a dummy matrix (= a matrix with 0 and 1) of each category $k_j$in variable j represented by $n \times k_j$. When an individual chose for a variable category $G_{ik} = 1$ in all other cases $G_{ik} = 0$. $\boldsymbol{Y}_j$ are the category quantifications. It is a $k_j \times p$ matrix of weights of the variable categories on p-dimensions. $\boldsymbol{X}$ denotes $n \times p$ $(\leq k_j)$ matrix of a p-dimensions of J categorical variables, these are called the object scores of all individual observations on each dimension p. The number of p-dimensions are smaller than the number of J categorical variables (Gifi, 1990).

Membership of the respondents to one of c clusters is denoted by $\boldsymbol{U}$ which is an $n \times c$ indicator matrix (Hwang et al., 2006). The centroids values of clusters is denoted by $\boldsymbol{\Gamma}$ which is a $c \times p$ matrix. α_1 and α_2 cannot be negative and are weights for the functions (Hwang et al., 2006). α_1 is the weight for the importance of MCA and α_2 is the weight for criterium the K-means clustering (Hwang et al., 2006).

4.2.2 The algorithm

Hwang et al. (2006) algorithm works as followed. With a loss function they minimize the sum of squares (SS):

$$f = \alpha_1 \frac{1}{J} \sum_{j=1}^{J} SS\left(\boldsymbol{X} - \boldsymbol{G}_j \boldsymbol{Y}_j\right) + \alpha_2 SS(\boldsymbol{X} - \boldsymbol{U}\boldsymbol{\Gamma}) \qquad (1)$$

with respect to $\boldsymbol{X}$ the centroid of observations, $\boldsymbol{G}_j$ the indicator matrix of the variable categories, $\boldsymbol{Y}_j$ the category quantifications, $\boldsymbol{U}$ the cluster membership and $\boldsymbol{\Gamma}$, the cluster centroids. The function is subjected to $\boldsymbol{X}^T\boldsymbol{X} = \boldsymbol{I}$ and $\alpha_1 + \alpha_2 = 1$ (Hwang et al., 2006). $\frac{1}{J}$ is added by Markos, D'Enza, & van de Velden (2019) to make sure that MCA and K-means will have equal weights when $\alpha_1 = 0.5$.

When $\alpha_1 = 1$ the method is a normal MCA of Gifi (1990) and when $\alpha_2 = 1$ the standard K-means clustering algorithm is used. When $\alpha_2 > \alpha_1$ clustering is more important than reducing dimensionality (Hwang et al., 2006).

To minimize the alternating least squares algorithm is used that iterates over $\boldsymbol{X}$, the first iteration t an arbitrary number $\boldsymbol{X}$ is chosen and randomly assigns objects to the clusters $\boldsymbol{U}$. For each iteration t there are four steps:

1. With keeping $\boldsymbol{X}$ and $\boldsymbol{U}$ constant, category quantifications $\boldsymbol{Y}_j$ and clusters means $\boldsymbol{\Gamma}$ are updated using

$$\widehat{\boldsymbol{Y}}_j = \left(\boldsymbol{G}_j^T \boldsymbol{G}_j\right)^{-1} \boldsymbol{G}_j^T \boldsymbol{X} \tag{2}$$

and

$$\widehat{\boldsymbol{\Gamma}} = (\boldsymbol{U}^T \boldsymbol{U})^{-1} \boldsymbol{U}^T \boldsymbol{X} \tag{3}$$

2. Now $\boldsymbol{X}$ will be updated with subjected to $\boldsymbol{X}^T\boldsymbol{X} = \boldsymbol{I}$, while keeping $\boldsymbol{Y}_j$, $\boldsymbol{\Gamma}$ and $\boldsymbol{U}$ constant, (2) and (3) will be substituted into the eigen equation (1):

$$\boldsymbol{X}\Lambda = \left(\alpha_1 \frac{1}{p} \sum_j \left(\boldsymbol{G}_j^T \boldsymbol{G}_j\right)^{-1} \boldsymbol{G}_j^T + \alpha_2\, \boldsymbol{U}\, (\boldsymbol{U}^T \boldsymbol{U})^{-1} \boldsymbol{U}^T\right) \boldsymbol{X} \tag{4}$$

3. Update the cluster membership $\boldsymbol{U}$ keeping $\boldsymbol{Y}_j$, $\boldsymbol{\Gamma}$ and $\boldsymbol{X}$ constant and the K-means with respect to $\boldsymbol{U}$.
4. Return to step 1 and determine the cluster membership and repeat this process until convergence. That is when cluster centers do not change anymore or decreases in the next iterations.

4.2.3 Selecting number of clusters and dimensions

The K-means needs a predefined number of clusters before running the method, therefore a optimization of the number of clusters needs to be analyzed. To assess the optimum number of clusters internal validity is used, this is a measurement with the information within the dataset (Liu, Li, Xiong, Gao, & Wu, 2010).

The Silhouette width is often used to find the optimal number of partitions (Rousseeuw, 1987). The Silhouette width measures the distance between points in a cluster(= the compactness) and to the points of the neighbor clusters(= the separation; Rousseeuw, 1987). The width indicates if the clusters are well separated and the closeness of the clusters. The values lie in between -1 and 1, where higher values mean that the clusters are better separated (Rousseeuw, 1987). A value of 1 indicates that neighboring cluster is far away and close to the cluster that it is assigned to. Negative values indicate that individuals could have been assigned to the wrong cluster.

4.2.4 Stability of the clusters

An indicator for the validity of clusters is stability, so if the data is modified without changing the underlying distribution the structure clusters would not disappear (Hennig, 2007). Different papers used the resampling of the data set to assess the stability of the clusters and use it as a tool to choose the true of number clusters (Hennig, 2007). To interpret the stability of the cluster the Jaccard coefficient in combination with a bootstrap(= resampling the dataset) is used (Hennig, 2007).

First, bootstrap samples of the data are created, than the bootstrap samples are applied to the dimension reduction and clustering method. They allocate each observation to the closest center. Then they measure the stability with two bootstrap samples and the original sample is measured with the average Jaccard coefficient (Hennig, 2007).

An average Jaccard coefficient of 0.75 or more would represent a stable cluster. When the cluster is between the values 0.6 – 0.75 there is indication that there are patterns in the data (Markos, D'Enza, & van de Velden, 2019). However, highly stable clusters do not automatically mean that they are valid clusters, interpretability of the clusters could further identify if the clusters are valid (De Soete & Carroll, 1994; Hennig, 2007).

4.2.1 Interpretation of visualization

For the interpretation of the clusters the interpretation of the MCA is used. It is based on the centroid principle, which characterizes a categorical variable as a set of category points. The observations chose a variable category and a variable category is the average(=centroid) of these observations. MCA displays variable categories and objects in a low dimensional space. This means that observations that are close are similar to each other (Hoffman & Leeuw, 1992).

The contribution of the variable categories is explained by the frequency, when the contribution is lower it means there is less frequency points and this explains a unusual profile (James et al., 2013). Therefore, MCA requires sufficiently filled categories for interpretation, because outliers with few frequencies can dominate the plots. Therefore, there needs to be checked if categories can be joined. A sufficiently filled category contains 5% of the observations (James et al., 2013). To decrease the influence of rare categories there are three possibilities (Husson, Lê, & Pagès, 2011). First, it is possible to group certain categories when they are sequential categories. Second, it is possible to randomly assign individuals associated to other categories based on the proportions. Last, it is possible to delete individuals with rare categories, however this should be avoided.

The biplot visualizes a low dimensional space of the object scores of the individual observations (= cloud of individuals) and category scores of all levels of the variables (= cloud of variables ;James et al., 2013). Dimensions are shown on the axis of the plot (Greenacre, 2010). The categories close to the origin are explaining the average object and are not used for interpretation. The categories far from the origin and are close from each other are homogeneous groups and will be interpreted (Gifi, 1990).

When the categories are close to each other, it means that they are positive correlated. If they are opposite from each other they are negatively correlated and if the direction is perpendicular they are uncorrelated (Govaert, 2009). This is best shown in the joint plot, where only the most fitting variable categories (according to the earlier discussed discrimination measure) are shown in a low dimensional space for the chosen dimensions.

There is a special case for interpretation. If there is a strong first dimension and the second dimension is quadratic function of the first dimension this creates a plot of objects scores in form of a horse shoe (the arch). The second dimension distinguishes the extremes from the average (Gifi, 1990).

4.3 Measuring associations

As discussed before, the types of engagement will be identified on a MCA K-means. The exploration of the associations of motivations and behavioral engagement with the identified subgroups of Twitch will be analyzed with a descriptive analysis.

The associations will be measured with a measure of central tendency and a measure of variability among the identified clusters. This method helps to explore the associations of the motivations and the behavioral engagement elements, because it gives general tendencies across the clusters.

The measure of central tendency is measured with the mean, because the mean is more precise then for example the mode (= most often chosen answer) or the median (= the value in the middle) (Ary, Jacobs, & Sorenson, 2010). Therefore, the Likert items need to be converted to numeric variables. There is discussion about this approach, because analyzing the average means that a normally distributed relationship is assumed (Sullivan & Artino, 2013). Next to that, there is also discussion of what an average on a Likert item means (= an agree and extremely agree is an agree-and a half?) and also what happens with two extremes going to the middle(Sullivan & Artino, 2013). However, in this case not individual Likert items will be analyzed, but a theoretical construct including multiple items identified by the literature (= Likert scale) are analyzed.

A Likert scale tries to capture the full understanding of each motivation based on the literature. Therefore, the mean will be used because this can provide information about the differences in central tendencies among groups and other motivations. The mean will give a central tendency, but does not give the full information. Therefore, the standard error is used. This provides the standard deviation on both sides of the average of the means. This statistic provides information about the precision of the mean. It helps to understand the distribution of the mean (Ary, Jacobs, Razavieh, & Ary, 2010). It gives an estimate of where the mean in the population is likely to be.

