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A hybrid SEM-neural network analysis of social media addiction

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ABSTRACT

Social media has been a phenomenon but it is a double-edge sword that can bring about negative effects such as social media addiction. Nevertheless, very less attention has been given in unveiling the determinants of social media addiction. In this study, artificial intelligence and expert systems were applied through a hybrid SEM-artificial neural network approach to predict social media addiction. An integrated model of the Big Five Model and Uses and Gratification Theory was validated based on a sample of 615 Facebook users. Unlike existing social media studies that used SEM, in this study, we engaged a hybrid SEM-ANN approach with IPMA as the additional analysis. The new SEM-IPMA-ANN analysis is a novel methodological contribution where useful conclusion can be drawn based on not only the construct's importance but also its performance in prioritizing managerial actions. Primary focus will be given in improving the performance of constructs that exhibit huge importance with relatively low performance. Based on the normalized importance of the ANN analysis using multilayer perceptrons with feed-forward-back propagation algorithm, we found nonlinear relationships between neuroticism and social media addiction. This is a significant finding as previously only linear relationships were found. In addition, entertainment is the strongest predictor followed by agreeableness, neuroticism, hours spent and gender. The artificial neural network is able to predict social media addiction with an 86.67% accuracy. The new methodology and findings from the study will give huge impacts to the extant literature of expert systems and artificial intelligence generally and social media addiction specifically. We discussed the methodological, theoretical and practical contributions of the study.

1. Introduction

The usage of social media has grown exponentially (Kizgin, Jamal, Dey, & Rana, 2018); however, the prevalence of social media including Facebook, Pinterest, Instagram, WhatsApp, SnapChat, WeChat, YouTube, Google+, Twitter, LinkedIn, etc. (Kapoor et al., 2018) has led to many users being addicted without even noticing it. The emergence of digital revolution such as smartphones, wearable devices, etc. may lead to an estimated 2.67 billion social media users in 2018 (Michael, 2018) from the current 2.03 billion users (TFE Times, 2017). Social media has contributed 28% of total media time spent (TFE Times, 2017) and on average, users aged from 15 to 19 spent no less than three hours daily while users aged 20–29 spent nearly two hours daily on social media. In addition to that, 1.23 billion users log into social media on average 17 min daily and collectively 39,757 years is spent on Facebook daily. TFE Times, (2017) has also reported that 18% of the users cannot leave for several hours without monitoring their Facebook while 16% of them depend on Facebook or Twitter for the morning news. Moreover, 5 million photos are posted on Instagram and over 500 million tweets are uploaded daily. The social media addiction can also be seen from the five billion daily presses of "Google+1" button and the addition of two new members within LinkedIn in every second. Furthermore, 28% of Twitter users check their feeds after getting up every morning. According to a report by Brandongaille (Gaille, 2018), there are about 350 million social media users showing the syndrome of Facebook addiction and it is especially obvious among users between 16 and 25 years old. Additionally, about 68% of the users admitted that they are checking social media feeds ten times each day and 61% said that they need to browse Facebook for more than once each day, while majority of the users are unable to live without social media for a day.

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Even though social media may bring positive job-related outcomes; however, excessive usage might bring negative impacts along, for example, addiction and low performance (Moqbel & Kock, 2018). It was also reported that 60–80% of the time used in social media is unrelated to work (Eslit, 2018). Some scholars e.g., Milosevic-Dordevic and Žeželj (2014) and Wang, Jackson, Gaskin, and Wang (2014) argued that social media addiction maybe a prospective source of serious problems and therefore deserve urgent attention. Social media addiction can be loosely conceptualized as a psychological dependency on the use of social media that can affect other more imperative events (Turel, Serenko, & Giles, 2017). More precisely, it is referred as "being overly concerned about social media, driven by an uncontrollable motivation to log on to or use social media, and devoting so much time and effort to social media that it impairs other important life areas" (Andreassen & Pallesen, 2014 p. 4054). IT addiction has become a very important issue for technology adopters and IS scholars (Vaghefi, Lapointe, & Boudreau-Pinsonneault, 2017). Lately, efforts have been taken to examine the range of IT addiction covering a wide spectrum of dysfunctional behaviors (Soror, Hammer, Steelman, Davis, & Limayem, 2015). However, owing to the dearth of study on addiction in social media, it's hard to ascertain the antecedents of social media addiction (Andreassen & Pallesen, 2014).

