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RESEARCH ARTICLE

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Understanding Characteristics of Popular Streamers on Live Streaming Platforms: Evidence from Twitch.tv

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Abstract

Live streaming platforms such as Twitch and Periscope have become some of the most popular synchronous social networking services. To attract viewers, streamers are motivated to broadcast exciting video content while actively interacting with viewers. The emerging stream of research on the live streaming community has examined streamers' motivations and how the viewers react to streamers. However, few studies have focused on understanding the characteristics of popular streamers. Popular streamers create tremendous business value for social media influencer investors, as they have high potential to create persuasive advertisements and endorsements for firms by promoting their products and services. We aim at examining the key characteristics associated with streamers' viewer base, namely their personality, professionalism, and streaming affordance. Based on text mining and analyses of video content, our results show: (1) certain personality traits (such as openness) are negatively associated with both cumulative and current popularity, (2) professional players are more likely to attract a larger viewer base, and (3) social affordance, including profile building affordance, social connectivity, and social interactivity, is positively associated with both cumulative and current popularity. Our results provide useful insights into measuring and evaluating streamers' popularity, which can, in turn, generate actionable strategies for social media influencer investors and platform operators.

Keywords: Live Streaming, Personality, Streamer, Popularity, Video analysis, Text Mining

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1 Introduction

Live streaming is an emerging form of media providing both exciting video content and timely interaction with users. Millions of individuals participate in this increasingly popular form of content creation and interaction (Hamilton et al., 2014), creating massive amounts of internet traffic for streaming platforms (Twitch.tv claims to be the fourth most visited platform in the US). By broadcasting on live streaming platforms, streamers can run their own businesses based on donations, subscriptions, personal brand merchandise sales, and advertisement revenue sharing from the platform (Zhang et al., 2015; Zhao et al., 2018; Chen et al. 2019). Video streaming is already a $30.29 billion industry (Research and Markets report, 2016), and its advertisement views grew 113% in the third quarter of 2015 (Yahoo report, 2016). Twitch.tv, a platform that mainly focuses on the gaming community (Ewalt, 2014), has accrued 45 million unique viewers since 2014. On average, Twitch's active users spend 95 minutes per day watching live streaming (Mediakix, 2017), which provides significant opportunities for advertisement revenue for business owners.

Currently, both the platform and sponsors face the question of whom to sponsor because of the overwhelmingly skewed distribution of streamer popularity. With the success of Twitch, a growing number of businesses are seeking to increase their sales and promote their products or services by sponsoring popular streamers on the platform. According to CNN Business, top Twitch streamers are paid millions of dollars per year through sponsorships with big companies like Adidas, Uber Eats, and Redbull (Briggs 2018). The *Wall Street Journal* reports that top game companies such as Electronic Arts, Blizzard, and Ubisoft extensively employ streamers to play their products, and smaller game companies have adopted similar strategies for years (Needleman 2018). Like other two-sided platforms, however, Twitch has a highly skewed popularity distribution among its streamers (Huang et al., 2020). A ranking mechanism displays streaming channels on the browsing page according to viewership, which provides even more visibility for the most popular streamers (Kaytoue et al., 2012). When a streamer already has a high viewership base, it generally becomes more expensive to sponsor them; however, the platform suffers from the loss or disengagement of unpopular streamers because the platform is not able to identify and promote lesser-known streamers with high potential. Also, viewers may be looking not merely for channels with vast numbers of viewers but may also be interested in streamers who broadcast unique, interactive, high-quality content (Bründl & Hess, 2016; Ducheneaut et al., 2007; Li et al., 2016). Therefore, the potential loss of streamers because of lack of exposure may disappoint viewers and damage the streaming ecosystem.

Unlike asynchronous online video platforms (e.g., YouTube), live streaming platforms allow viewers to consume unedited content and interact with streamers in real time. Streamers can also immerse themselves in the video content by speaking using a microphone and/or webcam. As such, streamers' behavior is particularly important for attracting a large viewer base. Furthermore, the community that follows live streaming is a niche community that may be substantially different from other online communities. Because video content on live streaming platforms is typically thematic and has a narrow objective (e.g., Twitch is a platform for game aficionados), the platform's unique streaming culture and atmosphere attract daily viewers who share the same interests. Thus, it is crucial to explore the time-invariant characteristics of Twitch streamers that are associated with their popularity. Such characteristics could be used to further develop advanced prediction models for streamer sponsorship selection and targeting.

Although the motives for watching live streamed content have been widely studied in the live streaming literature, viewer motive models cannot easily be applied to streamer targeting by sponsors or platforms when viewer engagement is not considered. In particular, it is difficult to identify and quantify viewers' motives (e.g., entertainment or knowledge) for specific channels. This problem calls for further streamer-level analysis to understand the key factors that relate to viewers' engagement.

In this paper, we explore the factors associated with Twitch streamers' popularity. We build our theoretical foundation by mapping streamer-centered characteristics to viewers' motives. Previous literature on live streaming has focused on viewers' needs, relying on uses and gratification theory (UGT) (Katz et al., 1973). Existing work suggests that viewers watch live streamed content for entertainment, knowledge, social interaction, social support, and a sense of community (Hilvert-Bruce et al., 2018; Sjöblom & Hamari, 2017). Accordingly, from the streamer's perspective, we propose three sets of measures that can match UGT metrics—personality (mined from video transcripts), professionalism, and social affordance.

We define a streamer's popularity in two ways. The first and most straightforward way to measure popularity is the number of viewers, which reflects the cumulative popularity of one streaming channel. This measure, however, cannot precisely capture the streamer's current popularity. For example, a channel created five years ago with a view count of 10 million may be less popular than a channel created two months ago with the same number of viewers. Therefore, we further consider another dimension of streamer popularity: their followers. On Twitch, viewers can follow streamers to receive email notifications and streaming recommendations when the streamer starts broadcasting. Viewers can opt-out if they are no longer interested in the streamer. We believe that follower count may be an accurate proxy for a streamer's current popularity and thus their associated economic value. Based on these considerations, we propose the following two research questions:

RQ1: How do the time-invariant characteristics of streamers associate with the cumulative popularity of their live streaming channels?

RQ2: How do the time-invariant characteristics of streamers associate with the current popularity of their live streaming channels?

To address these research questions, we collected real-time channel status and video data from 544 randomly selected streamers, who stream the games *League of Legends* and *Fortnite* on Twitch.tv. Leveraging voice recognition techniques, we extracted the audio transcripts of streaming videos with an average confidence level of 0.95. Then, using a text-mining approach, we extracted each streamer's personality traits from the streamer's audio transcript. Next, we manually captured the account name shown in the video and acquired the in-game information (level of the character) from the games' official APIs.[1] Using the streamers' names, we identified the profiles of professional teams on Gamepedia.com, a professional e-sports wiki webpage. Then, we analyzed the video data using face detection to examine whether a streamer uses a webcam as a measurement of the streamer's affordance. To evaluate whether our results could be generalized to other non-game-related categories, we applied our models to the Twitch.tv Just Chatting category and found consistent results in terms of personality traits and social affordance.

Our main results show that webcam use and membership on a professional e-sports team are positively associated with streamers' popularity. While professional players have a significant popularity advantage, we also observed that a large proportion of top streamers do not belong to professional teams. These streamers do not play professionally and are not playing to win prizes, meaning that these streamers are using features other than gaming skills to attract viewers. Specifically, we found personality traits that are associated with popular streamers, such as low scores in openness, conscientiousness, and extraversion, and high scores in neuroticism.

In summary, by combining econometric analyses and machine learning methods, this paper demonstrates the effect of personal characteristics and technology use on the popularity of live streamers. By offering an exploratory understanding of these features, we provide valuable insights into the live streaming market, which has been attracting significant attention from various stakeholders. To the best of our knowledge, this research is the first to analyze the personal characteristics of streamers and thereby provide actionable implications for investors and platform operators seeking to optimize their sponsorship strategies. Our results also offer critical insights into understanding the nature of the live streaming community by measuring streamer performance.