The standard error is calculated as followed: $SE = \frac{SD}{\sqrt{n}}$, where SD is the standard deviation and n is the sample size(Ary et al., 2010). A larger n will decrease the standard error. This metric will provide more certainty if a difference between the clusters is found(Ary et al., 2010).

5 Results

In the previous chapter the methods used for the statistical analysis have been discussed. This chapter will be focused on the results.

5.1 Data descriptive

In this paragraph the data descriptive of demographics and Twitch behavior are discussed.

5.1.1 Demographics

Table 1 displays the descriptive information about the demographics of the respondents. 14.4% of the respondents are females and 84.5% are males, 4 respondents did not report their gender. The age range is between 13 and 48 (M = 26.2) and most of the respondents are in the age range 22-28 years old. 60.8% of the respondents have a college/ university degree or higher. 49.7% of the respondents is a full time employee.

Table 1: Descriptive information demographics

Gender	%(freq)	Education	% (freq)	Occupation	% (freq)	Age	% (freq)
Female	14.3% (47)	College/University degree	33.1% (109)	Full-time	49.8% (164)	<16	3.6% (12)
Male	84.5% (278)	Doctorate degree	0.9% (3)	Part-time	6.4% (21)	16-21	23.1% (76)
Other	1.2% (4)	High school degree	13.1% (43)	Retired	1.2% (4)	22-28	40.1%(132)
		Master's degree	8.8% (29)	Student	32.5% (107)	29-38	29.2% (96)
		Some college/ university education	36.2% (119)	Unemployed	10% (33)	39-48	4% (13)
		Some high school education	7.9% (26)			Mean (SD)	26.1 (6.3)

5.1.2 Activity on Twitch

Table 2 shows the descriptive information of Twitch usage of the respondents. To increase the understanding of the data, the variables have been transformed from numeric to categories. 46.2% of the respondents watch daily. The respondents spend on average 12.8 hours (SD = 13.1) a week on Twitch and follow on average 5.4 (SD = 12.2) streams. On average, their favorite stream includes 8,314 other viewers. Most of the respondents (49.5%) have a preference to follow large streams. On average, Twitch streamers subscribe 16 months (SD = 27.1). 27.4% of the respondents are not subscribed to a channel and 18.8% respondents were more than 24 months subscribed. On average, Twitch viewers donated 57 USD (SD = 27) to streamers. 55% of the respondents did not donate at all and 9.7% donated more than 100 dollars.

Table 2: Descriptive information Twitch usage

item	Variable category	% (freq)	item	Variable category	% (freq)
Frequency per week	once a week	10% (33)	Size stream	Mean (SD)	8314.2 (57432.2)
	2-3 times a week	19.8% (65)		small (< 100)	24.3% (80)
	4-6 times a week	24% (79)		Medium(101-500)	15.2% (50)
	daily	46.2% (152)		Large(500-10,000)	49.5% (163)
Hours per week hours	Mean (SD)	12.8 (13.1)		XLarge (10,000 >)	10.9% (36)
	< 5 hours	34.7% (114)	Time subscribed	Mean (SD)	15.5 (27.1)
	5-10 hours	28.6% (94)		no	27.4% (90)
	10-20 hours	20.1% (66)		1-6months	24.9% (82)
	20-35 hours	10.6% (35)		6-12months	15.8% (52)
	> 35 hours	6.1% (20)		12-24Months	13.1% (43)
Number of streams followed	Mean (SD)	5.4 (12.2)		>24months	18.8% (62)
	no specific stream	9.7% (32)	Amount donated	Mean (SD)	56.9 (176.3)
	1 stream	17.6% (58)		0USD	55% (181)
	2 streams	20.7% (68)		0-10USD	9.7% (32)
	3 streams	13.7% (45)		10-100USD	25.5% (84)
	4 streams	17% (56)		>100USD	9.7% (32)
	5-10 streams	16.4% (54)			
	> 10 streams	4.9% (16)			

5.2 Problematic use results

In this paragraph the types of engagement are created based on the MCA K-means to answer the sub research question: *'What subgroups of engagement of Twitch viewers can be segmented and which of these groups can be identified as problematic?'*.

5.2.1 Preparation

The items that were taken from BSMAS (*Q16*) and the Passion Scale *(Q9 & Q10)* are used in this method to identify the types of engagement. These variables have been chosen, because literature have shown that they are able to identify general problematic patterns and separate them from (high) engaged behavior. To assess if someone is engaged with the platform, the passion criteria (*Q9*) to identify the level of engagement have been summed. Based on the rule to sum on or above the mid-value of the passion criteria (Vallerand, 2015), respondents have been identified engaged above or on the cut-off of 10 passion points.

To analyze the data the program R is used. To determine the types of engagement among Twitch viewers the 'clustrd' package is used. The 'clustrd' package includes the function 'clusmca' that performs the MCA simultaneously with the K-means using the algorithm of Hwang et al. (2006)

(Markos et al., 2019). Next to that, the package is able to tune the number of clusters and number of dimensions based on the Silhouette width, this will be the input for the number of dimensions and clusters used. Next to that, the package has a function that performs a bootstrap on the Jaccard coefficient to identify if the clusters are stable and valid implementing Hennig (2007).

The MCA needs to have at least 5% of the respondents in a variable category. This means every variable category needs at least 16 observations. From addiction literature, it is expected that there is only a small percentage (2% to 5%) of respondents displaying problematic behavior(Bányai et al., 2017). Combining variable categories that indicate problematic behavior will increase the number of identified problematic viewers. However, some variable categories need to be combined otherwise outliers will dominate the solution. Therefore, looking at the data and the expected rate of excessive behavior the cut-off have been lowered to 4%, meaning every variable category needs at least 13 respondents. These variable categories have been combined with the closest factor and renamed to both factors. This makes sure that the minimum number of problematic variable categories have to be combined, but also the number of outliers dominating the solution are minimized. Chosen is to exclude people with missing values, because they did not finish the study this could be for various reasons.

The process of analyzing the data will be as followed. First, the data is modified to have at least 4% of the respondents in the variable categories. Second, the clusters are tuned to find the optimal number of clusters and dimensions. Third, the optimal solution is checked on their validity with the bootstrap on the Jaccard coefficient. Last, the clusters will be interpreted based on the MCA visualizations.

To be sure that the results can be reproduced the seed 123 is set.

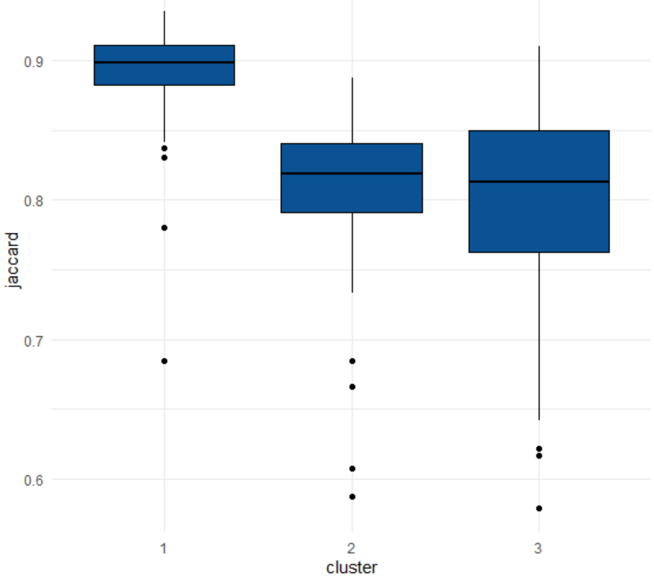
5.2.2 Diagnostics

To form the clusters they first have been tuned on a range of 3 to 8 clusters and 2 to 7 dimensions. The best fitted number of clusters have been chosen based on the Silhouette width, shown in table 3. Based on this the most fitting number of clusters is 3 with 2 dimensions with a Silhouette width of 0.196. The cluster sizes are 158 (48%), 144 (43.8%) and 27 (8.2%). The Silhouette widths of the identified clusters are 0.34, 0.06, 0.04. This means that the individuals in the first cluster are better matched to this cluster than the second and third cluster. The second and third clusters are close to 0. This indicates that these clusters are close to the decision boundary between two clusters.

Table 3: Silhouette Width Values of Tuning Clusters

Clus / dim	2	3	4	5	6	7
3	**0.196**					
4	0.163	0.122				
5	0.061	0.074	0.009			
6	0.052	0.096	0.075	0.072		
7	0.051	0.075	0.057	0.056	0.063	
8	0.021	0.021	0.056	0.048	0.064	0.0

Figure 1: Bootstrap results (b = 100) with Jaccard Similarity index



For looking at the stability of the found clusters a bootstrap is used on 100 bootstrap samples. In figure 1 the results of stability of the clusters are shown. The average Jaccard coefficient for the first cluster is 0.898. The figure shows that there is a low spread in the bootstrap on the Jaccard coefficient in this cluster in comparison to the other clusters. The average is above 0.85 that means it is a highly stable cluster. The second cluster has an average Jaccard coefficient of 0.831 and the third cluster has an average Jaccard coefficient of 0.809. There is variability in the bootstrap shown within these two clusters in figure 1, indicating more spread in the stability of the clusters. However, the average Jaccard of both clusters are above 0.75, meaning that these clusters are on average stable and valid clusters.

In the next section the interpretation of the clusters is discussed.

5.2.3 Interpretation

Figure 2 shows the results of the MCA K-means clustering based on three clusters and two dimensions. The translations from the item id on the axis to the specific items can be found in appendix B to ease the interpretation process. Before the clusters will be interpreted the dimensions will be analyzed.

Figure 2 shows the three clusters in grey. The points in the cluster on the right side are more condensed than the other two clusters. The individuals shown in rectangles in the top left and the individuals indicated with squares in the bottom left are more spread and expected to have more heterogenous preferences within the groups, as the Silhouette width also indicated.

Figure 2 also shows the variables of addiction in yellow, the passion variables in red, harmonious use variables in pink and obsessive use variables in blue.

