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Excessive use of online video streaming services: Impact of recommender system use, psychological factors, and motives

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A B S T R A C T

With the growing relevance of the Internet as a tool for communication and entertainment, researchers have examined the effects of individual's psychological factors and media use motives on their excessive use of Internet. Since Internet use has significant nuances, the excessive use of particular Internet application, such as social network services and online games, has been studied separately. However, as the major Internet application, online video streaming service has not been investigated. Moreover, other than psychological factors and media use motives, the IT features implemented in the application, such as the recommender system, could also induce excessive use behavior. This paper aims to examine individual's excessive use of online video streaming services and the effects of recommender system in such services. A survey of 490 video streaming service users was conducted. The results show that the use of recommendations, along with lack of self-control, lack of self-esteem and use motive of information seeking, lead to excessive usage of video streaming services. This study contributes to the literature of excessive Internet use by exploring individual's excessive use behavior in video streaming services and incorporating the salient role of recommender system in Internet applications.

1. Introduction

Excessive use or problematic use of Internet has been extensively studied since the late 1990s (Kardefelt-Winther, 2014b). Excessive use of Internet has been defined as a state that individuals lose control of their Internet use and keep using it excessively despite of experiencing negative outcomes, such as having conflicts with family members or facing problems concerning their professional and educational careers (Young, 1998). In the last two decades, researchers tend to examine the factors, which possibly lead to individuals' excessive uses of Internet, and two main categories of predictors have been explored. First, psychological vulnerabilities have been found to affect individuals' excessive uses of Internet, such as self-esteem (Kim & Davis, 2009), sensation seeking (Velezmoro, Lacefield, & Roberti, 2010), locus of control (Chak & Leung, 2004), and other various personal traits (Servidio, 2014). Second, use motives could also predict individuals' excessive uses of Internet (Khang, Kim, & Kim, 2013). It has been found that individuals' entertainment motives associate with reality escaping, which is the most intense dimension of excessive Internet use (Kim & Haridakis, 2009). The studies also emphasize the importance of combining use motives and psychological factors to examine excessive Internet use (Kardefelt-Winther, 2014b). These psychological vulnerabilities and media use motives are subjective factors which lead to individuals' excessive Internet uses. IT features implemented in Internet applications, which could also induce users to excessively use Internet, have been ignored by the existing literature. Moreover, there are various applications and services within the Internet, which have nuanced differences (Kardefelt-Winther, 2014a). Thus, it has been suggested to examine excessive use of different Internet applications and services separately, instead of examining excessive uses of Internet (Masur, Reinecke, Ziegele, & Quiring, 2014). Existing literature has examined the excessive use of online video games (Braun, Stopfer, Muller, Beutel, & Egloff, 2016), and social networking services (SNS) (Masur et al., 2014). Other than online video games and SNS, video streaming service is considered as one of the most popular Internet applications. For instance, individuals spend one billion hours per day on YouTube site (Etherington, 2017), and average viewing session is more than 40 min (Oreskovic, 2015). Despite its popularity and heavy uses, the excessive use of online video streaming service has not yet been examined.

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This study aims to address the abovementioned research gap by exploring individuals' excessive uses of online video streaming services and taking into consideration of specific IT features implemented in video streaming services. On video streaming sites, recommender systems have been widely deployed, which provide personalized sets of videos to individuals based on their online activities (Park, Kim, Choi, & Kim, 2012). Since recommended contents are highly relevant to individuals' interests, it induces them to continue watching the next videos and stay on the site (Li, Zheng, Yang, & Li, 2014). Thus, recommender systems potentially contribute to individuals' excessive uses of online video streaming services. With the help of an online questionnaire tool, we surveyed 490 Internet users, who regularly use online video streaming services (e.g., YouTube, Netflix, etc.), to find answers to the following questions: which factors predict individuals' excessive uses of online video streaming services? Whether the use of recommender system leads to individuals' excessive uses on video streaming sites?

2. Literature review and hypotheses development

2.1. Excessive internet use

In the last two decades, excessive use of Internet has been considered as public concern and a growing body of literature has explored this phenomenon (Kim & Davis, 2009). Excessive use of Internet is characterized as the obsessive activity that individuals have trouble placing appropriate limits on it and they exaggerate the value of the participation pleasure (Young, 1998). It has been found that excessive use of Internet leads to negative outcomes for individuals and their psychosocial well-beings and lives are affected (Young, 2004). For instance, it interferes with other important social practices of individuals and induces conflicts with family members and friends (Kardefelt-Winther, 2014b). Thus, researchers try to investigate the factors which result in individuals' excessive Internet use, and individual's psychological factors and vulnerabilities are widely believed as significant predictors (Kardefelt-Winther, 2014b). It has been found that low self-esteem (Kim & Davis, 2009), loneliness (Kim, LaRose, & Peng, 2009), low self-efficacy (Khang et al., 2013), depression (Young & Rodgers, 1998), shyness (Chak & Leung, 2004), low self-control or deficient self-regulation (Caplan, 2010), sensation seeking (Kim & Davis, 2009; Velezmoro et al., 2010), social anxiety (Kardefelt-Winther, 2014a), and locus of control (Chak & Leung, 2004) lead to excessive use of Internet. Moreover, big five personality traits (neuroticism, extraversion, openness, agreeableness, conscientiousness) have been found to influence individual's excessive Internet use (Kuss, van Rooij, Shorter, Griffiths, & van de Mheen, 2013). Specifically, agreeableness and extraversion negatively affect individual's excessive Internet use, whereas openness indicates positive effect (Servidio, 2014).

In addition to individual's psychological factors, media use motives also influence individuals' excessive uses of Internet (Khang et al., 2013). Originated from the uses and gratifications perspective (U&G) (McGuire, 1974; Rubin, 1985), it posits that individuals become actively involved in particular media due to the gratifications they receive from that involvement (Ruggiero, 2000). And individuals have specific motives to actively use the media, in order to fulfil their needs and obtain these gratifications (Young, 1998). For instance, individuals' entertainment motives associate with reality escaping, one dimension of excessive Internet use (Kim & Haridakis, 2009). The studies also highlight the importance of considering psychological factors in conjunction with use motives to examine excessive Internet use (Kardefelt-Winther, 2014a, 2014b). Despite of rich insights on excessive Internet use, researchers have argued that Internet use has significant nuances and different Internet applications should be treated as distinct activities (Kardefelt-Winther, 2014a). Moreover, individuals could have completely different motives for various applications and services within the Internet. Thus, it has been suggested to examine excessive use of Internet applications separately.