2 Theoretical Foundation

This section discusses theories and findings from previous research on the effect of personal characteristics on popularity. By systematically reviewing the existing literature on live streaming, we propose three popularity correlates, thereby extending findings from prior literature (see Table 1). Specifically, we establish a theoretical foundation on current UGT findings (i.e., why do people watch live streaming?). Then, using the needs-affordances-features (NAF) framework (Karahanna et al., 2018), we match streamer-centered features to the UGT motives (i.e., what streaming characteristics are associated with higher viewership?).

We survey four streams of literature. The first stream of literature relates to the current development of the live streaming community as our research context. Guided by the NAF framework, we then discuss the match between viewer-centered UGT metrics and streamer-centered characteristic measures. The second stream of literature concerns the Big Five Factor personality traits (Goldberg, 1990; Costa et al., 1991) and underscores the importance of personality traits for live streamers. Given the established theory on personality research, we focus on the application of theory in measuring personality traits. We then discuss the feasibility of using text mining techniques to measure personality traits in the domain of information systems, marketing, and psychology, which are expected to ultimately predict the performance of streamers. The third stream focuses on the professionalism (or expertise) of the live streamer. We discuss why professional e-sports players draw high levels of attention from viewers. The fourth stream introduces the concept of social affordance and applies this concept in the context of live streaming.

2.1 Online Game Live Streaming, UGT and Streamers' Characteristics

Founded in 2011, Twitch.tv is the most popular platform in the video live streaming community worldwide, boasting more than 43 million unique monthly viewers (Wilhelm, 2013) and a 43.6% market share in live streaming services (Eadicicco, 2014). Focusing on game-related content, Twitch.tv has taken a prominent position among online social media platforms and generates considerable income for its top streamers. The unique form of interaction and culture even changed the gaming community, as live streaming brings an element of activity beyond the traditional game spectatorship (Smith et al., 2013). The live streaming industry also draws the attention of both investors and researchers. For example, many small business owners (i.e., electronic equipment and clothing brands) actively sponsor popular live stream channels to expand their businesses through promotion and advertisements on live streamed videos. Because viewers enjoy watching content live streamed by professional players (Kaytoue et al., 2012), professional players with steaming channels have attracted a variety of sponsors in recent years. Because

[1] Roit API: https://developer.riotgames.com/

sponsorship on Twitch.tv has become a significant advertisement channel, extracting the success factors of top streamers is of critical importance for optimizing investors' sponsorship strategies.

There are two main streams of research related to the live streaming community: motivation and behavior. Regarding motivation, researchers have focused on two fundamental questions: Why do users broadcast, and why do people watch live streamed content? To answer the first question, Bründl and Hess (2016) examined data from 543 top streamers and found that the volume of live streamed content is influenced by streamers' motives, while the intention to continue live streaming is determined by streamers' social capital. With the growth of the live streaming community, viewers can also watch more live streamed content from full-time broadcasters because the income of top streamers has increased (Ewalt, 2014). The prospect of earning substantial money attracts more users to become streamers.

To answer the second question, there is a body of research in the live streaming community that focuses on UGT motives (Katz et al., 1973). UGT provides a theoretical framework for understanding why people actively consume media content, and it has been adopted to study viewer engagement on live streaming platforms (Hilvert-Bruce et al., 2018; Sjöblom & Hamari, 2017). Previous research on live streaming claims that UGT motives such as tension release, social integration, and affection could influence viewers' behaviors such as viewing duration, streamer selection, following, and subscription (Sjöblom & Hamari, 2017). More recent work specifies these factors into eight UGT motivations, such as entertainment, information seeking, and social interactions that could affect emotional connectedness, time spent viewing, and the gifting choices of viewers (Hilvert-Bruce et al. 2018). Additionally, escapism, sexual curiosity, viewer interaction, acquiring knowledge about game playing, the novelty of the game, and the aggressiveness of players have all been found to have an impact on the frequency of viewing behavior (Nam and Kwon, 2015; Hamari & Sjöblom, 2017). Furthermore, the professionalism of streamers is shown to be one of the key factors influencing viewer engagement (Ducheneaut et al., 2007; Bründl & Hess, 2016; Li et al., 2016).

Despite these research efforts, the literature offers little insight into the evaluation of the streaming channel on the basis of UGT motives, which makes it difficult for sponsors and platform operators to identify, classify, and target streamers. For example, the interaction between streamers and their viewers has been found to be a critical factor that influences whether or not a user will watch a live stream. Given the various styles of interaction (e.g., speaking and visual presentation), it is extremely challenging to identify which channels have higher levels of interaction. Hence, sponsors and platforms can only select streamers to promote based on their viewership numbers, which further exacerbates the popularity bias and marginalizes small streamers who actively interact with their viewers. Therefore, there is a strong need for a quantifiable, comprehensive, and streamer-based framework to help sponsors and platforms understand and target streamers.

This research gap has been observed by IS researchers. For example, Karahanna et al. (2018) suggest that social media platforms provide affordances and corresponding features to satisfy users' needs. They propose a theoretical framework, namely NAF, to match platform affordance with individuals' needs. Similarly, the live streaming platform provides streamers with attractive features to cater to their viewers. Guided by the NAF framework, we propose three features (see Figure 1) matched with existing UGT motives to understand viewer engagement with the live streaming platform. Table 1 showcases how our proposed measures connect to the existing literature from the streamer's perspective.

Prior research on behavior has shown that channels lose viewers very quickly at the end of each streaming session, while the majority of the viewers remain during the peak period (Nascimento et al., 2014). Furthermore, prior research indicates that viewership count can be predicted and ranked by the Condorcet method and that viewership peaks can be explained in the same fashion (Kaytoue et al., 2012). Previous studies have also examined gaming community culture, group dynamics, and structural features (Nascimento et al., 2014; Ducheneaut et al., 2007; Hamilton et al., 2014), as well as Twitch's network structure, player relationships (Churchill & Xu, 2016), and visualization (Pan et al., 2016).

Although the motivation and behavior of viewers have been studied, it remains unclear how streamers, who play a crucial role on live streaming platforms, impact viewer engagement. In other words, there is a lack of understanding about performance and motivation differences among streamers. Recent research in related contexts sheds light on some preliminary success factors. For example, Qiu et al. (2015) find that learning and network effects are positively correlated to video views on YouTube. Berger and Milkman (2012) claim that content that can evoke high arousal tends to be more successful. In this paper, we investigate success factors by utilizing a machine learning approach to understand the role of streamer characteristics, particularly the streamer personality.

Table 1. Summary of Literature Review on Viewer Motivation

Matched features	Viewer motivations	Description	Reference
Personality traits of streamers	Charm	Viewers are attracted to the individual characteristics of streamers, such as their sense of humor, their aggressiveness while streaming, and their openness to questions.	Sjöblom & Hamari, (2017); Chen & Lin, (2018); Hilvert-Bruce et al., 2018
	Novelty	Streamers' ability to provide original and unusual video content, which cannot be found anywhere else.	Nam & Kwon (2015); Sjöblom & Hamari (2017)
	Entertainment / stress relief	Streaming content contains casual features that entertain and help relieve stress.	Nam & Kwon (2015); Sjöblom & Hamari (2017); Hamari & Sjöblom (2017); Hilvert-Bruce et al. (2018)
	Affective	Streamers' moods, expressions, or attitudes that inspire viewers.	Sjöblom & Hamari (2017)
Professionalism/skill level	Information seeking	The incentive to acquire knowledge about art, cooking, communication, and gaming from streamers.	Kaytoue et al. (2012); Gros et al. (2017); Hamari & Sjöblom (2017); Hilvert-Bruce et al. (2018)
Social affordance	Interactivity	The willingness to communicate with viewers (e.g., answering questions, joking, and showing appreciation for gifts sent by viewers).	Nam & Kwon (2015); Sjöblom & Hamari (2017); Hilvert-Bruce et al. (2018); Sjöblom et al. (2019)
	Curiosity (regarding the type of live streaming)	The use of exclusive technologies (e.g., camera and microphone) to broadcast video in real-time.	David (2010); Sjöblom et al. (2019)
	Social integrative	The sense of belonging from being a fan of streaming channels or communities. (A fan can be defined as an individual viewer who follows the streaming channel.)	Sjöblom & Hamari (2017); Hamari & Sjöblom (2017); Hilvert-Bruce et al. (2018)