On the horizontal axis (dimension 1) it is shown that the passion yes and no are formed on the left and right side on the plot. Next to that, on the right side individuals both strongly disagree with symptoms of harmonious use, obsessive use and not having an addiction. On the left side is shown a differentiation in these symptoms. Therefore, this dimension will be called high-low engagement.

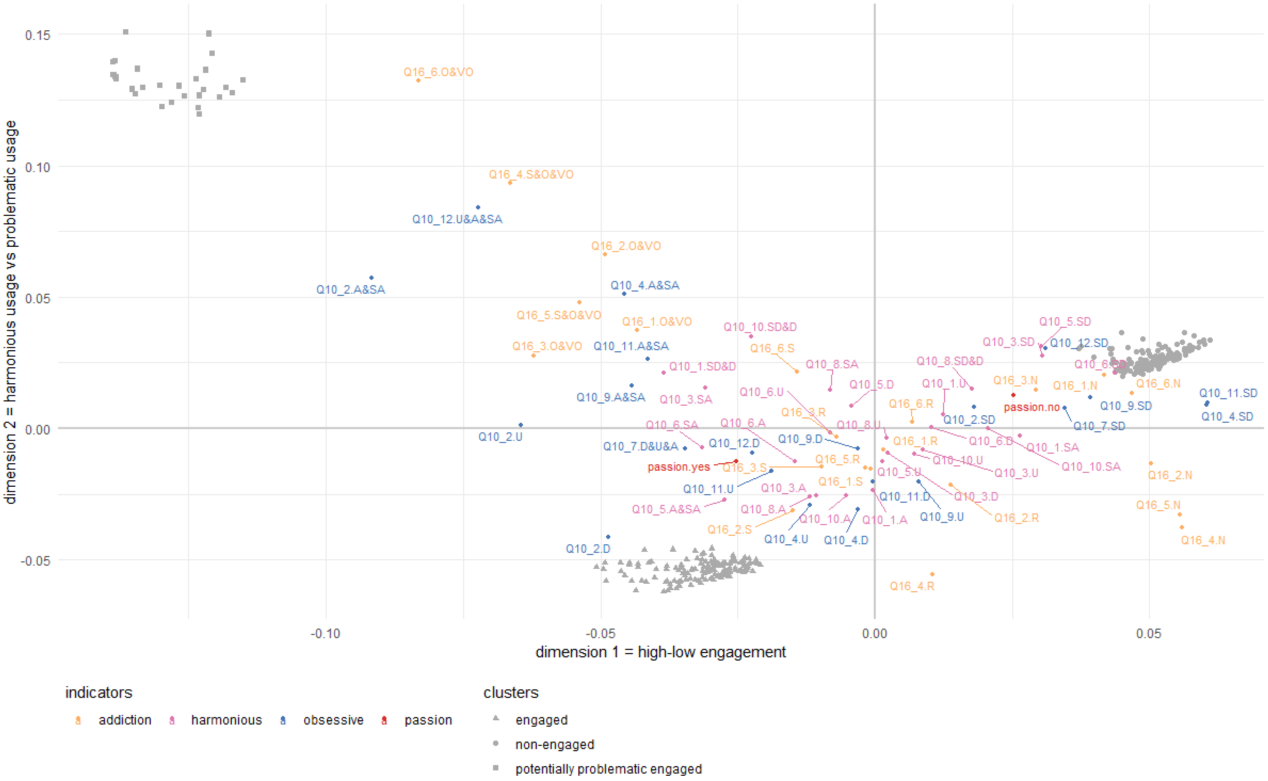
On the vertical axis (dimension 2) on the left side in the upper part there are items agreeing to obsessive use and addiction criteria (*Q10_2.A&SA, Q10_2.A, Q10_4.A&SA, Q16_6.O&VO, Q16_4.S&O&VO*). In the lower part there are items that agree to harmonious use of Twitch (*Q10_8.A, Q10_10.A)* and disagreeing to obsessive use *(Q10_2.D, Q10_4.D, Q10_11.D)*. However, this construct on the right side of the dimension of the harmonious versus obsessive is less interesting. As respondents on this side both strongly disagree with items from both harmonious as obsessive use. However, the vertical axis is still called problematic vs harmonious use.

The observations clustered in the problematic – high engagement correlate with passion and obsessive use of Twitch. This cluster includes 27 individuals (8.2% of the total sample). The cluster associates with appreciating the new things they discover on Twitch (*Q10_3.SA*). The cluster also correlates with items that reflect being out of control represented with the variables *Q10_2.A&SA, Q10_9.A&SA, Q10_11.A&SA* and *Q10_12.U&A&SA*. They also correlate with having problems with their important daily activities, such as a negative impact on school or job, because they were using Twitch. This is represented with the variables *Q10_1.SD&D, Q10_10.SD&D, Q16_6.O&VO, Q16_6.S*. They also associate with having obsessive feelings for Twitch represented with *Q10_4.A&SA*. This cluster is also associated continuing watching Twitch more and more (*Q16_2.O&VO*) and not being able to cut down time spend on Twitch (*Q16_4.S&O&VO*) during the last year. Next to that, they also correlate with spending a lot of time thinking about Twitch and planning how to use it (*Q16_1.O&VO*) and to forget about personal problems (*Q16_3.O&VO*) during the last year. Therefore, this cluster is named the potentially problematic engaged. It doesn't necessarily mean that they are problematic engaged, however they do correlate with both criteria of addiction as obsessive use of Twitch.

In the lower left side the a cluster of observations are grouped in the harmonious – high engaged dimension. This cluster includes 158 individuals (48% of the total sample). This cluster enjoys the new things they learn from Twitch and the variety of experiences it has to offer. The platform reflects qualities they like about themselves. This is displayed with the variable categories *Q10_3.A,* *Q10_5.A&SA, Q10_6.SA* and *Q10_6.A*. This cluster also correlates with being in harmony with Twitch and other activities that are important to them, shown with the variable categories *Q10_10.A* and *Q10_8.A*. Furthermore, they correlate with being most of the time in control of their time spend on Twitch (*Q10_2.D*). They also do not correlate with having obsessive feelings towards Twitch (*Q10_4.U, Q10_4.D*) and rarely feel side effects of being prohibit to use Twitch (*Q16_5.R*). Next to that, they correlate with sometimes spending a lot of time thinking about it and planning how to use Twitch (*Q16_1.S*), using Twitch to forget about personal problems (*Q16_3.S*) and having the urge to use Twitch more and more (*Q16_2.S*). However, this cluster is not correlated with having negative impact on their live. Therefore, this cluster is named the engaged viewers.

The third cluster of observations are displayed in the problematic-low-engagement dimension. This cluster includes 144 individuals (43.8% of the total sample). The individuals in this cluster are not necessarily engaged with Twitch (*passion.no)*. They correlate with not valuing the experiences on Twitch nor appreciate the new things they learn, shown with the variable categories *Q10_3.SD, Q10_6.SD*. This cluster also does not associate with Twitch reflecting their qualities that they like about themselves (*Q10_5.SD*). Besides, they are not correlated with problematic use of Twitch represented with the variables categories *Q16_1.N, Q16_3.N* and *Q16_6.N*. Next to that, this cluster is correlated with their Twitch usage being in harmony with other things that are important for them (*Q10_10.SA)*. They also do not correlate with Twitch being the main activity of their life (*Q10_7.SD).* Furthermore, they correlate with being always in control of their time spend on Twitch represented with the variable categories *Q10_2.SD, Q10_4_SD, Q10_11.SD* and *Q10_12.SD*. This cluster is not associated with passion or negative impact on their life based on the obsessive and addictive items. Therefore, the viewers in this cluster are called non-engaged.

Figure 2: Clustering results on different types of engagement



5.2.4 Conclusion

With support of the MCA K-means analyses, the sub research question *'What subgroups of engagement of Twitch viewers can be segmented and which of these groups can be identified as problematic?'* is answered.

Based on tuning the dimensions and clusters, an optimum number of three clusters with two dimensions is found. These clusters are engaged viewers (48%), potentially problematic engaged viewers (8.2%) and non-engaged viewers (43.8%). The bootstrap results have shown per cluster an average Jaccard coefficient above 0.75. This means that the clusters are on average valid and stable. The average Silhouette width of the clusters is 0.196, meaning that the individuals in the clusters are quiet well separated and the group members belong to that group, however this is mainly caused by the non-engaged viewers. Engaged viewers and potentially problematic engaged viewers are closer to 0, meaning that they are close to the decision boundary. Therefore, they are less well separated and are less similar in their behavior within their cluster.

The structure of the clusters in this study supports the binary structure of Vallerand (2015), where they claim that passionate people can be separated in a harmonious and obsessive construct.

The engaged viewers

The viewers in this cluster associate with enjoying Twitch, learning from it, getting new experiences from it, and reflecting their qualities that they like about themselves. They associate with being in harmony with other things that are part of them and they do not correlate with indications to obsessive behavior. These viewers are associated to be in control over their time spend on Twitch, sometimes have the urge to spend more time on Twitch, to think about it a lot or to forget about personal problems. But these viewers are associated with having rarely problems with other parts of their life that are important for them when engaging in Twitch. This is also found in previous literature, because spending a lot of time on your hobby and sometimes not being able to stop is also characterized with absorption in the general engagement (Schaufeli, 2017).

The potentially problematic engaged viewers

The potentially problematic engaged viewers are associated with appreciating Twitch more due the new things they discover on the platform. Next to that, they also associate with variables that indicate that they are out of control and having conflicts in their daily activities such as school or their job and other things that are part of them. They also correlate with having obsessive feelings for Twitch. Next to that, they are associated with often having addiction symptoms such as spending a lot of time thinking about using Twitch, continuing watching more and more, not being able to cut down time spend on Twitch and trying to forget personal problems during the last year.

These results are similar to Wang & Chu (2007), because this research also found that obsessive usage correlate with addiction symptoms. These results do not say that the identified problematic engaged viewers have problems, however they are correlated with symptoms of the addiction criteria as well as obsessive use.