As the most popular Internet applications, SNS and online video games have been extensively studied. Regarding the excessive use of SNS, it has been found that a lack of autonomy induces SNS use motives of self-presentation and escapism, a lack of competence induces the motives of information-seeking and self-presentation, and a lack of relatedness predicts the motives of self-presentation and meeting new people (Masur et al., 2014). These motives subsequently lead to excessive use of SNS (Masur et al., 2014). Similarly, other popular SNS use motives, such as diversion, relationship building (Chen & Kim, 2013), relationship maintenance, passing time, entertainment, and companionship (Ryan, Chester, Reece, & Xenos, 2014), are also associated with excessive SNS use. In addition to SNS use motives, big five personality traits also influence excessive SNS use. For instance, neuroticism and extraversion positively affect excessive SNS use (Andreassen, Torsheim, Brunborg, & Pallesen, 2012), while conscientiousness negatively affects it (Wilson, Fornasier, & White, 2010).

Concerning online video games, a number of individuals' personal traits and gaming motives have also been found to predict their excessive online gaming behavior. For instance, neuroticism, sensation seeking, trait anxiety, state anxiety, self-control and aggression influence excessive online gaming (Braun et al., 2016; Khang et al., 2013; Mehroof & Griffiths, 2010). Regarding gaming motives, need for escape, leisure, community, redemption, achievement, satisfaction, and entertainment, and pass time have been identified to predict excessive online gaming behavior (Caplan, Williams, & Yee, 2009; Kim & Park, 2007). These motives are also categorized into three overarching components, which are achievement, social, and immersion (Yee, 2007). Furthermore, gaming motives may better explain excessive gaming behavior in conjunction with individuals' psychological predictors. It has been found that the motives escapism and achievement mediate the relationship between stress and excessive online gaming (Kardefelt-Winther, 2014a). Besides individuals' psychological factors and gaming motives, the use of voice technology in online video games has been found as a positive predictor of excessive use, due to its capability to facilitate social interactions among gamers (Caplan et al., 2009). Thus, IT features implemented in Internet services may also play an important role in explaining individuals' excessive use behavior.

In spite of extended studies examining the services of SNS and video games, online video streaming service has been ignored in the existing literature of excessive Internet use. Furthermore, individuals' excessive uses of online video streaming service could be facilitated by certain IT feature, such as the recommender functions (Gawer & Cusumano, 2008). By having such personalized feature, individuals may be induced to continue watching the suggested videos and spend more time on it. In the next subsection, we introduce the recommendation feature within Internet services.

2.2. Use of recommender systems

Recommender systems are programs or systems designed to suggest the user the next activity to indulge in, based on their preferences, history or a variety of other factors (Park et al., 2012). Recommender system research has been one of the central streams in the domain of information consumption like e-commerce or news, video consumption to even SNS platforms. The vast array of information available online makes it very difficult for users to locate their preferred content or object (Fleder & Hosanagar, 2009; Häubl & Trifts, 2000; Pathak, Garfinkel, Gopal, Venkatesan, & Yin, 2010). For instance, Amazon USA had listed about 488 million products in 2015 (Grey, 2015), and Youtube has about 300 h of new videos uploaded every minute (Harris, 2017). It is very easy to get lost in these vast swathes of internet induced information wilderness. It is here that the recommender systems play a very important role. Recommender systems suggest users the most likely pages to visit after their current page. This may be next or related product on e-commerce platform like Amazon or next video on platform like Youtube.

Recommender system is not the only information discovery mechanism on online platforms. Search results are older and more exact way of locating preferred information source. However, search engines rely on the user knowing the complete details (or at least a significant part) of the information they are trying to seek (Fayyad, Piatetsky-Shapiro, & Smyth, 1996; Häubl & Trifts, 2000). This keeps the information search space limited to the cognizable memory zone of the user. New information is unlikely to be encountered by the user in this mechanism. Additionally, it puts a lot more cognitive load on the user to identify, remember the search terms to locate their preferred pages (Häubl & Murray, 2003; Häubl & Trifts, 2000). Hence, the importance of an IT artifact like a good recommender system, that introduces the user to new content and information while keeping it within the realms of the information they are expecting to seek, is very important.

Over past several decades multiple IT artifacts have been developed and refined to provide a higher degree of engagement with their clients (Turel, Serenko, & Bontis, 2010; Turel, Serenko, & Giles, 2011). These include artifacts like design of the platform, content positioning, information flow, UX/UI design to name a few. However, most of these artifacts were static in nature i.e. they are one time change targeted to get maximum engagement with a wide array of users. Recommender systems provide a unique IT artifact in a sense that it provides capability to engage with users on an individual level and present content designed to individual tastes and preferences in order to extend their engagement (Park et al., 2012).

Given that the importance of recommender systems, in an era of information overload in all dimensions, researchers and firms have invested to research and develop novel recommender engines that power these systems (Park et al., 2012). The recommender systems are based on psychological and demographic details of the user (Li et al., 2014) as well as based on the pattern of use that users of similar background or locality indulge in (Liu, Wei, Sun & Miao, 2014). Extant research has indicated that a suitably designed recommender system has the capacity to significantly enhance user's experience of the platform (Häubl & Trifts, 2000). This has been achieved by suggesting better content on SNS platforms (Guy, 2015), related books and merchandise to purchase on e-commerce websites (Häubl & Murray, 2003; Häubl & Trifts, 2000) as well as on news websites (Beam, 2014). Such targeted suggestions and usage behavior predictions have the power to enhance the user's exposure to the platform (Häubl & Murray, 2003; Häubl & Trifts, 2000). Users typically spend long hours as they find interesting and matching content and continue to be engaged with the platforms (Turel et al., 2011; Xiao & Benbasat, 2014).

While for SNS and online gaming systems, excessive usage is many times driven by peer pressure or social factors, the usage of video streaming websites is limited in terms of factors amenable to social influence. Hence recommender systems gain a disproportionate influence in shaping the way users consume videos online. Extant research has mostly ignored this critical artifact driving media usage. Fig. 1 shows the conceptual model of this study.