2.2 Personality Traits

Personality is a widely studied topic in information systems (IS) research and related disciplines because of its significant implications for business. Allport (1961) and Maddi (1989) claim that personality can be conceptualized as a representation of individual cognition and behavior, which can further reflect individuals' thoughts and personal characteristics (Barrick & Mount, 1991). Personality has a significant impact on domains such as job markets (Barrick & Mount, 1991), investment behavior (MacMillan et al., 1985; Cardon et al., 2009), attitudes toward information systems (Devaraj et al., 2008), and attitudes toward products or services (Jahng et al., 2002). Notably, personality plays an important role in product consumption decisions (Rentfrow & Fosling, 2003; Horton, 1979), which makes this topic particularly interesting. For example, for angel investors, the personality of project founders is carefully examined prior to making investments (MacMillan et al., 1985; Cardon et al., 2009), meaning that investors' expectations for project founders' personalities can impact project financing and thus the success of the project. Jahng et al. (2002) argue that the personality of online consumers may affect product presentation. Previous research has shown that watching live streamed content and following channels can significantly influence the success of streamers and their sponsors, and watching decisions are likely associated with streamer personality. Given that personality impacts consumer acceptance of products and services (Hu & Pu, 2011), our research explores how personality relates to streamers' popularity in terms of viewership, which has significant implications for investors and platform operators.

A variety of personality models and measures have emerged in recent years, providing ample opportunities for researchers to evaluate and quantify personality traits. Among these measures, the Big Five personality traits (Goldberg, 1990; Costa et al., 1991) are regarded as the gold standard for personality research. The corresponding model, called the five-factor model (FFM), has been widely used by researchers across disciplines. The FFM provides a classification methodology of personality as known as the "OCEAN" dimensions: i.e., Openness (to experience), Conscientiousness, Extraversion, Agreeableness, and Neuroticism (often termed "emotional range" to distinguish it from the psychology term). In general, previous research extracts those traits from a personal assessment via questionnaire items and treats the measurement using personality scores (Barrick & Mount, 1991; Costa et al., 1991). To better understand the FFM, we describe the five dimensions in further detail as follows: The first dimension is *openness*, or being open to experience. Individuals who score high in openness exhibit features of bravery, imagination, curiosity, and emotional awareness. Specifically, they are interested in new experiences, are easily bored by routines, are eager to learn new things, and have a rich inner world. The second dimension is *conscientiousness*. Individuals with high levels of conscientiousness are well-organized and confident in their abilities. They also pursue success and perfection and are willing to take on substantial responsibilities. Thus, conscientious individuals are described as achievement driven, responsible, orderly, and autonomic. The third dimension, *extraversion*, can be understood as the tendency to seek external stimulation, and is marked by high activity levels, cheerfulness, excitement seeking, and sociability. Individuals who score high in extraversion live fast-paced, busy lives, and perform tasks quickly and efficiently. The fourth dimension, *agreeableness*, reflects compassion and the willingness to cooperate, which can be described by characteristics such as altruism, modesty, sympathy, and trust. Individuals with high levels of agreeableness are more likely to cooperate with and trust colleagues, act in a humble manner, and are warm-hearted. The fifth dimension, *neuroticism*, captures emotional sensitivity. Individuals with high levels of neuroticism care about what others think of them and are easily rattled.

The five-factor model provides a fundamental conceptual model for studying personality. Based on this model, we focus on using machine learning techniques to extract the big five personality traits of live streamers to explore the effect of personality on their popularity.

2.3 Application of Personality Traits Model in Social Media

The majority of previous research on personality traits requires participants to fill out an assessment questionnaire, which introduces a scaling challenge as the sample size increases (De Montjoye et al., 2013). There are two particular challenges for social media research using this method. First, this method may introduce bias in the sampling process caused by accessibility issues related to social media users. For example, since some social media users may wish to remain anonymous to the platform and external sources, researchers are not able to access these users, who may be highly representative. Nonresponse bias may also be an issue because questionnaires may be rejected or ignored by a large portion of social media users who are sensitive to privacy concerns. Second, beyond these accessibility issues, it is extremely costly for researchers to collect a large number of valid questionnaire responses.

We avoid these pitfalls associated with survey-based research by instead relying on machine learning-based text mining techniques, which have been shown to be capable of reliably extracting personality traits using text-based social media content (Fast & Funder, 2008; Gill et al., 2009; Golbeck et al., 2011; Hirsh & Peterson, 2009; Hu et al., 2019; Yarkoni, 2010). A number of recent studies use the personality extraction technique to acquire personality traits, and previous research has shown that personality traits can be accurately predicted using individuals' social media (Twitter) profiles (Golbeck et al., 2011; Quercia et al., 2011, Qiu et al., 2012). Building on this line of work, Quercia et al. (2012) demonstrate that extraversion can serve as a predictor for a user's number of Facebook contacts, and Quercia et al. (2011) show that Twitter users with low neuroticism, high openness, and high conscientiousness are more likely to be popular. In terms of decision-making, certain personalities have also been found to relate to the diffusion and success of crowdfunding (Thies et al., 2016) and previous research has identified certain personalities that can drive word-of-mouth (Adamopoulos et al., 2018).

Current psychology work has demonstrated that online gamers show different personality patterns than nongamers. Whereas gamers have higher levels of conscientiousness (Teng, 2008), general social media users exhibit features of low scores in extraversion and openness and high scores in neuroticism (Amichai-Hamburger et al., 2002; Mehroof & Griffiths, 2010; Gil de Zúñiga et al., 2017), which is distinct from popular users (Quercia et al., 2011). However, streamers may be different from typical gamers or social media users because live streaming is often considered to be an actual job rather than casual playing. Furthermore, not all live streamers operate in the gaming context. Thus, the effect of personality on streamer success remains unclear.

In addition, Big Five personality traits can be matched to the existing UGT motives (Hilvent-Bruce et al., 2018; Sjöblom & Hamari, 2017). According to the definition of FFM, a streamer with high openness would be open to experiencing streaming in multiple categories (e.g., multiple games), which could potentially depress viewers who seek knowledge in streaming content (e.g., playing certain games) and who seek community belonging. This is contrary to the information seeking and social support motives. Thus, we propose:

H1a: The openness trait for streamers, as mined from streaming video transcripts, is negatively associated with streamer popularity.

Conscientiousness reflects a willingness for teamwork, which is consistent with the sense of community, meeting new people (in our context, it could be a new streamer), and social interaction motives. Therefore, we propose:

H1b: The conscientiousness trait for streamers, as mined from streaming video transcripts, is positively associated with streamer popularity.

Streamers with high extraversion tend to behave actively and generate excitement. This is consistent with the motives of entertainment and stress relief. Thus, we propose:

H1c: The extraversion trait for streamers, as mined from streaming video transcripts, is positively associated with streamer popularity.

Agreeableness represents tendencies of cooperation, altruism, sympathy, and trust, which can reasonably imply a willingness to support others. It corresponds to the social support and external support motives in UGT research. Thus, we propose:

H1d: The agreeableness trait for streamers, as mined from streaming video transcripts, is positively associated with streamer popularity.

Neuroticism has been widely studied, as it correlates with anxiety disorders (Bienvenu & Stein, 2003). However, it is unknown how viewers with social anxiety (i.e., stress relief) motives would react to content uploaded by sensitive and emotional streamers. As Sjöblom and Hamari (2016) show, viewers enjoy aggressive atmospheres and appreciate streamers' emotional expression. We thus expect the neuroticism score to be positively associated with streamer popularity and propose:

H1e: The neuroticism trait for streamers, as mined from streaming video transcripts, is positively associated with streamer popularity.