The non-engaged viewers

The non-engaged viewers are associated with having low engagement levels with the platform. This is also shown in the negative associations towards using Twitch for new experiences or using Twitch to learn new things. These viewers associate with their Twitch engagement being in balance with other things that are important, such as their job or studies and being able to control of their time spend on Twitch. Next to that, this cluster does not associate towards using Twitch to forget about personal problems.

Thus, the Twitch viewers of the cluster potentially problematic engaged correlate with symptoms of obsessive usage of Twitch and addictive usage of Twitch that are important indicating problematic use of Twitch. They correlate with loss of control which is in line with Deleuze et al. (2017) and Flayelle et al. (2019). Also, they associate with have an obsessive feelings towards Twitch and in less extent the impression that the usage of Twitch is controlling them. Next to that, they have conflicts with important activities in their live that also has been found to be problematic in the literature (Billieux et al., 2015; Flayelle et al., 2019; Vallerand et al., 2003).

5.3 Descriptive analysis of motivations

This paragraph describes the results of the descriptive analysis of the motivations.

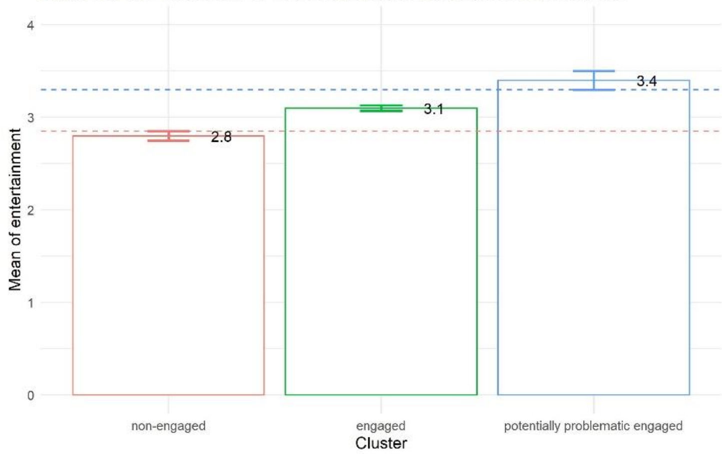
5.3.1 Preparation

To analyze the associations of motivations with the identified subgroups of Twitch a descriptive analysis is done. The general tendency have been assessed based on the mean and standard error of the mean among the different motivation scales identified in the literature. Therefore, the variables have been recoded to numeric variables ranging from 0 strongly disagree to 4 strongly agree. After, the mean and the standard error have been taken per individual per motivation scale.

5.3.2 Entertainment

Figure 3 displays the mean and the standard error differences on the entertainment motivations per cluster.

Figure 3: The difference in entertainment motivations across clusters



This shows that there are some differences among the groups. On average, potentially problematic engaged viewers have higher motivations for entertainment (M = 3.4, SE = 0.1) than engaged viewers (M = 3.1, SE = 0.03) and non-engaged viewers (M = 2.8 SE = 0.05). The precision of the mean among the potentially problematic engaged viewers is lower than the other groups. However, the groups of viewers do not overlap including the standard error bound. Therefore, it is likely that the groups differ in entertainment motivations.

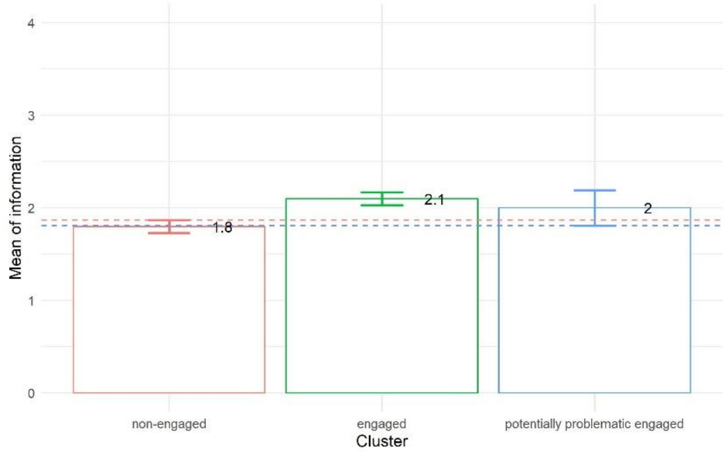
Looking across the variables it is shown that there is a general tendency to use Twitch for entertainment motivations in comparison to other motivations.

Potentially problematic engaged viewers tend to have higher motivations to use Twitch for entertainment than the other identified subgroups. Non-engaged viewers tend to have lower motivations to use Twitch for entertainment motivations than the other groups.

5.3.3 Information

Figure 4 displays the mean and the standard error of the information motivations per type of engagement.

Figure 4: The difference in information motivations across clusters



The engaged viewers on average have more motivations (M = 2.1, SE = 0.07) for using Twitch for information than potentially problematic engaged viewers (M = 2, SE = 0.19) and non-engaged viewers (M = 1.8, SE = 0.07). However, the differences in the mean are small. There tends to be more variability in the precision of the mean among the potentially problematic engaged viewers than the other viewers.

On average, engaged viewers tend to have slightly higher motivations to use Twitch for information than other viewers. However, looking at the standard error of the mean they are not likely to differ from problematically engaged viewers. Engaged viewers are likely to differ from the non-engaged viewers and tend to have higher motivations to use Twitch for information motivations. Potentially problematic engaged viewers are not likely to differ from engaged or non-engaged viewers.

5.3.4 Tension release

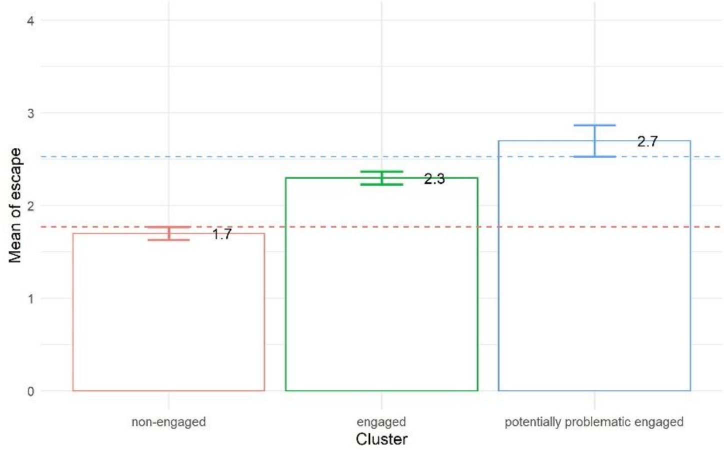
In the next subparagraphs discuss the results of escape motivations, distraction motivations and relax motivations to use Twitch.

5.3.4.1 Escape

Figure 5 shows the mean and standard error bars on the escape motivations per type of engagement. On average, the perception towards escape motivations among the potentially problematic engaged viewers is higher (M = 2.7, SE = 0.17) than the engaged viewers (M = 2.3, SE = 0.07) and non-engaged viewers (M = 1.7, SE = 0.07). On average, there seems to be quiet some difference between the potentially problematic engaged viewers and the other viewers. Also, when including the standard error around the mean these groups are still likely to differ in escape motivations.

Potentially problematic engaged viewers tend to use Twitch for escape motivations more than other viewers. Non-engaged viewers tend to use Twitch for escape motivations less than other viewers.

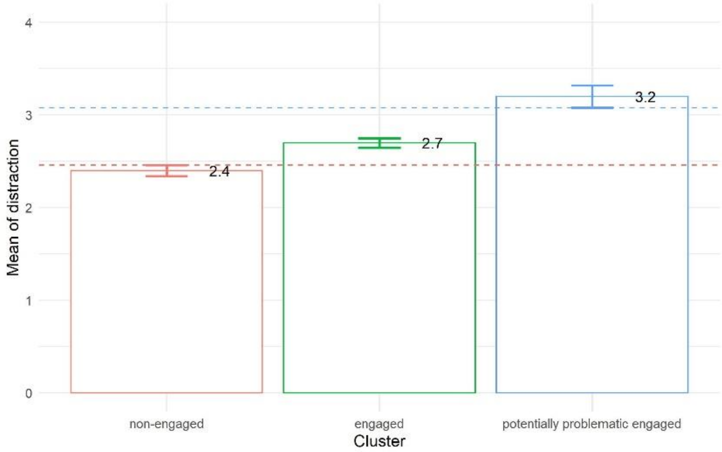
Figure 5: The difference in escape motivations across clusters



5.3.4.2 Distraction

Figure 6 displays the mean and the standard error bars of the distraction motivations per cluster.

Figure 6: The difference in distraction motivations across clusters



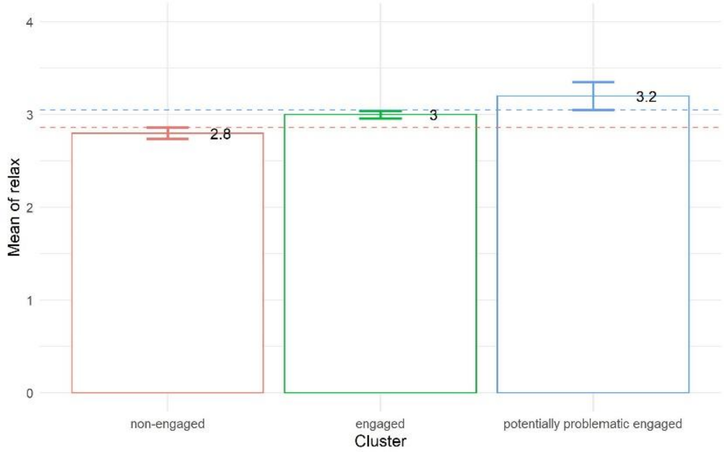
This shows that distraction motivations tend to differ among the groups. On average, the potentially problematic engaged viewers have higher motivations (M = 3.2, SE = 0.12) for distraction than the engaged viewers (M = 2.7, SE = 0.05) and non-engaged viewers (M = 2.4, SE = 0.06). It also shows that the variability around the mean of the potentially problematic engaged viewers is larger than for the other viewers. The boundaries of the standard errors around the mean do not cross among all groups, meaning that these motivations among these subgroups are likely to be different.