In the current IS literature, bulk of the current researches have concentrated primarily on the positive side of social media use and treated it as a positive phenomenon that may offer positive outcomes (Thadani et al., 2016). Despite that there is an increasing level of attention among IS scholars on the addictive behavior among social media users, for instance, the dark side of social media addiction (Moqbel & Kock, 2018) and the linkages between personality traits and addiction (Tang, Chen, Yang, Chung, & Lee, 2016a,b), this study proffers further contributions to the existing literature by unveiling the roles of Big Five Model (BFM) and Use and Gratification Theory (UGT) on social media addiction by using a hybrid Structural Equation Modeling Neural Network analysis, on top of ascertaining the moderating effects of hours spent on addiction in social media. Currently, the associations between personality traits and social media addiction are under-investigated (Błachnio, Przepiorka, Senol-Durak, Durak, & Sherstyuk, 2017). Further, there were mixed results in the previous studies (Błachnio & Przepiorka, 2016; Błachnio et al., 2017; Ho, Lwin, & Lee, 2017; Tang et al., 2016a,b). Hence, it is vital to further investigate the influences of personality on addiction in social media.

Among the motivations for this study are firstly, we used an integrated theoretical lens by integrating both BFM and UGT theories and this has provided a novel theoretical contribution to the extant literature of social media addiction. Though currently BFM has been used to examine social media addiction (Blackwell, Leaman, Tramposch, Osborne, & Liss, 2017; Marino et al., 2016; Milosevic-Dordevic & Žeželj, 2014; Tang et al., 2016a; Wang, Ho, Chan, & Tse, 2015), however, it was suggested that other factors can be included in order to boost the predictive power of the research model. Since personality cannot explain 100% variance of social media addiction, therefore, we have extended the existing framework by integrating a well-known IS theory namely the UGT as it is highly relevant in the social media adoption. Though UGT has been used in studying intention to use MySpace and Facebook (Raacke & Bonds-Raacke, 2008), however, its effects on social media addiction have been overlooked by existing studies. Therefore, with the use of an integrated BFM-UGT model, we are able to obtain a more holistic and in-depth understanding on what really lead to social media addiction besides personality. In addition, we also included age and gender as the control variables and hours spent on social media as the moderating variable. The inclusion of age and gender can provide a wider research scope in explaining the role of demographic factors in social media addiction. To the best of the authors' knowledge, except for a study on demographics effect on Internet addiction (Dhir, Chen, & Nieminen, 2015), there are hardly any other studies that examined the effects of demographics and social media addiction. Moreover, the moderating effect of hours spent on social on social media addiction has not been examined in existing related studies and hence the findings from this study would be an eye opener to the extant literature of social media addiction.

Secondly, unlike previous studies that have solely focused on Facebook addiction (Błachnio & Przepiorka, 2016; Hong, Huang, Lin, & Chiu, 2014a,b; Tang et al., 2016a,b), we further extended the scope to cover social media in general. This will enable the findings to be generalized not only to specific social media users such as Facebook but they are applicable to users of any social media platforms. The greater generalizability will provide holistic and accurate understandings compared to existing studies (Błachnio et al., 2017; Hong et al., 2014a; Mahmood & Farooq, 2014; Moretta & Buodo, 2018; Tang et al., 2016b) which have limited the scope to a particular social media platform.

Thirdly, dissimilar to existing studies that have used only linear models such as SEM (Błachnio et al., 2017; Hong et al., 2014a,b; Moqbel & Kock, 2018; Thadani et al., 2016), MRA (Andreassen et al., 2016) or hierarchical regression (Błachnio & Przepiorka, 2016; Tang et al., 2016a,b), which could only examine linear and compensatory relationships; this study engaged a hybrid PLS-neural network artificial intelligence approach to examine both non-linear and non-compensatory relationships that are presented in our model. Unlike in a linear compensatory model where the shortfall in a variable is compensated by other variables, variables in our model are not inter-exchangeable. For instance, a shortfall in agreeableness cannot be compensated by an increase in neuroticism. In addition, the use of artificial intelligence through neural network has enabled us to detect the nonlinear relationships that have been overlooked in existing studies. This is important because users' addictive behaviors may not be explained using linear relationships as human decision making processes are very complex and using linear relationships may over-simplify these decision making processes (Hew, Leong, Ooi, & Chong, 2016). In addition, the neural network is able to learn and robust against noise and non-normal distribution of data as well as outliers. Hence, with the use of the artificial intelligence and expert system of neural network, we are able to provide better results and predictions.

The use of an SEM-ANN approach in examining social media addiction is a novel approach in artificial intelligence and expert systems as previous social media addiction studies (Dhaha, 2013; Hong et al., 2014b; Kircaburun, Griffiths, & Billieux, 2019; Al-Maati, Rabaa'i, & Bhat, 2018; Moretta & Buodo, 2018; Pontes, 2017; Wegmann, Stodt, & Brand, 2015) used only linear and compensatory models with the absence of artificial intelligence and expert systems and this is perhaps the first time that artificial intelligence and expert systems were used as a value-added statistical analysis on top of a linear SEM model to predict addictiveness in social media. In addition to that, we have also improved the existing SEM-ANN approach by extending the SEM analysis with the Importance Performance Map Analysis (IPMA). IPMA not only assess importance of the independent constructs but also their performance on the dependent variable. More effective managerial focus can be given to constructs which are high important with low performances. The novelty of the SEM-ANN with IPMA approach has offered a methodological paradigm shift in the extant literature of social media addiction. This novel approach is able to address the deficiencies of linear model in detecting nonlinear relationships while offering the advantages of capturing nonlinear relationships in a non-compensatory model. In addition, the novel approach has also provided robustness against noise and enhanced predictive power of the model.