2.4 Game Player Professionalism

The emergence of the gaming industry has given rise to a new form of sports—e-sports, which was created by gaming companies and has rapidly become widely popular. In recent years, an increasing number of highly skilled gamers have chosen to work full-time for professional teams. Seo (2016) defines professional e-sports as a serious leisure activity focusing on video gaming-related competition and argues that players choose to become professional gamers because of the glory associated with the mastery of skills, as well as an interest in self-improvement and teamwork. Professional players have a unique fan group in the community, which may facilitate their popularity on live streaming platforms, and some casual players may also start working full-time as professional streamers. Martoncik (2015) investigates the differences between casual players and professional gamers in terms of their motivation for gaming, finding that professional players are motivated by self-improvement rather than playing for fun. Thus, while the majority of casual players may not perform well, their personalities may be capable of attracting high numbers of viewers pursuing relaxation, novelty, or curiosity (Sjöblom & Hamari, 2017). Thus, it is not clear whether professional players with higher skill sets are more popular than professional streamers that may or may not have great gaming talent. Further, it is unclear whether the identity of the professional player has a role in attracting viewers. To address these questions, we examine the effect of professionalism on streamers' popularity in this paper.

The term "professionalism" in this paper is defined along two dimensions: (1) whether a player plays on a professional team, and (2) the degree of gaming proficiency (the ranking level of the in-game character). According to UGT findings, viewers prefer watching live streaming that can facilitate learning (Kaytoue et al. 2012; Gros et al. 2017; Hamari & Sjöblom, 2017; Hilvert-Bruce et al. 2018). We thus expect that professionalism is positively associated with popularity, and propose the following hypotheses:

H2a: Streamers who play on a professional team tend to attract more viewers.

H2b: Streamers who have a higher degree of gaming proficiency tend to attract more viewers.

2.5 Affordance

The theory of affordance originates in the field of visual perception. Gibson (1979) conceptualizes affordance as the ability of the environment to provide animals with objects, which sheds light on the relationship between the environment and animals. Affordance has recently been widely studied and integrated into several streams of research in computer and human interaction and information systems. Norman (1988) uses this term to refer to realized objects offered by the environment. Most recently, affordance has been used in social media research to understand the capability of social media services. In this paper, we follow the theoretical framework proposed by O'Riordan et al. (2016) to measure and examine the feature-level social media affordance. O'Riordan et al. (2016) define social affordance in social media services as capabilities provided by social network services, which are broken down into the profile building affordance, social connectivity, and social interactivity. First, the profile building affordance refers to the capability of managing and organizing personal profile information. For example, the ability to display a personal photo or logo on the platform could be used as a profile building affordance since it can help users present themselves to the public (Qiu et al., 2017). Second, social connectivity can be understood as the "link" between focal users and their contacts, which can be either a reciprocal or a one-way connection, e.g., following. Third, social interactivity affords the possibility for users to communicate with each other. More recently, Sjöblom et al. (2019) investigated the social affordance of 100 live streamers and provided statistics about their stream and page elements to identify technology use. Despite the importance of these statistics, there remains a scarcity of evidence on how social affordance relates to popularity.

In our context, we treat the streamer's channel description, profile banner, and icon as the profile building affordance. We argue that social connectivity is covered by the streamers' personality traits in terms of their willingness to connect to others. Thus, we omit social connectivity in our analysis. Finally, we use the streamer's use of a webcam, the number of words they speak, and the presentation of their Twitter account on the streaming page as our social interactivity measures.

Intuitively, the viewer would prefer well-maintained channels that they can interact with (similar to the social interaction motive in UGT research). Additionally, webcams and microphones are widely used to attract more viewers (David, 2010; Sjöblom et al., 2019). We expect the profile building affordance and social interactivity affordance to be positively associated with streamers' popularity, and propose the following hypotheses:

H3a: The profile building affordance, mined from channel status, positively correlates with streamers' popularity.

H3b: Social interactivity positively correlates with streamers' popularity.

Figure 1 presents the conceptual model of our hypotheses.

3 Research Methodology

In this section, we first present our data, which includes Twitch streamers' channel information and video content. We then discuss the econometric methodology for our empirical analysis. We collected streamers' channel information and their videos from Twitch.tv and used the social media handles shown on the streamers' profile pages to collect their Twitter accounts. Then, leveraging a state-of-the-art deep learning approach, we transformed our video into text transcripts (including punctuation) to represent what streamers are talking about during the streaming sessions. Then, we extracted the personality scores by processing the transcript in the IBM Bluemix API under the text mining settings. We also employed a face detection model to measure whether a streamer uses webcams, which we refer to as social interactivity. We recorded streamers' gaming sessions from the video to acquire the proficiency score for each streamer, and also extracted the streamers' text-based personality scores based on their recent tweets. Figure 2 shows the construction of the main measurement.

We measured our dependent variable based on our objective to infer the popularity and value of streaming channels. Then, we integrated the results from video analysis, face detection, voice recognition, and personality extraction and preprocessed the dataset within the context of our research. Finally, we empirically estimated the effect of selected features on the dependent variable. Based on the results of the regression, we summarized the insights for the characteristics patterns of popular streamers. Our study not only provides platform operators and channel managers with more profound insights for streamer selection but also helps investors and viewers better understand the nature of live streaming.

3.1 Dataset

We constructed the unique dataset for this study using a multitude of data collection efforts, including Twitch API, weblink detection, and Twitter API, over a period of three weeks. We targeted the gaming category using the domain knowledge of the authors, and considered the accessibility of gaming data, the game's maturity, representativeness, and the viewer base. We ultimately selected *League of Legends* and *Fortnite*, two of the most popular games globally that provide in-game data access and have e-sports wikis.

To reduce sampling bias, we created a streamer pool containing 26,763 unique streamers who played *League of Legends* and *Fortnite* at least once by tracking the live status of each streamer. We then consolidated our streamer pool by excluding channels in languages other than English to avoid misinterpretation. Since companies and platform operators seek candidates for investment or promotion based on live streamers who actively contribute to the community, we also adjusted our sampling strategy to fit this need and confirmed that each streamer in our sampling pool was a qualified streamer rather than a one-time user. Specifically, we excluded streamers who had (1) zero views and streamed for less than 30 minutes within three weeks, (2) zero views and fewer than two followers, and (3) streaming accounts that were suspended or canceled. Additionally, we randomly sampled 400 streamers in each category and recorded their identifiers in one name list. Using this list, we collected information from the channel profile (e.g., channel language, time of creation, and channel description) and panel description (e.g., social media links) that indicate channel status.