2.3. Hypotheses development

The central research question that we are trying to answer through our work in this paper pertains to the technological and psychological factors that drive the excessive usage of video streaming services. The central research questions can be summarized as:

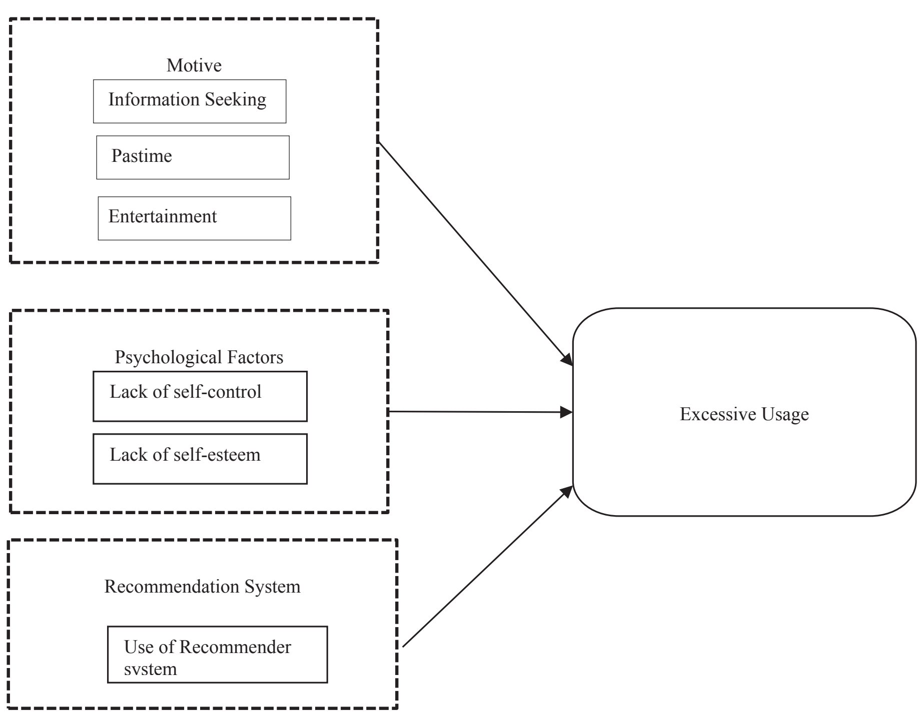

Fig. 1. Conceptual model.

RQ: How do the individual factors and recommender system as an IT artifact influence the video streaming website usage behavior and lead to excessive usage?

Based on our analysis of the literature of the field, we identify three major factors which play an important role in the way, we consume content on video streaming websites.

2.3.1. Motive

The first such factor is the motive of use. Motive of use drives the expectation and hence the gratification that a user derives from the use of any object, device or media. Extant research classifies the usage motives into three sub-factors – information seeking, pastime and entertainment (Amiel & Sargent, 2004; Luchman, Bergstrom, & Krulikowski, 2014).

The first factor deals with the inclination of a user to gather information through the use of any platform or media source. Video streaming websites act as a great way of collecting information related to either work or leisure in many cases. In the content of social network or mobile device usage, the need for information has been shown to be an important factor driving the usage (Amiel & Sargent, 2004; Khang et al., 2013). We hypothesize that for videos which have much higher content with easier information transmission capacity:

H1. *Information seeking needs have a positive and significant effect on excessive video usage behavior*

The second usage intention is pastime. Pastime refers to human activity aimed at making use of leisure time with no apparent aim or objective (Khang et al., 2013). While amateur sports, talking etc. played the role of pastime activities in physical world, it has been replaced by SNS, video games, and video streaming in online space (Granich, Rosenberg, Knuiman, & Timperio, 2011). This brings us to our second hypothesis where we hypothesize:

H2. *Pastime seeking needs have a positive and significant effect on excessive video usage behavior*

The third usage intent is entertainment. The need for humans to keep themselves entertained is highly researched and established to be of prime importance (Amiel & Sargent, 2004; Hsu & Lu, 2007; Khang et al., 2013). Seeking entertainment via video watching has increased in importance steadily since the day television was invented. The advent of video streaming services which have personalized the content and delivery has further increased the reach by providing a higher variety of content to keep different usage choices for entertainment served. Hence, we hypothesize:

H3. *Entertainment seeking needs have a positive and significant effect on excessive video usage behavior*

2.3.2. Psychological factors

As explained in section 2.1, prior research has indicated the role of psychological factors in driving excessive usage and even addiction of various internet platforms like SNS (Rosen, Whaling, Rab, Carrier, & Cheever, 2013; Valkenburg, Peter, & Schouten, 2006) and online video game services (Ng & Wiemer-Hastings, 2005). As a source of information and entertainment, video streaming websites' usage is also prone to individual level factors like their psychological traits. The most critical of these traits are self-control and self-esteem. Since, video streaming websites have limited social influence capacity in terms that others do not know what you see or influence what you watch, the importance of internal factors become much more important. While, self-control as a factor becomes essential in ensuring that the user desists from spending too much time on these platforms, self-esteem defines the importance that a person places on getting out of the world they immerse themselves in. A person with low self-control would be more likely to be excessively engaged with the video streaming services. Similarly, a person with low self-esteem has a higher probability of being engaged with video streaming website where there is no peer-pressure or judgement. Hence, we hypothesize:

H4. *Lack of Self-control has a direct and significant effect on excessive video usage behavior*

H5. *Lack of Self-esteem has a direct and significant effect on excessive video usage behavior*

2.3.3. Recommender system use

As explained in the previous section, the recommender systems are designed to suggest interesting and relevant content to users of the platform and extend their engagement with the platforms. Over years and with huge usage behavior dataset, the recommender systems have become more sophisticated and better at predicting content to user's liking (Guy, 2015; Park et al., 2012). Such targeted content suggestion has the capability to extend the usage of the platform much beyond the intended time limits. We thus hypothesize that:

H6. *Use of recommender systems to drive content use on video streaming websites has a significant and positive impact on excessive usage behavior*

Table 1
Descriptive statistics.