Finally, in contrast with existing studies that have not tested or partially tested the multivariate assumptions, we have fully tested all multivariate assumptions namely linearity, normality, homoscedasticity and multicollinearity to warrant that the outcomes of the multivariate analyses are valid and reliable. This is very important because any violations to the fundamental multivariate assumptions will render the results and findings invalid and void. Therefore, by assessing these assumptions prior to further multivariate statistical analyses will enable us to ensure that the results and findings are valid and sound.

This article begins with the introduction section succeeded by a comprehensive literature review. Then, we explicate the research methodology and subsequently the outcomes of the statistical analysis. This is trailed by a discussion of outcomes and research implications. Lastly, the article finishes with limitations and future research directions.

2. Theory

2.1. Defining social media addiction

According to Błachnio amd Przepiorka (2016), social media addictive usage has been referred to as a special type of technological addiction commonly known as "*Internet gaming disorder*" by American Psychiatric Association in Section 3 of DSM-5 list. Thadani et al. (2016) asserted that the pathological and dependence utilization of social media is a relatively novel issue in IS literature and the symptoms of social media addiction are reflected by salience (i.e., social media use dominates users' behavior and thinking), mood modification (i.e., involvement in social media modifies mood), tolerance (i.e., increment of social media use is needed to maintain or achieve the preferred positive emotion), withdrawal (i.e., termination of social media use will lead to unpleasant feelings or emotions), conflict (i.e., involvement in social media use will lead to conflicts in relationships, education, job and others) and relapse (i.e., a propensity to return to previous forms of social media usage after control or abstinence).

Social media addiction refers to a subcategory of Internet addiction which includes other context-related addictions such as computer addiction (e.g., programming), smartphone addiction, net compulsions (e.g., online shopping, gaming and trading), cyber sexual addiction, information overload, Internet gaming addiction, online auction addiction, etc. (Moqbel & Kock, 2018). According to Brand, Laier, and Young (2014), there are 5 categories of Internet addiction which are computer addiction (i.e. online games), net compulsions (i.e. online shopping or gambling), online-sexual addiction (i.e. online pornographies), information overload (i.e. online surfing) and online-relationship addiction (i.e. online relationship). Social media addiction belongs to the last category and is considered as a condition in which users are extremely worried about social media activities with an irrepressible urge to accomplish the act and devote a lot of effort and time to it until it affects other imperative life areas (Turel, Brevers, & Bechara, 2018). Even though social media addiction possesses the general underlying etiological properties of other behavioral and substance-related addictions, nevertheless, since engagement in social media is dissimilar in terms of the real expression of Internet addiction, this phenomenon seems worthy of personal consideration (Kuss & Griffiths, 2011). Hence, it is essential to study social media addiction as it can adversely affect the social functioning, wellbeing, health as well as academic and work performances among social media users (Kuss, Van Rooij, Shorter, Griffiths, & Van De Mheen, 2013).

2.2. Big Five Model (BFM) and behavioral addictions

IS scholars have acknowledged for decades that personal factors are important predictors for technology usage and adoption (Moon, Kim, & Armstrong, 2014). There are two main categories of personal factors namely dispositional factors (e.g., personality, cognitive style and self-efficacy) and mutable factors (e.g., attitudes and perceptions). However, McElroy, Hendrickson, Townsend, and DeMarie (2007) opined that dispositional factors have been commonly ignored in IS studies and the effects of dispositional factors in IS adoption and usage are poorly documented thus far.

Andreassen, Pallesen, and Griffiths (2017) asserted that the BFM constitutes among the most significant personality theories that differentiates individuals according to five key components of conscientiousness (i.e., organized and prompt), openness to experience (i.e., intellectually oriented and imaginative), neuroticism (i.e., anxiety prone and being nervous), extraversion (i.e., outgoing and talkative) and agreeableness (i.e., warm and sympathetic). Previously, BFM has been used to examine employees' job burnout and engagement (Vieira da Cunha, Carugati, & Leclercq-Vandelannoitte, 2015); however, its effects on social media addiction remain unexplored.