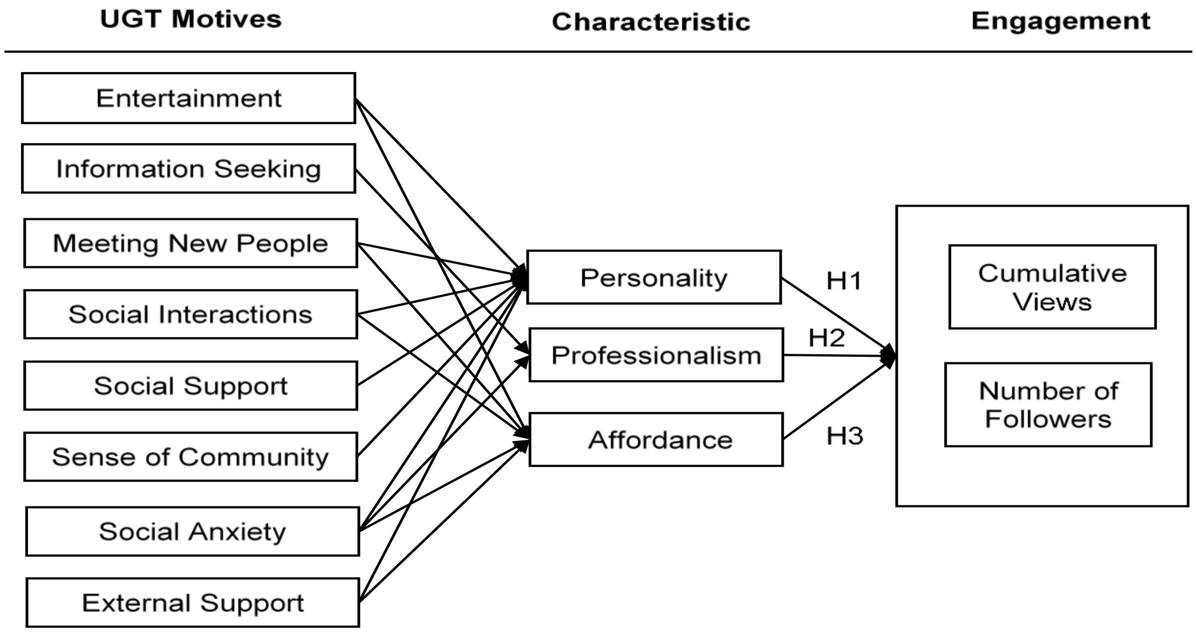

Figure 1. Conceptual Model for Hypothesis

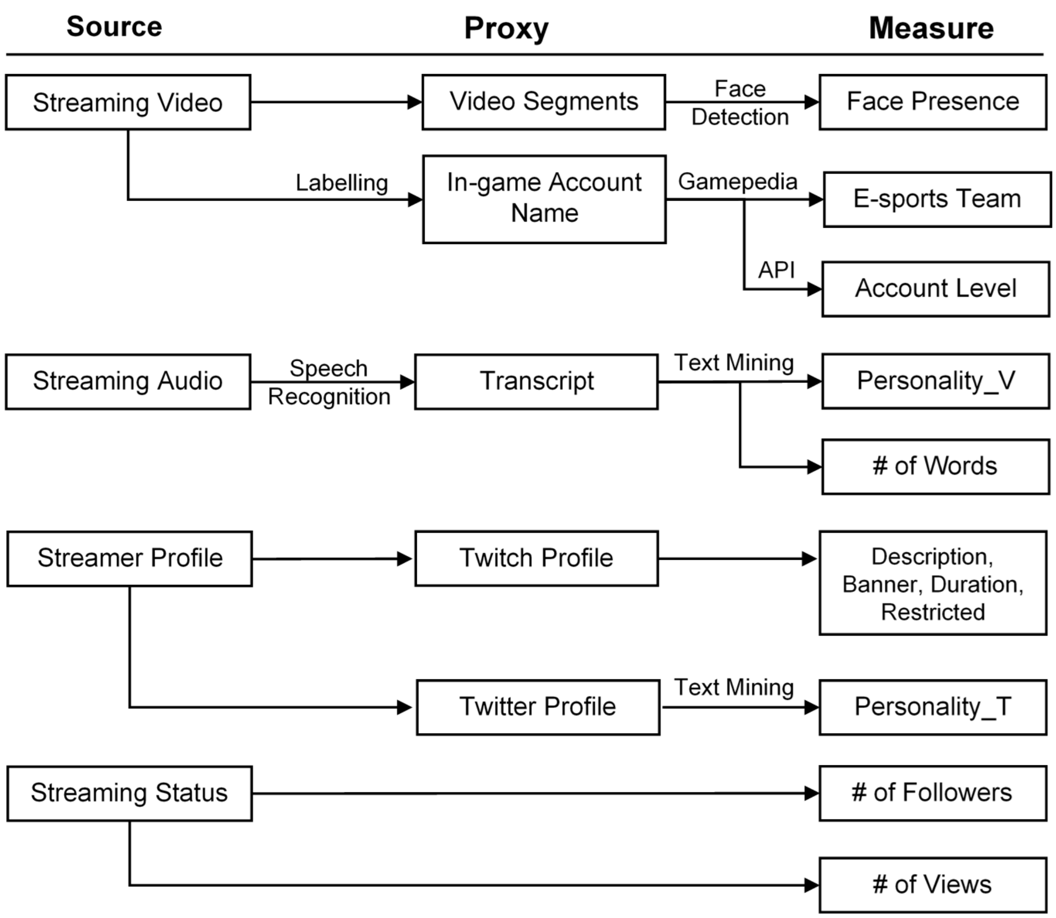

Figure 2. Measurements Construction

We randomly selected one streaming video from each streamer and qualified the video by checking the length in order to acquire a complete transcript. We excluded channels hosted by companies, organizations, or groups because (1) such channels typically have large budgets and stable sponsors and do not represent typical individual streamers, (2) the personality traits derived from analyzing speech would be inaccurate, as these channels typically feature multiple streamers, and (3) the channels are not typically gaming channels but are used to host events. Following the preprocessing, we then separated the audio and video tracks and sent the files to the Google Cloud (2018) speech recognition service to acquire the transcripts. Notably, we obtained reliable results of speech recognition with an average confidence level of 95.4%.

For personality measures, we used two alternative approaches. First, we leveraged the IBM personality insight API to process the transcripts and obtain five traits from FFM. The measures, we collected captured the real-time personality of the streamer during an active live session. Second, we processed 200 tweets for each streamer using the IBM personality insight API to acquire their personality traits.

To measure the professional skills of the streamers, we manually captured the game account names by watching each video. Then, we sent the account name to the game API (Riot API for *League of Legend* and Rapid API for *Fortnite*) to collect information at the streamer account level, which we used to evaluate the streamer's proficiency in game playing. Additionally, we determined whether a streamer in our sample played on a professional team by searching and matching their names on Gamepedia.com, which is a popular wiki for e-sports.

For affordance measures, we constructed the building profile affordance by using the channel status data we collected. Specifically, for the building profile affordance, we assessed whether a channel had a description and whether a channel used a logo and banner. We constructed the social interactivity measure using a deep learning approach. We utilized face detection models to check whether streamers used a webcam in selected videos. For social interactivity measures, we used the number of words in a transcript and determined whether the streamer provided Twitter account links in the channel description.

Overall, after capturing, preprocessing, and transforming the data, we obtained information from a sample of 516 streamers, comprising information about their profiles (i.e., view count, banner and icon links), video profiles, scores for five personality traits, information at the game account level, professional player status, the number of words and content in their transcripts, presence of Twitter account link, and webcam use.

3.2 Variables

Our first dependent variable, view count, represents how many times a particular channel has been viewed. Intuitively, this variable would seem to reflect the degree of popularity among viewers. Furthermore, view count is used as the key ranking factor on various live streaming platforms (Social Blade, 2017), making it the most critical metric for measuring a channel's value. High view counts can also significantly increase the channel prorogation force (CPF), thereby attracting advertisers.

However, view count distribution has been found to be highly skewed (Kaytoue et al., 2012) and can be approximately referred to as a power-law distribution, meaning that popular streamers with high view counts are more likely to attract viewers, creating a feedback loop that makes popular channels even more popular. This phenomenon thus creates a barrier for both new and currently unpopular streamers to make progress toward becoming popular streamers. Meanwhile, since view count represents accumulated popularity that depends on the history of the channel, the tenure of the streamer may have a significant impact on the number of views. For instance, a channel created three years ago that has three million views may not be more popular than a channel created six months ago with two million views. Even if we use monthly or annual views combined with the duration of the streams, these statistics still do not comprehensively reflect streamer popularity because their active periods are not accounted for.