The distraction motivations of potentially problematic engaged viewers tend to be higher than other viewers. Next to that, non-engaged viewers tend to use Twitch for distraction motivations less than the engaged viewers and potentially problematic engaged viewers.

5.3.4.3 Relax

Figure 7 displays the differences in mean and standard error of relax motivations across the types of engagement. This shows that on average, the tendency for the relaxation motivations do not differ a

Figure 7: The difference in relax motivations across clusters



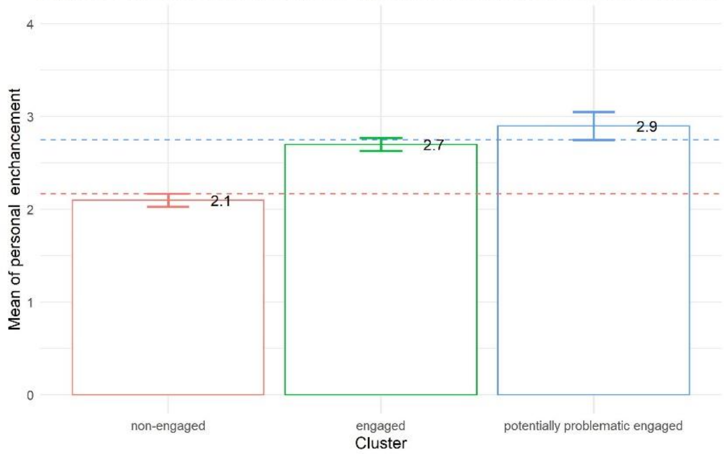
lot. The potentially problematic engaged viewers on average have higher motivations to use Twitch to relax (M = 3.2, SE = 0.15) than the engaged viewers (M = 3, SE = 0.04) and non-engaged viewers (M = 2.8, SE = 0.06). The difference in mean between the subgroups of Twitch viewers are small but do not overlap with the standard error of the mean around it, meaning these means are likely to differ.

Therefore, potentially problematic engaged viewers tend to use Twitch more for relax motivations than other viewers. Next to that, non-engaged viewers tend to use Twitch less for relax motivations than other viewers.

5.3.5 Personal enhancement

Figure 8 displays the mean and the standard error bars of the personal enhancement motivations per cluster.

Figure 8: The difference in personal enchancement motivations across clusters



This shows that the perception towards personal enhancement among the potentially problematic engaged viewers is on average higher (M = 2.9, SE = 0.15) than the engaged viewers (M = 2.6, SE = 0.07) and non-engaged viewers (M = 2.1, SE = 0.07). On average, there is quiet some difference between the (potentially problematic) engaged viewers and the non-engaged viewers, indicating that the non-engaged viewers on average have less interest for personal enhancement. The standard errors of the engaged viewers and potentially problematic viewers slightly overlap, indicating that these might not differ.

Thus, the personal enhancement motivations to use Twitch among non-engaged viewers tend to be lower than other viewers. Next to that, it is unclear if potentially problematic engaged viewers and engaged viewers tend to differ.

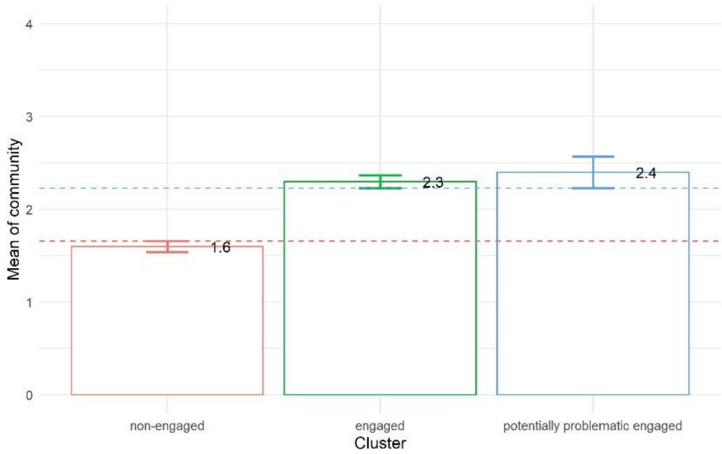
5.3.6 Social

In every subparagraph the descriptive analysis of a social motivation will be discussed.

5.3.6.1 Community

Figure 9 displays the mean and the standard error differences of the community motivations per cluster. On average, the motivations towards community on Twitch among the potentially problematic

Figure 9: The difference in community motivations across clusters



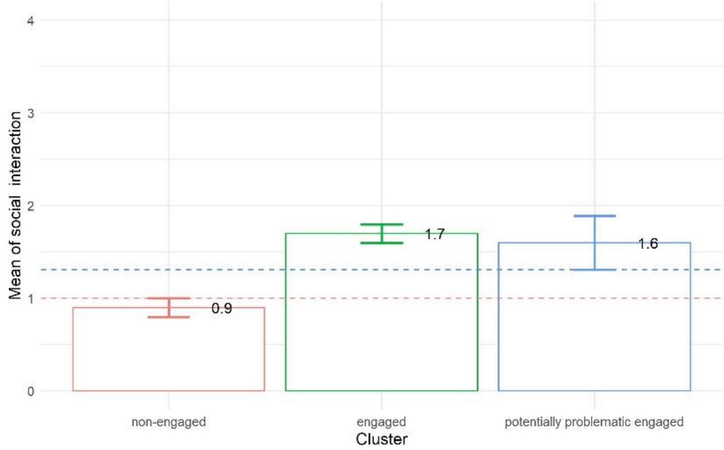
engaged viewers is higher (M = 2.4, SE = 0.17) than the engaged viewers (M = 2.3, SE = 0.07). However, this is a small difference between the means. Next to that, the standard errors of the potentially problematic engaged viewers and the engaged viewers overlap, meaning that they are not likely to differ. There is a bigger difference between the (potentially problematic) engaged viewers and non-engaged viewers (M = 1.6, SE = 0.06). Including the standard error non-engaged viewers do not overlap in their motivations with the other viewers, therefore are likely to differ from (potentially problematic) engaged viewers.

Engaged viewers and potentially problematic engaged viewers are not likely to differ in community motivations. Non-engaged viewers differ from the other viewers and they tend to use Twitch less for community motivations.

5.3.6.2 Social interaction

Figure 10 displays the differences in the mean and the standard error on the social interaction motivations per cluster.

Figure 10: The difference in social interaction motivations across clusters



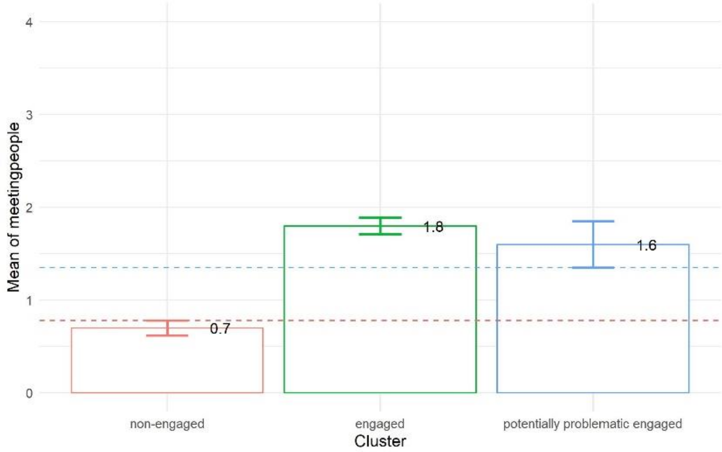
It shows that on average, engaged viewers have higher motivations towards interaction (M = 1.7, SE = 0.1) than the potentially problematic engaged viewers (M = 1.6, SE = 0.29) and non-engaged viewers (M = 0.9, SE = 0.1). There tends to be quiet some variability in standard error of the means among all groups. The precision of the mean among the potentially problematic engaged viewers tends to be lower. Next to that, the standard error of the mean of potentially problematic engaged viewers and engaged viewers overlap, and therefore are not likely to differ from each other for social interaction motivations. Non-engaged viewers do not overlap with other viewers when including their standard error. Therefore, they are likely to differ from the other viewers.

The general tendency to use Twitch for social interaction motivations is lower than other motivations among all groups. Next to that, non-engaged viewers tend to not have motivations for using Twitch for social interaction motivations in comparison to other viewers. Engaged viewers and potentially problematic engaged viewers are not likely to differ in social interaction motivations to use Twitch.

5.3.6.3 Meeting people

Figure 11 displays the differences in the mean and standard error of the meeting people motivations across the types of engagement.

Figure 11: The difference in meetingpeople motivations across clusters



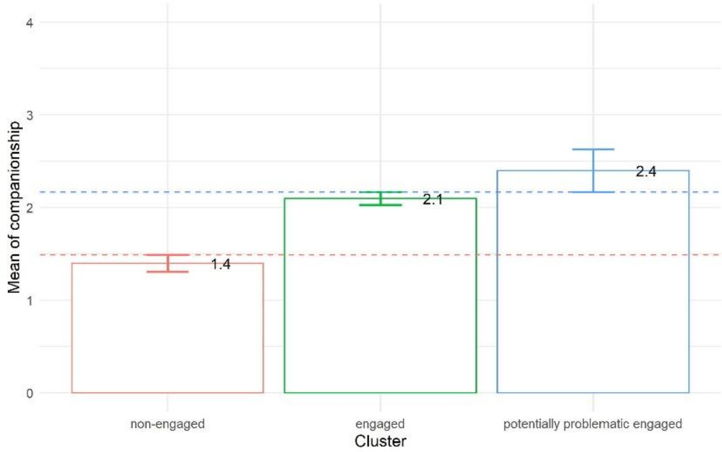
This shows that on average, the motivations towards meeting people on Twitch among the engaged viewers are higher (M = 1.8, SE = 0.09) than the potentially problematic engaged viewers (M = 1.6, SE = 0.25) and non-engaged viewers (M = 0.7, SE = 0.08). Also, looking across the motivations the general tendency to meet people on Twitch is lower than other motivations among all groups. However, there is quiet some variability around the mean of this motivation. Including the standard error of the mean it is shown that engaged viewers and potentially problematic engaged viewers overlap in the motivations towards meeting people. On average non-engaged viewers tend to be further away from the (potentially problematic) engaged viewers, also when the standard error is included. Therefore, non-engaged viewers are likely to differ from the other viewers.