Variable Definition	Frequency	Percentage
Gender		
Male	290	59.18%
Female	200	40.82%
Age range		
18–24	69	14.08%
25–34	255	52.04%
35–44	114	23.27%
45–54	36	7.35%
55–64	9	1.84%
65–74	7	1.43%
Education level		
High School and Below	143	29.18%
Bachelor degree	257	52.45%
Masters degree and Above	90	18.37%
Occupation type		
Working full time	325	66.33%
Working part-time	85	17.35%
Retired	6	1.22%
Home maker	37	7.55%
Unemployed	37	7.55%
Video website usage hours		
Less than 1 h	41	8.37%
1 h	101	20.61%
2 h	195	39.80%
3-5 h	124	25.31%
5 h and above	29	5.92%
Types of Devices		
Mobile	94	19.18%
Tablet (Ipad etc.)	36	7.35%
Laptop-PC	246	50.20%
TV or equivalent	114	23.27%
Places Video Watched		
Home	457	93.30%
School/College/Universities	12	2.4%
Work Place	21	4.3%

3. Research methods

3.1. Participants and procedures

For this research, 490 respondents were recruited using Amazon's Mechanical Turk (MTurk) website. MTurk is a recruitment website that has become popular for conducting online user surveys in recent years (Kittur, Chi, & Suh, 2008). Several MTurk related assessments have convinced that it is a valid and reliable source of Psychological data (Buhrmester, Kwang, & Gosling, 2011; Paolacci, Chandler, & Ipeirotis, 2010). To ensure the reliability of the collected data, respondents were not allowed to put their response more than once by using browser based cookies and IP address. Also, a question was asked twice during the survey to check that Mturkers are paying attention to the study. Though a convenience sample, another advantage of using MTurk is that respondents of MTurk can more demographically varied than other traditional methods (Berinsky, Huber, & Lenz, 2012; Buhrmester et al., 2011). For this research, the responses were received from different geographies like North America, Bangladesh, Canada, China, France, Greece, Georgia, Mexico, Nepal, India, Poland, Thailand, etc. Descriptive statistics of respondents' characteristics is provided in Table 1. Also, MTurk participants were paid $0.50 USD per survey. At the end of the survey, each respondent was given a randomly-generated unique number, which they used to receive payment through MTurk.

The study was performed on regular users of at least one of the major video streaming websites – Youtube, Netflix and Amazon Prime. The survey instrument was divided into multiple sections. In the first section, we collected demographic and video usage information of the subjects. We rejected subjects which did not fit our study sample i.e. users who do not use one of the 3 main video streaming sites of the study. Though, there are other video streaming websites as well, the three services chosen are globally present and represent the widest array of choices to be studied while maintaining simplicity required.

3.2. Measures

The instrument was adapted from the well-established constructs of literature to ensure the reliability and validity of the items. In the subsequent sections, the instrument collected information regarding their video usage behavior, usage motives, psychological traits, and use of recommender systems. The instrument consisted of 28 items formulated with Likert type scales. 7- point Likert scales were used for the majority of constructs because seven-point Liker scales capture greater variation in responses. Table 2 shows the items for various constructs in the study as well as the sources from which these items have been adapted. During the course of the adaptation, some items were dropped which were not relevant to the study like purchase behavior in e-commerce, etc. The measurement model was used to ensure that the items and constructs were valid.

3.3. Statistical analysis

We used PLS-SEM to perform the analysis for this study. PLS-SEM was appropriate to test the theoretical model of this

Table 2
Survey instrument.

	Constructs and Items	Source
	Excessive Video Usage (Mean = 3.75, SD = 1.30)	
Dependent Variable- Video Usage	1. It is hard for me to go a day without watching videos online	Khang et al., 2013;
	2. Although I think I should stop watching online videos, sometimes I continue to watch them	Lee, Lee, Choi, & Choi, 2005
	3. I often watch videos online for a longer time than I intended	
	4. When I watch videos on platform like youtube, Netflix, etc., sometimes I feel guilty	
	5. I keep thinking about spending less time watching videos online	
	6. I think I am addicted to video streaming sites	
	Information Seeking (Mean = 4.78, SD = 1.29)	
Motive	1. I watch videos online in order to get new ideas	Khang et al., 2013; Amiel & Sargent, 2004
	2. I watch videos online in order to learn things that I need to know	
	3. I watch videos online in order to accomplish work assigned to me	
	4. I watch videos online in order to know what is going on in the world	
	Pastime (Mean = 5.42, SD = 1.19)	
Motive	1. I watch videos online in order to kill time	Khang et al., 2013; Amiel & Sargent, 2004
	2. I watch videos online in order to avoid boredom	
	3. I watch videos online in order to have fun	
	Entertainment (Mean = 5.92, SD = 0.87)	
Motive	1. I watch videos online in order to enjoy	Hsu & Lu, 2007
	2. I watch videos online in order to keep myself entertained	
	3. I watch videos online as it is convenient to use anytime anywhere	
	Lack of Self Esteem (Mean = 4.75, SD = 0.66)	
Psychological Factor	1. All in all, I am inclined to feel that I am a failure	Showers, Ditzfeld, & Zeigler-Hill, 2015
	2. I wish I could have more respect for myself	
	3. I certainly feel useless at times	
	Lack of Self Control (Mean = 4.00, SD = 1.55)	
Psychological Factor	1. I wish I had more self-discipline	Tangney, Baumeister, & Boone, 2004
	2. Pleasure and fun sometimes keep me from getting work done	
	3. Sometimes, I can't stop myself from doing something even if I know it is wrong	
	Use of Recommendations (Mean = 4.83, SD = 1.27)	
Recommendation	1. I frequently watch the recommended videos after a video I am watching on online video platform	Tan & Hornik, 2014
	2.I frequently use recommendations to help refine choices regarding the videos to watch	
	3. I frequently use recommendations to help select the video to watch	
	4. I frequently use recommendations to drive my video usage to introduce me to new content	
	5. I frequently use recommendation to drive my video usage to save time in search for relevant content	
	6. I frequently use recommendation to drive my video usage as it introduces me to the trending or popular content	

Table 3
Zero-order correlations of observed variables.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Age	1												
2	Devices	0.158	1											
3	Education	0.095	−0.112	1										
4	Entertainment	0.119	0.153	−0.067	1									
5	Excessive Usage	−0.273	−0.15	0.12	−0.156	1								
6	Gender	0.076	0.057	−0.1	−0.009	−0.118	1							
7	Information Seeking	−0.166	−0.27	0.128	−0.187	0.429	−0.111	1						
8	Occupation	−0.017	0.035	−0.185	0.066	−0.02	0.217	−0.191	1					
9	Pastime	−0.261	0.058	−0.008	−0.047	0.201	0.015	0.033	0.031	1				
10	Places Video Watched	−0.093	−0.032	−0.015	−0.05	0.156	−0.059	0.151	−0.114	0.034	1			
11	Recommendation	−0.172	−0.108	0.116	−0.066	0.318	0.045	0.352	−0.124	0.087	0.088	1		
12	Lack of Self Control	−0.226	−0.129	0.024	−0.052	0.507	−0.092	0.207	0.035	0.198	0.145	0.081	1	
13	Lack of Self Esteem	−0.26	−0.076	−0.03	−0.126	0.459	−0.075	0.187	0.102	0.164	0.157	−0.068	0.614	1
14	Video Usage	−0.238	0.117	−0.107	0.027	0.238	−0.043	0.142	0.006	0.147	0.019	0.15	0.011	0.052

research because this model is a mixed model (which comprises of both formative and reflective indicators) (Jarvis, MacKenzie, & Podsakoff, 2003) and this model has not previously been empirically validated, and in light of this may still be considered as exploratory. Therefore, SmartPLS 3.0 was used to analyse the data. Zero-order correlations of observed variables are provided in Table 3.