Therefore, we chose the number of followers as our second dependent variable to reflect popularity. Followership in Twitch indicates that viewers follow the channel and are willing to be notified when streaming sessions begin, which in turn usually reflects the loyalty of viewers (Sharp et al., 2002; Dick and Basu, 1994). By following a streamer, viewers receive channel announcements and update emails, and increased loyalty can develop the channel's brand reputation and market share (Jacoby & Kyner, 1973; Dick & Basu, 1994; Steenkamp & Dekimpe, 1997; Zhang et al., 2016; Zhang & Moe, 2018), and high follower counts should eventually accelerate a channel's popularity. Therefore, the number of followers generally represents the streamer's ability to attract more future viewers. We also used a set of control variables to account for alternative explanations. Our control variables contained personality scores mined from Twitter accounts, whether a channel contains adult content, the duration of streamers, and streamers' partnership (a description of these variables can be found in Table 2).

3.3 Social Interactivity

Following the framework proposed by O'Riordan et al. (2016), we adopted webcam use during streaming sessions, the number of words in the streaming transcript, and whether streamers linked their Twitter in their profile as the social interactivity affordance measures. We utilized a Haar classifier proposed by Wilson and Fernandz (2006) to detect streamers' faces in the collected video. First, we created three video snapshots of the start point, middle point, and endpoint of each video, respectively. We then implement the face detection algorithms to detect whether there is a human face in the video based on the OpenCV computer vision framework (https://opencv.org/). In cases in which a human face was detected in two of the three snapshots from one video, we concluded that the streamer was using a webcam. If there was only one snapshot that contained a face, we took five additional snapshots from the video and subjected them to a new round of detection. When face features were detected in at least half of the snapshots, we added the streamer to the webcam group. Otherwise, we concluded that the streamer was not using a webcam. Figure 3 provides an example of a snapshot that contains a human face.

Table 2. Main Variables Description

Variable	Description	Mean	SD	Min.	Max.
ViewCount	The number of viewers who have watched the focal channel.	120178	19942925	23	85875802
Follower	The number of followers.	112175	46953.6	25	3140281
PBADescription	Profile building affordance. Whether the channel created a description.	0.84	0.37	0	1
PBABanner	Profile building affordance. Whether the channel uploaded a customized banner.	0.90	0.28	0	1
OpennessV	Openness personality score mined from video and speech.	0.56	0.19	0.07	0.98
ConscientiousnessV	Conscientiousness personality score mined from video and speech.	0.36	0.22	0.01	0.98
ExtraversionV	Extraversion personality score mined from video and speech.	0.27	0.25	0	0.97
AgreeablenessV	Agreeableness personality score mined from video and speech.	0.38	0.23	0	0.98
NeuroticismV	Neuroticism personality score mined from video and speech.	0.42	0.24	0	0.97
Professional	Whether the streamer plays on a professional team.	0.11	0.41	0	1
AccountLevel	The level of the in-game character used in the streaming.	68.22	60.12	1	292
Webcam	Social interactivity affordance. Whether the streamer uses webcams in the video.	0.72	0.40	0	1
NumberOfWords	Social interactivity affordance. The number of words in the transcript.	2214	874.42	107	5821
TwitterAccount	Social interactivity affordance. Whether the streamer displays his/her Twitter link in the profile.	0.79	0.23	0	1
Control Variable	**Description**	**Mean**	**SD**	**Min.**	**Max.**
Duration	Length of time in days since channel created.	1724.33	722.31	21.47	3526.78
Restricted	Whether the channel may contain inappropriate contents or words.	0.31	0.47	0	1
OpennessT	Openness personality score mined from Twitter posts.	0.31	0.24	0	1
ConscientiousnessT	Conscientiousness personality score mined from Twitter posts.	0.38	0.26	0	0.99
ExtraversionT	Extraversion personality score mined from Twitter posts.	0.29	0.27	0	0.99
AgreeablenessT	Agreeableness personality score mined from Twitter posts.	0.21	0.22	0	0.98
NeuroticismT	Neuroticism personality score mined from Twitter posts.	0.31	0.28	0.01	0.98

Figure 3. Face Detected in One of Video Snapshots

3.4 Personality Measurement

As mentioned in Section 2.2, the majority of previous research uses questionnaires or interviews to assess personality traits, which limits accuracy and scalability. We take an alternative approach and adopt state-of-the-art text-based linguistic analysis to extract personality traits from video content. Specifically, our implementation of the personality trait assessment is based on the service provided by the IBM Bluemix Platform (IBM Bluemix, 2017). This service reveals individual needs, personalities, and values to provide deep insights for social media researchers and psychologists (LIWC, 2015; IBM Bluemix, 2017). The service matches the text-based transcript and tweets words we provide with psychological meanings from the dictionary and then calculates personality scores according to FFM.

In order to generate accurate personality scores, we collected additional data. Specifically, we randomly selected a qualified video that lasted for more than one hour for each streamer in our sample. We then separated the audio and video tracks, and used the Google Cloud (2018) speech recognition service to transform our audio data into a text transcript. The transformed texts have an average confidence level of around 95%, and we manually verified a random sample of transcribed text to ensure consistency with a sequentially sampled set of videos. On average, we obtained 2,214 words for each streamer, sufficient to acquire accurate personality scores from the mined text (IBM Watson, 2017).

For the Twitter data, we excluded nontextual or auto-generated tweets that were purely images, web page links, video, or audio content. We removed tweets in languages other than English to avoid misinterpretation and then chose 200 of the latest tweets for each streamer as the API input. To improve the data quality, we followed best practices adopted in previous research, including stemming and removing stop words. Following this preprocessing, each streamer's set of tweets contained an average of 21,870 words. Notably, since the accuracy of assessment levels off at around 3,000 words (IBM Bluemix, 2017), the length of text content in this study is much higher than the service requirement. We present the variable correlation in Appendix Table A1.

3.5 Model

Since our first dependent variable, view count, is highly skewed in its distribution, we used a common approach to log transform the dependent variable. To further handle the normalization, we also log-transformed overdispersed independent and control variables. The model can be described as follows:

$$
\begin{aligned}
& log(Viewcount) = \\
& \beta_0 + \ \beta_1 PBADescription + \ \beta_2 PBABanner \\
& + \beta_3 NumberOfWords + \ \beta_4 Professional \\
& + \beta_5 AccountLevel + \beta_6 TwitterAccount \\
& + \beta_7 OpennessV + \ \beta_8 ConscientiousnessV \\
& + \beta_9 Extraversion_V + \ \beta_{10} AgreeablenessV \\
& + \beta_{11} Neuroticism_V + \ \beta_{12} Camera \\
& + \beta_{13} Control + \varepsilon
\end{aligned}
\tag{1}
$$

where β_i are coefficients for the independent variables, β_0 is the intercept, and ε is the error term. We used β_1 and β_2 to capture the impact of profile building affordance on the accumulated popularity. Based on H3a, we expect both β_1 and β_2 to be positive, indicating the positive correlation between profile building affordance and accumulated popularity. The correlation between professionalism and popularity is represented by β_4 and β_5. Based on H2a and H2b, we expect β_4 and β_5 to be positive. We used β_7 to β_{11} to denote the personality traits of streamers. Based on H1a - H1e, we expect β_8, β_9, β_{10} and β_{11} to be positive and β_7 to be negative. The relationship between social interactivity affordance and popularity is represented by β_3, β_6 *and* β_{12}. Based on H3c, we expect these coefficients to be positive.

The second dependent variable in our paper, the number of followers, is also highly dispersed. Our second model can be described as follows:

$$\begin{aligned}
&log(Follower) = \\
&\beta_0 + \beta_1 PBADescription + \beta_2 PBABanner \\
&+\beta_3 NumberOfWords + \beta_4 Professional \\
&+\beta_5 AccountLevel + \beta_6 TwitterAccount \\
&+ \beta_7 OpennessV + \beta_8 ConscientiousnessV \\
&+ \beta_9 Extraversion_V + \beta_{10} AgreeablenessV \\
&+ \beta_{11} Neuroticism_V + \beta_{12} Camera \\
&+ \beta_{13} Control + \varepsilon \qquad (2)
\end{aligned}$$

Like Model (1), Model (2) examines the association between characteristics and current popularity. We expect confidences in Model (2) to have the same correlation as Model (1).