Non-engaged viewers tend to have less motivations for using Twitch to meet new people in comparison to other viewers. Engaged viewers and potentially problematic engaged viewers are not likely to differ on meeting people motivations to use Twitch.

5.3.6.4 Companionship

Figure 12 displays the mean and the standard error bars of the companionship motivations per type of engagement.

Figure 12: The difference in companionship motivations across clusters



On average, the global tendency for the companionship motivations differ across the types of viewers. In this motivation potentially problematic engaged viewers on average have higher motivations for seeking companionship on Twitch (M = 2.4, SE = 0.23) than the engaged viewers (M = 2.1, SE = 0.07) and non-engaged viewers (M = 1.4, SE = 0.09). There tends to be some variability among the mean of the potentially problematic engaged as the standard error is quiet large. Including the standard error around the group means all subgroups do not overlap, therefore it is likely that the viewers differ.

The motivations of potentially problematic engaged viewers tend to be higher for companionship motivations in comparison to other viewers. The motivation of non-engaged viewers to use Twitch tends to be lower towards companionship in comparison to other viewers.

5.3.7 Conclusion

This paragraph will answer the sub research question: *'What motivations are associated with the identified subgroups of Twitch viewers?'*.

To analyze the associations of motivations with the identified subgroups of Twitch a descriptive analysis is done. The general tendency have been assessed based on the mean and standard error of the mean among the different motivation scales that were identified in the literature. Overarching associations of among the motivations and groups are as followed.

Entertainment motivations and relax motivations tend to be higher among all viewers in comparison to other motivations. Meeting people motivations and social interaction motivations to use Twitch tend to be lower among all viewers in comparison to other motivations. Potentially problematic engaged viewers tend to have less precision towards the mean, this is mainly caused by the smaller cluster size in comparison to the other subgroups.

On average, engaged viewers and potentially problematic engaged viewers tend to be close in their motivations to use Twitch in comparison to non-engaged viewers. On average, potentially problematic engaged viewers tend to have higher motivations than other viewers, except for information motivations, social interaction motivations and meeting people motivations. These motivations to use Twitch are on average higher for engaged viewers. However, including the standard error around the mean shows that not all motivations are likely to differ when taking this measure into account.

Potentially problematic engaged viewers tend to have higher motivations for using Twitch for distraction motivations, escape motivations, companionship motivations, relax motivations and entertainment motivations. Engaged viewers and potentially problematic engaged viewers slightly overlap in the standard error in the personal enhancement motivations, therefore it is unclear if these motivations are likely to differ. Engaged viewers and potentially problematic engaged viewers tend not to differ in community motivations, social interaction motivations and meeting people motivations. These motivations to use Twitch tend to be lower for non-engaged viewers in comparison with (potentially problematic) engaged viewers.

Non-engaged viewers tend to have lower motivations then (potentially problematic) engaged viewers for entertainment motivations, companionship motivations, community motivations, distraction motivations, escape motivations, personal enhancement motivations, social interaction motivations and meeting people motivations. Non-engaged viewers are not likely to differ in information motivations from the other identified subgroups.

5.4 Descriptive analysis of behavioral engagement

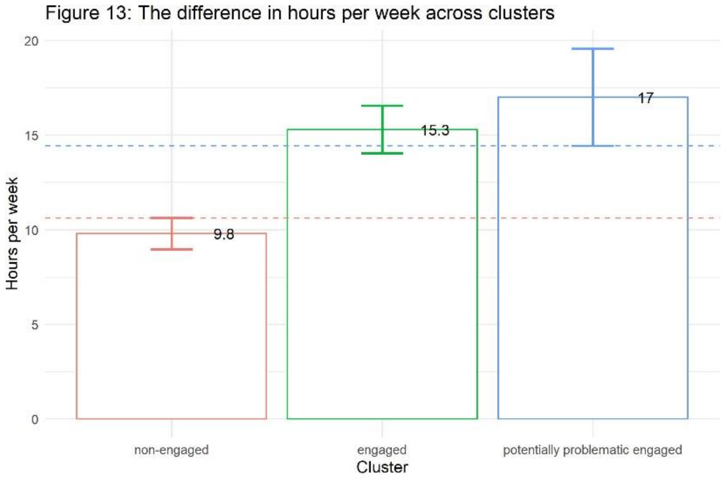
This paragraph will discuss the results of the descriptive analysis of the behavioral engagement elements of each cluster.

5.4.1 Preparation

To analyze the associations between behavioral engagement and the identified subgroups of Twitch the descriptive analysis is done. For each item the mean and standard error of the mean have been measured per type of engagement, so the differences of behavioral engagement elements across the clusters could be assessed.

5.4.2 Number of hours

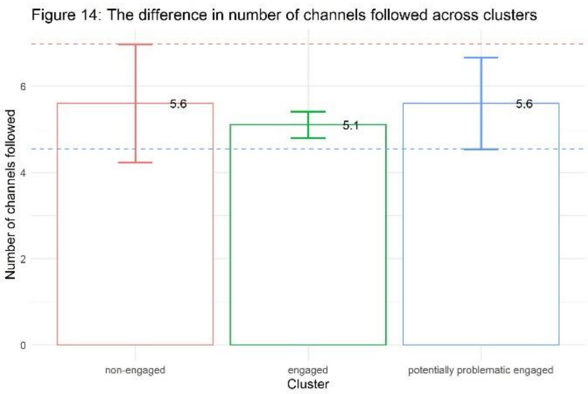
Figure 13 displays that the non-engaged viewers watch on average 9.8 hours per week (SE = 0.83). The engaged viewers watch on average 15.3 hours per week (SE = 1.25). The potentially problematic engaged viewers watch on average 17 hours per week (SE = 2.56).



On average, potentially problematic engaged viewers tend to watch more hours per week than engaged viewers. However, including the standard error these viewers overlap in the number of hours watched. Hence, it is likely that these viewers do not differ. Non-engaged viewers do not overlap and it is likely that they differ from (potentially problematic) engaged viewers.

Engaged viewers and potentially problematic engaged viewers tend not to differ in the hours watching Twitch. Non-engaged viewers tend to watch Twitch less hours than other viewers.

5.4.3 Streaming preferences



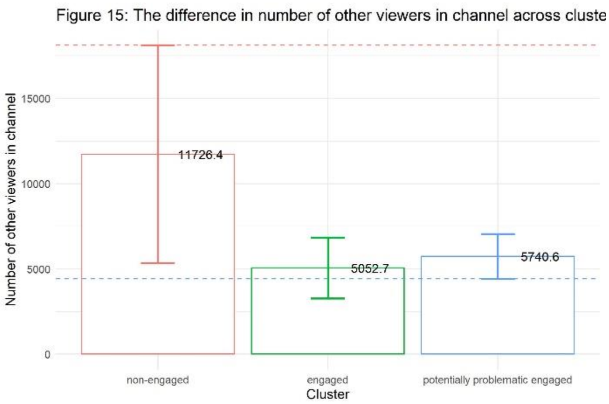
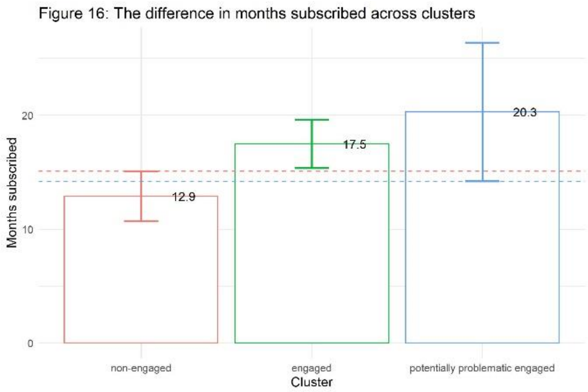


Figure 14 gives the means and error bars of the number of streams followed per type of engagement. It shows that the non-engaged viewers watch on average 5.6 streams (SE = 1.37). The engaged viewers watch on average 5.1 streams (SE = 0.31). The potentially problematic engaged viewers watch on average 5.6 streams (SE = 1.06). Engaged viewers seems to watch on average less streams. However, including the standard error the viewers are likely to watch the same number of streams. Concluding, that the number of streams watched tend not to differ among groups.

Figure 15 gives the means and errors of the number of viewers watching to the live stream at the same time per cluster. The favorite streams of the non-engaged viewers include on average 11,817 other viewers (SE = 6,385). In the favorite stream of the engaged viewers are on average 4,954 other viewers (SE = 1,789). Potentially problematic viewers watch in their favorite stream on average together with 5,920 other viewers (SE = 1,318).

On average, non-engaged viewers tend to watch bigger streams than other viewers. However, due to the lower precision around the mean it shows that the number of other viewers of Twitch do not differ across the identified types of viewers.

5.4.4 Financial support



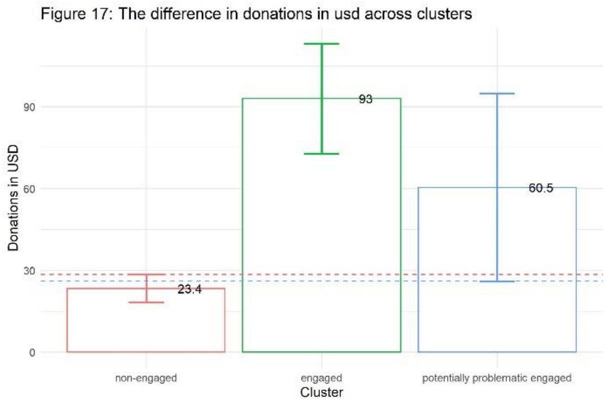


Figure 16 displays the means and error bars of the number of months subscribed per type of engagement. This shows that on average the non-engaged are subscribed for 12.9 months (SE = 2.19) to Twitch streamers. The engaged viewers have an average subscription to Twitch streamers of 17.5 months (SE = 2.13). The potentially problematic engaged viewers have an average subscription to Twitch streamers of 20.3 months (SE = 6.08).