4. Results

4.1. Measurement model

The convergent validity, reliability and discriminant validity of all constructs were assessed before testing of the proposed research model. The reliability and validity of reflective constructs were tested through the use of PLS by running a bootstrapping sample of 5000. To assess convergent validity, a Confirmatory Factor Analysis (CFA) was conducted as part of the PLS run. This research first identifies whether the items loaded with significant values on their respective theoretical constructs (Lowry & Gaskin, 2014). It is found that all reflective items of Table 4 are statistically significant at the 0.05 level. Therefore, it appears that items of the reflective constructs are loaded accurately to their theoretical constructs.

After assessing convergent validity, the reliability of the reflective constructs of the proposed model was checked. We use PLS to compute Cronbach's Alpha and composite reliability score, which measures the internal consistency of reflective constructs (Lowry & Gaskin, 2014). Each reflective construct of the proposed model conferred a greater degree of reliability than the recommended threshold of 0.70 (Chin, 1998). The results of testing reliability are provided in Table 5.

This research also assessed the discriminant validity of reflective constructs (See Table 5). Therefore, correlations of each construct with each other were computed, and these correlations were compared with the Average Variance Extracted (AVE) square roots for each construct (Lowry & Gaskin, 2014). According to Lowry and Gaskin (2014), the inter-construct correlations (off-diagonal numbers in Table 5) should be lower than the square root of AVE (diagonal numbers in Table 5) to provide evidence of discriminant validity.

Then, the convergent validity of formative measurement models was assessed by correlating the formatively measured constructs with their global items, and these global items summarise the essence of the constructs the formative items purport to measure (Sarstedt, Wilczynski, & Melewar, 2013). For example, one global item related to entertainment construct was "Please assess to which degree you watch videos online (Youtube, Netflix, etc.) for entertainment". These global items related to formative constructs were measured on a scale of 1 (Not at all) to 7 (A great deal). The path coefficients of this analysis are provided in Table 6. So far, there is no established minimum threshold value for the convergent validity of formative indicators (e.g. Rai, Patnayakuni, & Seth, 2006). However, higher path coefficients represent that items are making a substantive contribution to formative construct. It appears from Table 6 that these path coefficients provide support for good convergent validity.

In addition, this research also reduces the likelihood of Common Method Bias (CMB) by following some procedural remedies suggested by Podsakoff, MacKenzie, Lee, and Podsakoff (2003).

Table 4
Factor loadings for the measurement model.

Constructs	Items	Factor loading (>0.7)
Excessive Usage	Excessive Usage 1	0.707
	Excessive Usage 2	0.790
	Excessive Usage 3	0.829
	Excessive Usage 4	0.706
	Excessive Usage 5	0.745
	Excessive Usage 6	0.675
Lack of self-esteem	Lack of self-esteem 1	0.907
	Lack of self-esteem 2	0.799
	Lack of self-esteem 3	0.875
Recommendation	Recommendation 1	0.890
	Recommendation 2	0.894
	Recommendation 3	0.850
	Recommendation 4	0.878
	Recommendation 5	0.844
	Recommendation 6	0.870
Lack of self-control	Lack of self-control 1	0.816
	Lack of self-control 2	0.878
	Lack of self-control 3	0.866

4.2. Structural model and analysis

The proposed model of this research was tested through the use of PLS by running a bootstrapping sample of 5000. The findings of this test consisted of path coefficients and the coefficient of determination (R-square value). Path coefficients represented the strength of the relationship between the dependent and independent constructs, and R-square value represents that the variance explained by the independent constructs.

From Fig. 2, it appears that information-seeking motive has a significant positive influence on the excessive usage of video websites ($\beta = 0.233$, $p < 0.05$), thus supporting H1. Also, the influence of information seeking motive was moderated by video usage such that the effect will be greater for less video usage

Table 5
Reliability and validity.

	Cronbach's Alpha	Composite Reliability	AVE	Excessive Usage	Use of Recommendation	Lack of Self-Esteem	Lack of Self-control
Excessive usage	0.837	0.881	0.554	**0.744**			
Use of recommendation	0.937	0.950	0.759	0.314	**0.871**		
Lack of Self-esteem	0.826	0.896	0.742	0.462	−0.068	**0.862**	
Lack of Self-control	0.815	0.898	0.728	0.506	0.077	0.614	**0.753**

Table 6
Convergent validity of formative constructs.

Constructs	Path Coefficient of Global Item
Information Seeking	0.780
Pastime	0.743
Entertainment	0.680

($\beta = -0.078$, $p < 0.05$). Two other motives: 1) Pastime and 2) Entertainment do not have a significant influence on the excessive usage of video websites. However, pastime motive was found to influence excessive usage of video websites when moderated by devices ($\beta = 0.065$, $p < 0.05$). Also, entertainment motive was found to influence excessive usage of video websites when moderated by age ($\beta = 0.056$, $p < 0.05$). Lack of self-control personality trait had a significant positive influence on the excessive usage of video websites ($\beta = 0.282$, $p < 0.05$), thus supporting H4. Also, the influence of lack of self-control personality trait was moderated by occupation such that the effect will be greater for full time working employees ($\beta = -0.144$, $p < 0.05$). Lack of self-esteem personality trait also has a significant positive influence on the excessive usage of video websites ($\beta = 0.204$, $p < 0.05$), thus supporting H5. It also appears that the influence of lack of self-esteem personality trait was moderated by places video watched such that the effect will be greater for workplace ($\beta = 0.087$, $p < 0.05$). Finally, use of recommender systems has a significant positive influence on the excessive usage of video websites ($\beta = 0.180$, $p < 0.05$), thus supporting H6. The R-square value of this proposed model is 51%, which means that 51% variance is explained by the independent constructs of this proposed model. We also tested the proposed model after excluding the recommender systems, and the R-square value was 48.50%, which means that 2.50% variance is explained by recommender systems. Then, we tested the proposed model after excluding the motives, and the R-square value was 45.10%, which means that 5.90% variance is explained by motives. Finally, we tested the proposed model after excluding the psychological factors, and the R-square value was 31.10%, which means that 19.90% variance is explained by psychological factors.