To check the robustness of our models, we tested these two models with different combinations of independent variables and employed OLS regression with log-transformed DV (results are presented in the following section). There are five personality factors in our study that can be used to represent personality traits, given that the accuracy of the personality assessment was proven by comparing the score derived from the LIWC text analysis with the personality score derived from the survey (Yarkoni, 2010).

To assess the generalizability of our results from the gaming context to non-game-related live streaming categories, we further applied our models to the Just Chatting category on Twitch.tv. In contrast to game-related streaming, streamers in the Just Chatting category record and share aspects of their daily lives with viewers (e.g., parties, makeup, and sports). Thus, the gaming proficiency professionalism measure does not apply in this context.

4 Main Results

We first measured the respective impact of the personality traits mined from the video and the measures of professionalism and social affordance on streamers' two-dimensional popularity (see Table 3 for results). We selected Model (4) as the baseline model. We evaluated the robustness of the findings by comparing results from our baseline model with the other models.

The primary results show that the openness trait is negatively associated with both cumulative popularity (-1.21, p < 0.001) and current popularity (-0.818, p < 0.001), and indicate that when the streamer's openness score increases by 0.5 units (e.g., from low openness to high openness), their cumulative popularity decreases by 60.5% and their current popularity decreases by 40.9%, given that other variables in the model remain constant (we apply this to the results below). Thus, H1a is supported. Conscientiousness is negatively and significantly associated with both cumulative (-1.67, p < 0.001) and current popularity (-0.774, p < 0.001). This suggests that when the conscientiousness score increases by 0.5 units (e.g., from low conscientiousness to high conscientiousness), the cumulative popularity and current popularity decreases by 83.5% and 38.7% respectively. Therefore, H1b is not supported. Extraversion is negatively associated with current popularity (0.337, p < 0.05), indicating that when streamers' extraversion scores increase by 0.5 units, their current popularity increases by 16.85%. However, the association between cumulative popularity and extraversion is statistically insignificant. Thus, the results partially support H1c. The neuroticism score is positively associated with both cumulative (1.302, p < 0.001) and current popularity (0.835, p < 0.001), indicating that when the neuroticism score increases by 0.5 units, streamers' cumulative and current popularity increase by 65.1% and 41.75% respectively. This result is consistent with H1e. The coefficient of agreeableness was found to be insignificant. Overall, our results support H1a, H1c (partially), and H1e.

Regarding professionalism, the coefficient is positive and significant at the 0.1% level, showing that the streamers who play on a professional team have 213.7% more cumulative popularity and 124.1% more current popularity than other streamers, supporting H2a. Surprisingly, the account level is negatively associated with cumulative popularity (-0.031, p <0.001), indicating that streamers playing games with lower account levels tend to have higher accumulative views. Thus, H2b is not supported.

For social affordance, the coefficient of the channel description is positively associated with both cumulative (0.233, p < 0.001) and current popularity (0.910, p <0.001), suggesting that streamers with channel descriptions have 23.3% more cumulative and 91% more current popularity than streamers without descriptions. However, this result is not significantly correlated with the effect of channel banners. Thus, these results partially support H3a.

Table 3. Results Based on Personality Mined from Video Transcript

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(ViewCount)	ln(ViewCount)	ln(ViewCount)	ln(ViewCount)	ln(Follower)	ln(Follower)
Dependent variables						
PBAdescription			0.291*** (0.065)	0.233*** (0.061)	0.697*** (0.200)	0.910*** (0.245)
PBABanner			0.075 (0.090)	0.158 (0.183)	-0.010 (0.100)	-0.191 (0.125)
Webcam			1.632*** (0.330)	1.722*** (0.251)		2.631*** (0.067)
WordsCount (log transformed)			0.011*** (0.001)	0.008*** (0.001)		0.003*** (0.001)
TwitterAccount			0.350** (0.107)	0.243* (0.104)		0.012*** (0.004)
Professional	1.921*** (0.412)			2.137*** (0.378)	1.300*** (0.109)	1.241*** (0.114)
Account:evel	-0.011*** (0.001)			-0.031*** (0.004)	-0.001* (0.0001)	0.001 (0.001)
OpennessV		-0.826*** (0.154)	-0.909*** (0.167)	-1.21*** (0.132)		-0.818*** (0.227)
ConscientiousnessV		-1.451*** (0.257)	-1.479*** (0.242)	-1.670*** (0.223)		-0.774*** (0.107)
ExtraversionV		0.189 (0.163)	0.222 (0.144)	0.376 (0.287)		0.337* (0.159)
AgreeablenessV		0.280 (0.190)	0.278 (0.260)	-0.173 (0.211)		-0.168 (0.210)
NeuroticismV		1.768*** (0.188)	1.504*** (0.178)	1.302*** (0.170)		0.835*** (0.146)
Control variables						
Duration (log transformed)	2.784*** (0.233)	0.503*** (0.055)	0.477*** (0.048)	0.411*** (0.069)	0.596*** (0.105)	0.230*** (0.049)
Restricted	-0.122 (0.099)	-0.312** (0.107)	-0.345** (0.107)	-0.245* (0.103)	-0.234** (0.076)	-0.347*** (0.082)
Partner	2.092*** (0.124)	2.439*** (0.118)	2.402*** (0.118)	2.080*** (0.124)	1.497*** (0.096)	1.517*** (0.098)
TextPersonality	YES	YES	YES	YES	YES	YES
Streaming Program FE	YES	YES	YES	YES	YES	YES
R^2	0.514	0.493	0.505	0.546	0.463	0.517
Adj. R^2	0.511	0.485	0.500	0.536	0.458	0.506
N	516	516	516	516	516	516

Note: Standard errors in parentheses. Constant is examined but not reported. Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001

Table 4. Results Based on Non-game Category

	ln(ViewCount)	ln(Follower)
Dependent variables		
PBAdescription	0.482*** (0.044)	0.203*** (0.019)
PBABanner	-0.482 (0.760)	0.100 (0.285)
Webcam	3.216*** (0.450)	2.670*** (0.376)
WordsCount (log transformed)	0.144*** (0.015)	0.046** (0.022)
TwitterAccount	0.114* (0.048)	0.056*** (0.017)
OpennessV	-0.757*** (0.116)	-0.366* (0.146)
ConscientiousnessV	0.375 (0.375)	0.280 (0.500)
ExtraversionV	-0.492 (0.494)	-0.294 (0.403)

AgreeablenessV	-0.076 (0.211)	-0.229 (0.397)
NeuroticismV	**0.190***** (0.074)	**0.175***** (0.060)
Control variables		
Duration (log transformed)	**0.179***** (0.028)	**0.377***** (0.045)
Restricted	-0.004 (0.250)	-0.027 (0.204)
Partner	**2.80***** (0.242)	**2.380***** (0.197)
TextPersonality	YES	YES
Streaming Program FE	YES	YES
R^2	0.519	0.525
Adj. R^2	0.485	0.491
N	141	141
Note: Standard errors in parentheses. Constant is examined but not reported. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$		

Social interactivity factors (webcam, number of words, display of Twitter account in profile) all positively correlated with cumulative and current popularity. Notably, streamers who use webcams have 172.2% more cumulative popularity and 263.1% more current popularity than streamers who do not. Also, viewers seem to prefer streamers who actively speak during streaming (0.008, $p < 0.001$) and those who display their Twitter account in their profile (0.243, $p < 0.05$). These results support H3b.

To evaluate whether our results can be generalized to non-gaming-related live streaming categories, we conducted additional analysis on streamers from the Just Chatting category on Twitch.tv. Following the same approach as our main analysis, we estimated how the personality and social affordance of streamers in the Just Chatting category correlate to their popularity. The results are presented in Table 4.