Potentially problematic engaged viewers on average tend to subscribe more months than engaged and non-engaged viewers. However, there is quiet some variability around the mean of the potentially problematic engaged viewers. They overlap with engaged viewers and non-engaged viewers. But engaged viewers are likely to differ from non-engaged viewers, because they do not overlap. Hence, the number of months subscribed tend to be lower for non-engaged viewers in comparison of engaged viewers. Next to that, potentially problematic engaged viewers are not likely different from non-engaged viewers and engaged viewers.

Figure 17 shows that the non-engaged donate on average 23.4 USD (SE = 5.14) to streamers. The engaged viewers donate on average 85.3 USD (SE = 20.14) to streamers. The problematic engaged users on average spend 60.5 USD (SE = 34.45) on donations.

On average, engaged viewers tend to donate more than the other viewers. However, including the standard error around the mean they overlap with potentially problematic engaged viewers. Therefore, it is not likely that potentially problematic engaged viewers and engaged viewers donate differently. However, they do tend to donate more than non-engaged viewers.

5.4.5 Conclusion

The descriptive analysis on the behavioral engagement and the identified the subgroups is used to answer the following sub research question: '*What behavioral engagement are associated with the identified subgroups of Twitch viewers?'*.

All groups tend to watch a similar number of streams. Mean differences have been found in the financial support of the streamers, engaged number of hours and preferences for stream size. However, when the standard error of the mean is included, it is likely that the behavioral engagement elements do not differ between potentially problematic engaged viewers and engaged viewers. Therefore, can only be concluded that engaged viewers and potentially problematic engaged viewers tend to watch more hours and financially support the streamers more than non-engaged viewers.

6 Conclusion

Instead of focusing on motivations to increase the number of hours watched, this study tried to explore the ethical side of engaging for longer periods on the live streaming platform Twitch. In this chapter the answer will be given to the main research question.

'Which motives and types of engagement are associated with problematic use of Twitch viewers?'

The types of engagement are identified using the MCA K-means. Based on the optimization of the Silhouette width three clusters were identified: engaged viewers (48%), potentially problematic engaged viewers (8.2%) and non-engaged viewers (43.8%). The clusters have been found valid and stable using the Jaccard coefficient (> 0.75). The clusters have an average Silhouette width of 0.194. But the identified potentially problematic engaged viewers have an average Silhouette width close to 0, which means that the individuals in this cluster are close to neighboring clusters and they are on or close to the decision boundary. This shows, how closely problematic viewers are from other viewers.

Looking into the potentially problematic engaged viewers. The viewers correlate with symptoms of both obsessive behavior and addictive behavior. The potentially problematic engaged viewers have been found associated appreciating Twitch more due the new things they discover on Twitch. Next to that, they also have been associated with variables that indicate that they are out of control and having conflicts in their daily activities such as school or their job and other things that are part of them. They also correlate with having obsessive feelings for Twitch. Furthermore, they are associated with addiction symptoms: salience, tolerance, conflict and mood modification and to a less extent to relapse and withdrawal symptoms.

The descriptive analysis on the associations between the types of engagement and motivations have shown that there were tendencies specific to potentially problematic engaged viewers.

A tendency for higher motivations for using Twitch for relax motivations have been found among potentially problematic engaged viewers in comparison to other viewers. Also, a tendency towards higher motivations are found for entertainment motivations among these viewers. Potentially problematic engaged viewers tend to use Twitch to seek companionship more in comparison to other viewers. Next to that, their engagement tends to be higher for escape motivations and distraction motivations in comparison to other viewers. They try to escape multiple important aspects of their life such as school or job, family and others. Information motivations, community motivations, social interaction motivations and meeting people motivations have not been found to discriminate between engaged and potentially problematic engaged viewers.

The descriptive analysis on the associations between the types of engagement and behavioral engagement have shown that it is not likely that tendencies differ for potentially problematic engaged viewers and engaged viewers. Therefore, engaged viewers and potentially problematic engaged viewers cannot be distinguished based on these behavioral engagement elements.

7 Discussion

In this chapter the limitations and future research will be discussed.

7.1 Theoretical implications

Based on this study, it is found that problematic usage of Twitch follow similar results as in the related leisure literature of problematic gaming and binge-watching.

This study shows the dual construct of Vallerand (2003), where harmonious passionate viewers are separated from obsessive passionate viewers. Next to that, obsessive usage symptoms have been found correlate with addiction symptoms, that was also found in an earlier study of problematic gaming (Wang & Chu, 2007). Also, a tendency among the problematic engaged viewers have been found towards escape motivations of multiple important aspects of their life such as school or job, family and others. These results are in line with Flayelle et al. (2019), because they argue that conflicts need to rise on multiple areas of their live to be problematically engaged with the platform.

There are associations found with potential problematic engagement with Twitch and seeking companionship. In related fields such as binge-watching and internet usage loneliness also have been found as a predictor for problematic usage (Flayelle et al., 2019; Pontes, Griffiths, & Patrão, 2014).

There is no general tendency found towards community or meeting people online among these viewers. These general associations are in line with related fields such as problematic gaming (Ko, 2014) and binge-watching (Flayelle et al., 2019). According to this research, people wanting to meet new people, interacting with them and building a community are not likely to associate with problematic behavior, because these motivations also correlate with engaged behavior.

In this study no differences among information motivations have been found across the types of engagement. This is a different result than Flayelle et al. (2019), where they argue that need for information is a predictor for (high) engagement. Next to that, the entertainment motivations have been found to be higher for potentially problematic engaged viewers. This is also not in line with earlier research of binge-watching and problematic gaming (Charlton, 2002; Flayelle et al., 2019). This result is similar to Griffiths (1996, 2005), where they argue that euphoria criterium within the mood modification is a predictor for problematic engagement. Charlton (2002) argues that entertainment is a predictor of milder symptoms of problematic engagement and could also indicate high engagement. The results have not been tested for significance. Therefore further research could be done to further specify entertainment motivations.

Behavioral engagement elements have not been found to associate with problematically engaged viewers more than with engaged viewers. This is in line with Vallerand et al. (2003) and Deleuze et al.

(2018), where they argue investing a lot of time and effort in a hobby does not necessarily mean that it is obsessive or problematic. It is the viewer autonomous choice to spend his resources or time to the platform, when the viewer loses control over their time spend on Twitch and have conflicts in their life, it starts to become problematic.

7.2 Practical implications

Based on this study most Twitch viewers in the sample do not show any problematic usage of the live streaming platform Twitch. However, a small percentage does have symptoms of problematic usage during a time period of a year.

This study has found that it is not likely that differences in behavioral engagement differ among viewers. Therefore, it is not likely that the platform or streamers could identify problematic usage of Twitch from only behavioral engagement elements.

Better indications of problematic usage happens when the viewer loses control over the time spend of Twitch and have negative consequences on important parts of their life. Problematic usage tend to not associate with the interaction with community or the community feelings. They do associate with people who seek companionship or who try to escape from multiple areas of their life. For streamers and for the platform it is hard to identify problematic usage in an online environment. Based on this research it is hard to distinguish if the signals they have are indeed caused by the platform or they interact normally with the platform. More research in the actual behaviors such as communications in chats and actual hours of viewing in combination with a survey could support the platform and streamers to better identify potentially problematic viewers on Twitch.

7.3 Limitations

The limitations of this study are as followed.

This study suffers from the usual self-report limitations such as memory recall, lack of self-reflection and social desirability. To make sure respondents were reading the questions thoroughly two checks have been included.

Due to the use of two problematic behavior scales (the Passion Scale and BSMAS) more sides of problematic use are researched. Next to that, the uniqueness of the live streaming platform is taken into account. However, addiction in social media has been criticized a lot, therefore the results need to be interpreted cautiously.

Next to that, this research has a limited research sample (329) with a chance of overestimation or underestimation of problematic behavior (Bányai et al., 2017). Due to the small amount of identified potentially problematic viewers the results include some variability, which could mean that outside the research sample the results could not be found. This could occur when the underlying distribution would change.

The sample of this study comes from groups in Reddit (Serious gaming group and Twitch group). This could lead to a bias to viewers that interact on Twitch and Reddit. However, this study gave an broad perspective of the Twitch viewers, because especially the r/Twitch subforum is one of the biggest forums where Twitch users come together. This gives a broader perspective of different Twitch users with different engagement preferences then when only viewers of specific Twitch streamers are targeted.

The statistical analysis did not test significances of the associations between the motivations and behavioral engagement, but this research is exploratory and the goal was not to find significant results but to find patterns as a first exploration.

7.4 Future research

Therefore, future research needs to be conducted to investigate if differences in motivations differ significantly between highly engaged and problematic viewers. Furthermore, in this study distraction, escaping and relaxation motivations are included for tension release motivations. These motivations have shown similar tendencies toward potentially problematic engaged viewers that further need to be explored to distinguish between problematic behavior and normal behavior in live streaming. As it is possible that elements of tension release affect viewers positively, as shown in (Flayelle et al., 2019). Including depression symptoms could further help understand the distinction of problematic behavior in Twitch.

It is hard for live streaming platforms such as Twitch and streamers to recognize problematic use of viewers. This study has the limitations of self-reported questionnaires. To better understand the implications of problematic usage for streamers, live streaming platforms and viewers behavior of Twitch viewers could be web scrapped. This provides rich information if problematic viewers behave differently with the Twitch platform in comparison to normal viewers. These actual behavior information overcomes the standard self-report limitations. This information of actual behavior on the platform could give more tools to better recognize problematic behavior in Twitch such as the interaction frequency and the usage of language.