5. Discussions and implications

The results described in the previous section lead to some interesting observation and implications. The video usage motive hypotheses, H1, indicate that only information seeking motive leads to excessive usage behavior for video streaming websites. We could not find support for the effect of pastime and entertainment motives leading to excessive usage. These results seem to be in line with the nature of the platforms. We believe that this has a huge relationship with the way our world and technology usage has evolved. While people do use video platforms for pastime and entertainment, other internet enabled services like social media, gaming, chats have a much higher entertainment and pastime capability and hence users with such motives are more inclined to be addicted to these platforms. Past research in addiction and excessive usage behavior has found entertainment and pastime motives to be significant predictors for platforms like SNS and online gaming (Amiel & Sargent, 2004; Hsu & Lu, 2007; Khang et al., 2013). However, these platforms have a more social nature

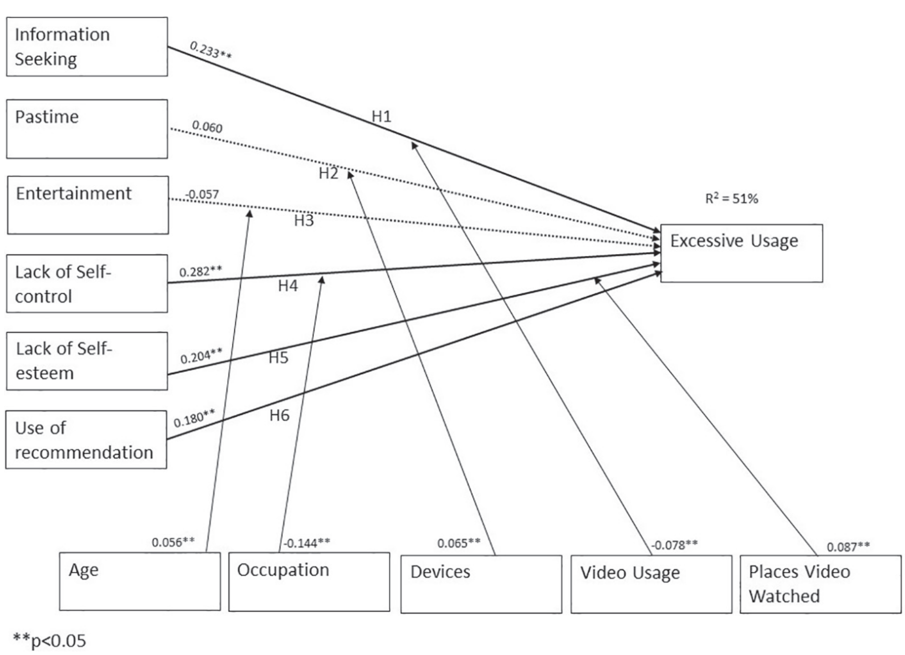

Fig. 2. Findings of the proposed research model.

with peer interaction as an important component to them. Eliminating peer human interaction removes a huge block from a platform's ability to act as relaxation media, since the video platforms are inclined towards solitary use independent of social effects. The interactions with control variables explain the results better. Though entertainment is not a significant predictor of excessive usage, when considering its interaction with age, it turns significant. This implies that for users in higher age brackets, video streaming does act as a media for entertainment, while for people in lower age brackets it is not a strong entertainment media to lead to excessive usage. Similarly, though hypothesis H2 could not be supported, we find an interesting result based on the device used to watch streaming videos. It leads to an interesting conclusion towards excessive use when considering the interactions of the pastime motive and the device type. Though pastime as itself is not a significant predictor for excessive usage, usage of devices tuned for relaxation like television increases the probability of excessive usage by the user.

Videos with their rich information content and conveying capability as compared to almost any other media like text, audio, images, etc. (Dimitrova et al., 2002), make it a great source for any kind of skill development or learning or information gathering of any other sense. H1 supports the assertion that information seeking as a usage motive leads to excessive usage. However, the results show that pastime and entertainment motives are not significantly impacting excessive video usage on online platforms. In line with prior research on addiction and excessive usage, we find that personal psychological factors are the most significant predictors of the user's probability to use these platforms excessively. We find lack of self-control to be the most significant factor in our analysis. People with lower self-control tend to have a much higher propensity to excessively watch online streaming videos. This behavior is further influenced by the occupation of the users. Unemployment, retirement and part-time jobs tend to accentuate the excessive usage behavior of people with low self-control while on the other hand it decreases the probability of excessive usage by people of low self-control for more gainfully employed people. Similarly, lack of self-esteem is also a significant predictor of excessive usage of the video streaming services. Past literature suggests that people with low self-esteem tend to find solace in solitude (Kim & Davis, 2009). Video streaming services provide a mechanism of engagement without any social grouping or peer pressure. This accentuates the probability of people with lower self-esteem to use video streaming services excessively. Its interaction with the control variable, places video watched, supports this phenomenon further. We also find that the impact of lack of self-esteem on excessive usage is influenced by the place of usage of these platforms. For people with lower self-esteem, the usage of video streaming tends to be higher at public places like school or office rather than at home where there are other escaping mechanisms. We find that technologies and medium such as video streaming services provide an escaping mechanism for users with low self-esteem to escape from social setups and interactions by immersing themselves in such media leading to excessive usage.

This study enriches the literature of excessive Internet use in several ways. First, it explores individuals' excessive uses of video streaming service, an Internet application which has yet to be examined. Compared with other two popular Internet services, online video games and SNS, the factors which contribute to the excessive use of online video streaming service are different. Second, it considers the effects of IT features implemented in Internet applications on individuals' excessive use. The existing literature on excessive Internet use has mainly focused on individuals' media use motives and psychological factors. Third, the adoption of new devices for Internet surfing, such as Smartphone and Tablet, has changed individuals' interactions with Internet services (Khang et al., 2013). This paper explores the effect of devices individuals use on their excessive use behavior.