The results from the nongaming category are largely consistent with the results from the main analysis, except for the coefficient of conscientiousness. We found that the coefficient of conscientiousness becomes positive and is no longer significant. Regarding UGT motives in live streaming, conscientiousness corresponds to meeting new people and sense of community motives, which are much better aligned with chatting events than game events. Streamers in the chatting category may be more likely to be welcoming and team-oriented. However, some streamers in this category may belong to other game-related categories—streaming as an after-gaming event, for example. Thus, we believe that the effect of conscientiousness is content sensitive.

There are a number of interesting findings based on the above results. First, particular personality patterns are associated with streamers' popularity. The personality of popular streamers can be described as low in openness, high in conscientiousness, and high in neuroticism. By adding these personality traits to the model, the predictive power increases by 3% to 5%, which proves that these traits can be used to identify and target streamers with great potential, similar to how personality information is used in job market screening (Barrick & Mount, 1991).

Second, streamers' personality traits can help reveal the culture of the live streaming community. Viewers prefer to watch streamers who are focused, unconventional, and emotionally sensitive. These characteristics may further satisfy viewers' entertainment and curiosity needs.

Third, the professionalism measures indicate that although playing on a professional team positively correlates with streamer popularity, this correlation is negative for the account level. Professional team players are likely to be highly skilled, which may contribute to popularity. Also, these results confirm the UGT motives of information seeking and gaining knowledge. However, the viewers appear to prefer watching game matches that can quickly be learned from. The matching mechanism of *League of Legends* and *Fortnite* matches players that have similar rankings. Using a lower-level account for matching can potentially enable viewers to better understand and appreciate the player's skill (see Jia et al., 2016).

Finally, our results confirm and extend the existing research findings on live streaming. As suggested by prior literature, viewers watch live streaming mostly because of its interactive features (Nam & Kwon, 2015; Sjöblom & Hamari, 2017; Hilvert-Bruce et al., 2018; Sjöblom et al., 2019). In this study, we found positive associations between a streamer's popularity and using a webcam, speaking, and displaying social media to viewers. These results confirm the importance of social interaction motives and can also guide sponsors, live streaming agents, and platform operators seeking to identify efficient streamers.

5 Discussion

This study investigates the factors that characterize popular streamers in the live streaming community, specifically on Twitch.tv. By applying voice detection and text-based linguistic analysis to streaming videos, we extracted inferred FFM personality scores to represent these characteristics. Using the face detection model, we were able to extract streamers' social interactivity affordance and further specify and analyze streamers' interaction patterns. We demonstrate that low openness, low conscientiousness, and high neuroticism are positively associated with the cumulative and current popularity of streamers. This finding extends several studies on viewer motivation in live streaming research (Nam & Kwon, 2015; Sjöblom & Hamari, 2017; Hamari & Sjöblom, 2017; Chen & Lin, 2018; Hilvert-Bruce et al., 2018; Sjöblom et al., 2019) and the psychology of gamers and social media users (Amichai-Hamburger et al., 2002; Teng, 2008; Mehroof & Griffiths, 2010; Gil de Zúñiga et al., 2017).

Although high openness scores are often associated with popular users on Twitter (Quercia et al., 2011), we found openness to be negatively associated with popularity. We ascribe this difference to motivation and the community culture. Since users in the live streaming community—specifically in the gaming live streaming community—often have unique motivations, such as escaping from reality (Sjöblom & Hamari, 2017), different personality effects likely exist between gamers and average social media users. We also found that account rankings to be negatively associated with popularity. The intuition behind this is that streamers tend to emphasize their individual skills (Jia et al., 2016). Thus, by using a lower-level account, players can more easily show off their skills and further attract viewers.

Beyond personality traits, we found the social affordance of streamers to be positively associated with popularity, suggesting that streamers should consider using technologies such as webcams and microphones to heighten the interactive experience for the viewers. A well-maintained streaming channel with streamer descriptions can also attract more viewers.

The findings in this paper provide several social and psychological insights for evaluating streamers. First, the effect of the personal characteristics examined in our models improve the understanding of the online gaming culture and live streaming communities, or more broadly, user-generated content (Pu et al., 2018). For instance, the use of mature labels (to avoid misinterpretation, we use "restricted" in this paper) observed on Twitch, indicating that a particular channel may contain profanity, positively correlates with streamer popularity. This finding suggests that there is a dark side to the gaming community, which may suggest ethical concerns.

Second, the results can assist platform operators, investors, and even viewers interested in engaging with certain streamers. Given the high skewness in the distribution of streamers' popularity and the ranking mechanism of the platform, unpopular streamers are typically underestimated and placed at the bottom of the browser page, which may disappoint viewers seeking various streaming content and may make it more difficult for unpopular streamers to attract viewers. Based on our results, we recommend that platform operators create tags (e.g., professional players) for streaming channels to help unpopular streamers improve their channel visibility.

Third, our results provide an alternative approach for brands with limited budgets to target non-top streamers. Currently, limited-budget brands are actively seeking streamers with certain characteristics (Needleman, 2018) but have few means of finding them beyond collaborating with agent platforms such as Powerspike.tv[2] and Wehype.it[3] , which, however, offers little information about streamers' characteristics. Our results can help brands identify currently unpopular streamers with great potential to become top streamers. Our results can also enable platforms to introduce streamers with certain characteristics to brands. Finally, our findings could be used to guide the recommendation and identification of live streamers using personal characteristics.

We acknowledge several limitations of this study, which also offer avenues for future research. First, since our study is built on data collected from two gaming categories, this assumes that the personal characteristics of streamers playing in these two categories are the same or similar to the characteristics of streamers playing in other gaming categories. However, leisure game players in other gaming categories may exhibit different personality patterns in their streaming. Thus, we expect that our results can only be generalized to the games with competitiveness, aggressiveness, and teamwork features that are similar to the games addressed here. Second, we excluded streamers in languages other than English to avoid misinterpretation during the data preprocessing. However, streamers in other languages, such as Korean, Chinese, and French, constitute a considerable portion of top streamer groups. Since different-language streaming channels may reveal different patterns of characteristics, a more comprehensive method that considers various languages should be used in future research. Lastly, given the emerging

[2] https://www.powerspike.tv/

[3] https://wehype.it/

nature of the phenomenon and the observational nature of this study, we do not claim that the identified factors causally affect popularity. Instead, we use these factors to characterize popular streamers. Future research could build on this work to either seek to identify causal effects or utilize the factors we identified as features for building advanced prediction models.

In conclusion, this study takes a first step toward examining the effect of personal characteristics on online social media platforms by using machine learning and deep learning techniques. It also provides multiple insights to extract factors from individual users and video content, which could help investors, platform operators, viewers, and streamers better understand the nature of live streaming and further enhance and optimize their strategies. We hope this study is of interest to researchers across different disciplines who wish to explore social media users' personal characteristic factors and those who use video and textual analysis in their empirical studies.

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Appendix

Table A1. Pearson Correlation (two-tailed)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Openness	1.00												
2. Conscientiousness	0.14	1.00											
3. Extraversion	0.06	0.12	1.00										
4. Agreeableness	-0.03	0.57	0.17	1.00									
5. Neuroticism	-0.29	-0.48	-0.18	-0.28	1.00								
6. Professional	0.01	-0.10	-0.01	-0.21	-0.01	1.00							
7. AccountLevel	0.16	-0.09	-0.23	-0.14	0.22	0.31	1.00						
8. Webcam	-0.11	0.21	0.37	0.25	-0.09	0.23	0.17	1.00					
9. PBADescription	-0.06	0.05	-0.12	0.05	0.03	0.21	0.06	-0.11	1.00				
10. ViewCount	0.07	0.10	-0.11	0.04	0.07	0.25	0.04	0.21	0.05	1.00			
11. TwitterAccount	0.01	-0.05	0.18	-0.02	-0.08	0.18	0.13	0.08	0.87	0.11	1.00		
12. PBABanner	0.05	0.07	-0.04	0.12	0.05	0.05	0.09	0.11	-0.01	0.03	0.04	1.00	
13. Follower	-0.07	0.08	0.12	0.02	-0.06	0.28	0.03	0.14	0.05	0.87	0.22	0.07	1.00

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