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Appendix A: Statements for questionnaire

item_id	items	Response
	Twitch Usage (Hilvert-Bruce et al., 2018)	
Q2	On average, how often do you watch Twitch?	less than once a week, once a week, 2-3 days a week, 4-6 days a week, Daily
Q3	On average, how many hours do you spend watching Twitch per week?	Numeric
Q4	Approximately how many channels/streams do you watch regularly?	Numeric
Q5	Consider the channels/streams you spend most time in. Estimate how many viewers this/these streams usually have?	Numeric
Q6	How many months total have you been subscribed to a Channel/Stream on Twitch? (For example, if you never subscribed to a channel the answer is 0. If you are subscribed to 2 different channels for a month the answer is 2 and if you are subscribed to one channel for 4 months the answer is 4.)	Numeric
Q7	Estimate how much money (US$) you have donated in total to broadcasters on Twitch?	Numeric
	The Passion Scale (Vallerand et al., 2003) *All passion questions have been answered in the same way*	**5-point Likert scale** **Strongly disagree – strongly agree**
Q9_1	I spend a lot of time using Twitch.	
Q9_2	I like to use Twitch.	
Q9_3	Twitch is important for me.	
Q9_4	Twitch is a passion for me.	
Q9_5	Twitch is part of who I am.	
Q10_1	Using Twitch is in balance with the other activities in my life.	
Q10_2	I have difficulties controlling my urge to use Twitch.	
Q10_3	The new things that I discover with using Twitch allow me to appreciate it even more.	
Q10_4	I have almost an obsessive feeling for Twitch.	
Q10_5	Using Twitch reflects the qualities I like about myself.	
Q10_6	Using Twitch allows me to live a variety of experiences.	
Q10_7	Using Twitch is the only thing that makes me excited.	
Q10_8	Twitch is well integrated in my life.	
Q10_9	If I could, I would only use Twitch	
Q10_10	Using Twitch is in balance with other things that are part of me.	
Q10_11	Using Twitch is so exciting that I sometimes lose control over it.	
Q10_12	I have the impression that using Twitch controls me.	
	Motivational Questions *All motivational questions have been answered in the same way*	**5-point Likert scale** **Strongly disagree – strongly agree**
	Entertainment motivations (Sjöblom & Hamari, 2017)	

Q11_1	I find using Twitch to be enjoyable.
Q11_2	Using Twitch is exciting.
Q11_3	I have fun using Twitch.
Q11_4	Using Twitch is entertaining
	Information motivations (Hilvert-Bruce et al., 2018)
Q12_1	I use Twitch to keep up to date on current trends and games.
Q12_2	I use Twitch to get useful information.
Q12_3	I use Twitch to learn about unknown things.
Q12_4	I use Twitch to get the information I need.
	Escape motivations (Sjöblom & Hamari, 2017)
Q13_1	Using Twitch, I can forget about school, work, or other things
Q13_2	Using Twitch, I can get away from the rest of my family or others
Q13_3	Using Twitch, I can get away from what I'm doing.
	Distraction motivations (Sjöblom & Hamari, 2017)
Q13_4	Using Twitch is a habit, just something I do.
Q13_5	When I have nothing better to do, I use Twitch.
Q13_6	Using Twitch passes the time away, particularly when I'm bored
Q13_7	Using Twitch gives me something to do to occupy my time.
	Relax motivations (Sjöblom & Hamari, 2017)
Q13_8	Using Twitch allows me to unwind.
Q13_9	Using Twitch relaxes me
Q13_10	Using Twitch is a pleasant rest
	Personal enhancement motivations (Sjöblom & Hamari, 2017)
Q14_1	I like when other Twitch users take my comments into account
Q14_2	I feel good when my comments prove to other Twitch users that I have knowledge about the game being played.
Q14_3	I try to improve my reputation among other Twitch users with my comments.
Q14_4	I like when streamers on Twitch take my suggestions into consideration.
	Companionship motivations (Sjöblom & Hamari, 2017)
Q15_1	Using Twitch, I don't have to be alone.
Q15_2	I use Twitch when there's no one else to talk or be with
Q15_3	Using Twitch makes me feel less lonely
	Community motivations (Sjöblom & Hamari, 2017)
Q15_4	It is very important to me to be a part of the Twitch community.
Q15_5	I spend time with other Twitch community members a lot and enjoy spending time with them.
Q15_6	I expect to be a part of the Twitch community for a long time.
Q15_7	Members of the Twitch community have shared important events together.
Q15_8	Members of the Twitch community care about each other.
	Meeting people motivations (Hilvert-Bruce et al., 2018)
Q15_9	I use Twitch to meet new people.
Q15_10	I use Twitch to find new people with the same interests.
Q15_11	I use Twitch to increase my social network.
	Social interaction motivations (Hilvert-Bruce et al., 2018)

Q15_12	I maintain close social relationships with some users on Twitch.	
Q15_13	I spend a lot of time interacting with some users on Twitch.	
Q15_14	I know some users on Twitch on a personal level.	
	Bergen Social Media Addiction Scale *All addiction questions have been answered in the same way*	**5-point Likert scale** **Never - always**
Q16_1	spent a lot of time thinking about Twitch or planning how to use it.	
Q16_2	felt an urge to use Twitch more and more.	
Q16_3	used Twitch in order to forget about personal problems.	
Q16_4	tried to cut down on the use of Twitch without success.	
Q16_5	became restless or troubled if you are prohibited from using Twitch.	
Q16_6	used Twitch so much that it has had a negative impact on your job/studies.	
	Demographics	
Q17	What is your gender ?	Female, Male, other
Q18	What is your age ?	Numeric
Q19	What is the highest level of education you have completed ?	College/University degree Doctorate degree High school degree Master's degree Some college/ university education Some high school education
Q20	What is your current employment status?	Full-time Part-time Retired Student Unemployed

Appendix B: All variables in the MCA K-means.

Results from the MCA K-means translated to the questions and belonging answer		
upper left side passion - problematically engaged		
Q10_1.SD&D	Using Twitch is in balance with the other activities in my life.	strongly disagree/ disagree
Q10_10.SD&D	Using Twitch is in balance with other things that are part of me.	strongly disagree/ disagree
Q10_11.A&SA	Using Twitch is so exciting that I sometimes lose control over it.	agree/ strongly agree
Q10_12.U&A&SA	I have the impression that using Twitch controls me.	undecided/agree/ strongly agree
Q10_2.A&SA	I have difficulties controlling my urge to use Twitch.	agree/ strongly agree
Q10_3.SA	The new things that I discover with using Twitch allow me to appreciate it even more.	strongly agree
Q10_4.A&SA	I have almost an obsessive feeling for Twitch.	agree/ strongly agree
Q10_9.A&SA	If I could, I would only use Twitch	agree/ strongly agree
Q16_1.O&VO	spent a lot of time thinking about Twitch or planning how to use it.	often/very often
Q16_2.O&VO	felt an urge to use Twitch more and more.	often/very often
Q16_3.O&VO	used Twitch in order to forget about personal problems.	often/very often
Q16_4.S&O&VO	tried to cut down on the use of Twitch without success.	sometimes/often/very often
Q16_5.S&O&VO	became restless or troubled if you are prohibited from using Twitch.	sometimes/often/very often
Q16_6.O&VO	used Twitch so much that it has had a negative impact on your job/studies.	often/very often
Q16_6.S	used Twitch so much that it has had a negative impact on your job/studies.	sometimes
lower left side - passion - harmonious engaged		
Q10_10.A	Using Twitch is in balance with other things that are part of me.	agree
Q10_2.D	I have difficulties controlling my urge to use Twitch.	disagree
Q10_3.A	The new things that I discover with using Twitch allow me to appreciate it even more.	agree
Q10_4.U	I have almost an obsessive feeling for Twitch.	neutral
Q10_4.D	I have almost an obsessive feeling for Twitch.	disagree
Q10_5.A&SA	Using Twitch reflects the qualities I like about myself.	agree/ strongly agree
Q10_6.SA	Using Twitch allows me to live a variety of experiences.	strongly agree
Q10_6.A	Using Twitch allows me to live a variety of experiences.	agree
Q10_8.A	Twitch is well integrated in my life.	agree

Q16_1.S	spent a lot of time thinking about Twitch or planning how to use it.	sometimes
Q16_2.S	felt an urge to use Twitch more and more.	sometimes
Q16_3.R	used Twitch in order to forget about personal problems.	rarely
Q16_5.R	became restless or troubled if you are prohibited from using Twitch.	rarely
passion.yes	Passion yes or no. Based on passion points with cut-off of 10 points	yes
upper right side - low engagement		
passion.no	Passion yes or no. Based on passion points with cut-off of 10 points	no
Q10_10.SA	Using Twitch is in balance with other things that are part of me.	strongly agree
Q10_11.SD	Using Twitch is so exciting that I sometimes lose control over it.	strongly disagree
Q10_12.SD	I have the impression that using Twitch controls me.	strongly disagree
Q10_2.SD	I have difficulties controlling my urge to use Twitch.	strongly disagree
Q10_3.SD	The new things that I discover with using Twitch allow me to appreciate it even more.	strongly disagree
Q10_4.SD	I have almost an obsessive feeling for Twitch.	strongly disagree
Q10_5.SD	Using Twitch reflects the qualities I like about myself.	strongly disagree
Q10_6.SD	Using Twitch allows me to live a variety of experiences.	strongly disagree
Q10_7.SD	Using Twitch is the only thing that makes me excited.	strongly disagree
Q10_9.SD	If I could, I would only use Twitch	strongly disagree
Q16_1.N	spent a lot of time thinking about Twitch or planning how to use it.	never
Q16_6.N	used Twitch so much that it has had a negative impact on your job/studies.	never
Q16_3.N	used Twitch in order to forget about personal problems.	never
lower right side - high engagement		
Q10_1.SA	Using Twitch is in balance with the other activities in my life.	strongly agree
Q10_5.U	Using Twitch reflects the qualities I like about myself.	neutral
Q16_2.R	felt an urge to use Twitch more and more.	rarely
Q16_4.N	tried to cut down on the use of Twitch without success.	never
Q16_5.N	became restless or troubled if you are prohibited from using Twitch.	never