6. Conclusion

This study explores individual's excessive usage behavior of video streaming services. Like other popular Internet applications, such as SNS and online video games, several individual's psychological factors and use motives lead to excessive use of video streaming services. In addition, the use of recommender system also contributes to individual's excessive use. Our results reveal the salient role of IT features embedded in Internet applications, which could induce individuals to use such applications excessively. As with all studies, the current work has its share of limitations. First, we have based our analysis on the recommender systems of Web sites like Youtube and Netflix. The underlying assumption is that the recommendations are very efficient and similar in nature across users and platforms. The efficacy and quality of recommendations may vary from person to person and from platform to platform. However, by limiting ourselves to the most popular services and using a large sample with high usage experience, we have controlled for the variation to a great extent. Second, instead of examining individuals' excessive use of Internet, this study only examines their excessive use of its contextual Internet application, online video streaming service. Multiple research in the past (for instance Servidio, 2014 and others as discussed in the literature section) has established the factors leading to internet addiction and its consequences. Same as previous studies which explore individuals' excessive use of respective Internet applications (e.g., SNS, online video games, etc.), the underlining assumption is that individuals' excessive use of respective applications could indicate their excessive use behavior of Internet, since the use of these applications fully rely on Internet access. In addition, existing literature on excessive use of Internet has suggested to examine excessive use of different Internet applications separately (Masur et al., 2014). However, future study may include the construct of excessive use of Internet in the model to further verify it. Finally, lack of prior work and theory in the field has led us to perform this first level analysis to establish the relationships of the psychological factors, motives and use of recommender systems. More research, drawing from different methods and theories, is required to extend this exploratory study.

References

Amiel, T., & Sargent, S. L. (2004). Individual differences in Internet usage motives. *Computers in Human Behavior, 20*(6), 711–726.

Andreassen, C., Torsheim, T., Brunborg, G., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports, 110*(2), 501–517.

Beam, M. A. (2014). Automating the news: How personalized news recommender system design choices impact news reception. *Communication Research, 41*(8), 1019–1041.

Berinsky, A., Huber, G., & Lenz, G. (2012). Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis, 20*, 351–368.

Braun, B., Stopfer, J., Muller, K., Beutel, M., & Egloff, B. (2016). Personality and video Gaming: Comparing regular gamers, non-gamers, and gaming addicts and differentiating between game genres. *Computers in Human Behavior, 55*, 406–412.

Buhrmester, M. D., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk: A new source of inexpensive, yet high-quality data? *Perspectives on Psychological Science, 6*, 3–5.

Caplan, S. (2010). Theory and measurement of generalized problematic internet use: A two-step approach. *Computers in Human Behavior, 26*(5), 1089–1097.

Caplan, S., Williams, D., & Yee, N. (2009). Problematic Internet use and psychosocial well-being among MMO players. *Computers in Human Behavior, 25*(6), 1312–1319.

Chak, K., & Leung, L. (2004). Shyness and locus of control as predictors of internet addiction and internet use. *Cyberpsychology & Behavior, 7*(5), 559–570.

Chen, H. T., & Kim, Y. (2013). Problematic use of social network Sites: The interactive relationship between gratifications sought and privacy concerns. *Cyberpsychology, Behavior, and Social Networking, 16*(11), 806–812.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.

Dimitrova, N., Zhang, H. J., Shahraray, B., Sezan, I., Huang, T., & Zakhor, A. (2002). Applications of video-content analysis and retrieval. *IEEE Multimedia, 9*(3), 42–55.

Etherington, D. (2017). *People now watch 1 billion hours of YouTube per day*. https://techcrunch.com/2017/02/28/people-now-watch-1-billion-hours-of-youtube-per-day/. (Accessed 1 July 2017).

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD process for extracting useful knowledge from volumes of data. *Communications of the ACM, 39*(11), 27–34.

Fleder, D., & Hosanagar, K. (2009). Blockbuster culture's next rise or fall: The impact of recommender systems on sales diversity. *Management Science, 55*(5), 697–712.

Gawer, A., & Cusumano, M. A. (2008). How companies become platform leaders. *MIT Sloan Management Review, 49*(2), 28.

Granich, J., Rosenberg, M., Knuiman, M. W., & Timperio, A. (2011). Individual, social, and physical environment factors associated with electronic media use among children: Sedentary behavior at home. *Journal of Physical Activity and Health, 8*(5), 613–625.

Grey, P. (2015). *How many products does Amazon sell?*. https://export-x.com/2015/12/11/how-many-products-does-amazon-sell-2015/. (Accessed 13 July 2017).

Guy, I. (2015). Social recommender systems. In *Recommender systems handbook* (pp. 511–543). Springer US.

Harris, R. (2017). *Improving our brand safety controls*. https://www.blog.google/topics/google-europe/improving-our-brand-safety-controls/. (Accessed 13 July 2017).

Häubl, G., & Murray, K. B. (2003). Preference construction and persistence in digital marketplaces: The role of electronic recommendation agents. *Journal of Consumer Psychology, 13*(1–2), 75–91.

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science, 19*(1), 4–21.

Hsu, C. L., & Lu, H. P. (2007). Consumer behavior in online game communities: A motivational factor perspective. *Computers in Human Behavior, 23*(3), 1642–1659.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research, 30*(2), 199–218.

Kardefelt-Winther, D. (2014a). Problematizing excessive online gaming and its psychological predictors. *Computers in Human Behavior, 31*, 118–122.

Kardefelt-Winther, D. (2014b). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior, 31*, 351–354.

Khang, H., Kim, J., & Kim, Y. (2013). Self-traits and motivations as antecedents of digital media flow and addiction: The Internet, mobile phones, and video games. *Computers in Human Behavior, 29*, 2416–2424.

Kim, H.-K., & Davis, K. (2009). Toward a comprehensive theory of problematic Internet use: Evaluating the role of self-esteem, anxiety, flow, and the self-rated importance of Internet activities. *Computers in Human Behavior, 25*, 490–500.

Kim, J., & Haridakis, P. (2009). The role of internet user characteristics and motives in explaining three dimensions of internet addiction. *Journal of Computer-Mediated Communication, 14*(4), 988–1015.

Kim, J., LaRose, R., & Peng, W. (2009). Loneliness as the cause and the effect of problematic Internet use: The relationship between Internet use and psychological well-being. *Cyberpsychology, Behavior, and Social Networking, 12*(4), 451–455.

Kim, Y., & Park, S. (2007). A study on the online game use influences in game flow and addiction: Focusing on the uses and gratifications approach. *Korean Journal of Journalism and Communication Studies, 51*(1), 355–377.

Kittur, A., Chi, E. H., & Suh, B. (2008). Crowdsourcing user studies with mechanical turk. In *Proc. CHI '08* (pp. 453–456).

Kuss, D., van Rooij, A., Shorter, G., Griffiths, M., & van de Mheen, D. (2013). Internet addiction in adolescents: Prevalence and risk factors. *Computers in Human Behavior, 29*(5), 1987–1996.

Lee, S. M., Lee, H. C., Choi, Y. K., & Choi, S. Y. (2005). *A study of internet addiction proneness scale for adults*. Seoul: Addiction Prevention Team, Reverse Function Prevention Center, Korea Agency for Digital opportunity and Promotion.

Liu, Y., Wei, W., Sun, A., & Miao, C. (2014, November). Exploiting geographical neighborhood characteristics for location recommendation. In *Proceedings of the 23rd ACM international conference on conference on information and knowledge management* (pp. 739–748). ACM.

Li, L., Zheng, L., Yang, F., & Li, T. (2014). Modeling and broadening temporal user interest in personalized news recommendation. *Expert Systems with Applications, 41*(7), 3168–3177.

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal Theory: When to choose it and How to use it. *IEEE Transactions on Professional Communication, 57*(2), 123–146.

Luchman, J. N., Bergstrom, J., & Krulikowski, C. (2014). A motives framework of social media website use: A survey of young Americans. *Computers in Human Behavior, 38*, 136–141.

Masur, P., Reinecke, L., Ziegele, M., & Quiring, O. (2014). The interplay of intrinsic need satisfaction and Facebook specific motives in explaining addictive behavior on Facebook. *Computers in Human Behavior, 39*, 376–386.

McGuire, W. (1974). Psychological motives and communication. In J. Blumler, & E. Kaatz (Eds.), *The uses of mass Communications: Current perspectives on gratifications research* (pp. 167–196). Beverly Hills, CA: Sage Publications.

Mehroof, M., & Griffiths, M. (2010). Online gaming Addiction: The role of sensation seeking, self-control, neuroticism, aggression, state anxiety, and trait anxiety. *Cyberpsychology, Behavior, and Social Networking, 13*(3), 313–316.

Ng, B. D., & Wiemer-Hastings, P. (2005). Addiction to the internet and online gaming. *Cyberpsychology & Behavior, 8*(2), 110–113.

Oreskovic, A. (2015). *BusinessInsider: The average YouTube viewing session on mobile devices is now 40 minutes*. http://uk.businessinsider.com/youtube-video-watch-time-grew-60-2015-7/. (Accessed 1 July 2017).

Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon mechanical turk. *Judgment and Decision Making, 5*, 411–419.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert Systems with Applications, 39*(11), 10059–10072.

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems, 27*(2), 159–188.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Rai, A., Patnayakuni, R., & Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Quarterly*, 225–246.

Rosen, L. D., Whaling, K., Rab, S., Carrier, L. M., & Cheever, N. A. (2013). Is Facebook creating "iDisorders"? The link between clinical symptoms of psychiatric disorders and technology use, attitudes and anxiety. *Computers in Human Behavior, 29*(3), 1243–1254.

Rubin, A. (1985). Uses and gratifications: Quasi-functional analysis. In J. Dominick, & J. Fletcher (Eds.), *Broadcasting research methods* (pp. 202–220). Boston: Allyn and Bacon.

Ruggiero, T. (2000). Uses and gratifications theory in the 21st century. *Mass Communication and Society, 3*(1), 3–37.

Ryan, T., Chester, A., Reece, J., & Xenos, S. (2014). The uses and abuses of Facebook: A review of Facebook addiction. *Journal of Behavioral Addictions, 3*(3), 133–148.

Sarstedt, M., Wilczynski, P., & Melewar, T. C. (2013). Measuring reputation in global markets—a comparison of reputation measures' convergent and criterion validities. *Journal of World Business, 48*(3), 329–339.

Servidio, R. (2014). Exploring the effects of demographic factors, Internet usage and personality traits on Internet addiction in a sample of Italian university students. *Computers in Human Behavior, 35*, 85–92.

Showers, C. J., Ditzfeld, C. P., & Zeigler-Hill, V. (2015). Self-concept structure and the quality of self-knowledge. *Journal of Personality, 83*(5), 535–551.

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality, 72*(2), 271–324.

Tan, A. S., & Hornik, R. C. (2014). Measuring exposure to direct-to-consumer advertising: A validation study in the context of cancer-related treatment advertising. *Communication Methods and Measures, 8*(1), 52–78.

Turel, O., Serenko, A., & Bontis, N. (2010). User acceptance of hedonic digital artifacts: A theory of consumption values perspective. *Information & Management, 47*(1), 53–59.

Turel, O., Serenko, A., & Giles, P. (2011). Integrating technology addiction and use: An empirical investigation of online auction users. *MIS Quarterly, 35*(4), 1043–1062.

Valkenburg, P. M., Peter, J., & Schouten, A. P. (2006). Friend networking sites and their relationship to adolescents' well-being and social self-esteem. *CyberPsychology & Behavior, 9*(5), 584–590.

Velezmoro, R., Lacefield, K., & Roberti, J. (2010). Perceived stress, sensation seeking, and college students' abuse of the Internet. *Computers in Human Behavior, 26*(6), 1526–1530.

Wilson, K., Fornasier, S., & White, K. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior, and Social Networking, 13*(2), 173–177.

Xiao, B., & Benbasat, I. (2014). Research on the use, characteristics, and impact of e-commerce product recommendation agents: A review and update for 2007–2012. In *Handbook of Strategic e-Business Management* (pp. 403–431). Springer Berlin Heidelberg.

Yee, N. (2007). Motivations of play in online games. *Cyberpsychology & Behavior, 9*, 772–775.

Young, K. (1998). Internet addiction: The emergence of a new clinical disorder. *CyberPsychology & Behavior, 1*, 237–244.

Young, K. (2004). Internet addiction: A new clinical phenomenon and its consequences. *American Behavioral Scientist, 48*, 402–415.

Young, K., & Rodgers, R. (1998). The relationship between depression and internet addiction. *CyberPsychology & Behavior, 1*(1), 25–28.