Andreassen et al. (2013) found that the BFM dimensions are related to behavioral addictions. For examples, Wilson, Fornasier, and White (2010) discovered that extraversion was positively associated while conscientiousness was negatively associated to social networking obsession. In addition, Andreassen, Griffiths, Hetland, and Pallesen (2012) found that neuroticism and extraversion have positive effects while conscientiousness has negative effect on Facebook addiction. Likewise, extraversion (Huh & Bowman, 2007) and neuroticism (Huh & Bowman, 2007; Peters & Malesky, 2008) were positively associated to video game addiction. However, agreeableness (Collins, Freeman, & Chamarro-Premuzic, 2012), conscientiousness and extraversion (Peters & Malesky, 2008) have negative influences on video game addiction. In terms of Internet addiction, neuroticism (Bulut Serin, 2011) was positively associated while extraversion and conscientiousness (Gnisci, Perugini, Pedone, & Di Conza, 2011) were negatively associated to Internet addiction. Nonetheless, some found that extraversion has positive linkage with Internet addiction (Bulut Serin, 2011). On another hand, extraversion (Bianchi & Phillips, 2005) and neuroticism (Augner & Hacker, 2012) have positive effects on mobile phone addiction. These studies have clearly showed that the impacts of BFM on behavioral addictions are scattered with mixed findings. Therefore, there is indeed a need to conduct further investigation especially in context of social media addiction to obtain a better insight.

2.3. Uses and gratifications theory

Grounded on the mass communication literature, UGT offers a user-centered context in explaining why a particular channel or technology is selected over other options (Li, Guo, & Bai, 2017). Developed in the 1940s, UGT is considered as a unified effort to explore users' involvements in a particular technology or medium covering from conventional media like newspapers, radio, TV to modern online technologies like the Internet, blogs, online games, mobile applications and more recently social media. It is a renowned sociological paradigm that explicates the process and reasons of choosing a particular media to fulfill the needs of users (Ifinedo, 2016).

Instead of serving as passive channels by which media exerts persuasive effect, the UGT paradigm theorizes that the users are consciously and dynamically choosing media content with the hopes that these contents can fulfill their psychological needs, like the needs for entertainment, info, socializing and escape (York, 2017). UGT proponents believe that the users want to obtain gratifications through technology and media usage according to their motivations and personal needs and once these needs have been fulfilled they tend to recapture such experience

(Huang, Hsieh, & Wu, 2014). As such, the UGT has enabled scholars to gain more understanding on users' needs especially in terms of media usage (Stafford, Stafford, & Schkade, 2004).

Contemporary studies on gratifications have extended the scope to cover psychological stimuli that drive the utilization of social media. For instance, the core reasons of adopting MySpace and Facebook are to seek information and meet with acquaintances (Raacke & Bonds-Raacke, 2008). Similarly, Kim, Sohn, and Choi (2011) opined that the main intentions for social media use are to search for acquaintances, info, convenience, entertainment and social support. Likewise, Ku et al. (2013) asserted that the key reasons for social media adoption are entertainment, information seeking, maintaining relationships, sociality and style. More recently, Bae (2018) discovered that UGT consists of five fundamental categories namely information (cognitive needs), entertainment (emotional needs), connection (social needs), escape needs and personal integrative needs. Cognitive needs are linked to obtaining info, understanding and knowledge while emotional needs are linked to enhancing pleasant experiences. Escape needs are linked to isolating oneself from social responsibilities whereas personal integrative needs are linked to fortifying status and confidence. Finally, social needs are linked to getting connected with friends, family and the community at large. Scholars e.g., Whiting amd Williams (2013) and Zhang, Tang, and Leung (2011) have indicated that seeking entertainment is a key antecedent of social networking. Furthermore, other scholars Bondad-Brown, Rice, and Pearce (2012), Park (2013) and Plume and Slade (2018) noticed that seeking information is the most powerful driver of social networking. Finally, existing UGT studies on conventional and new media have unveiled two trivial motives for consumptions of media namely entertainment and information seeking (Shao, 2009). Therefore, similar to Hilvert-Bruce, Neill, Sjöblom, and Hamari (2018), these two categories were included in examining social media addiction.

2.4. Past relevant studies

Grounded on the Social Cognitive Theory, Moqbel and Kock (2018) examined the impacts of social networking site (SNS) addiction on individual and working settings. The study revealed that SNS addiction leads to negative impacts on both personal and working surroundings. The addiction lessens positive emotions that enhance health and performance, but promotes task distraction that impedes performance. Nonetheless, the study did not examine the factors that drive social media addiction and this has significantly limited the study's contributions as the antecedents that lead to SNS addiction remain in darkness. Furthermore, the study did not assess all multivariate assumptions (e.g., linearity and homoscedasticity), and this renders the validity and generalizability of the study questionable.

Further, Błachnio and Przepiorka (2016) examined the influences of personality characteristics on Facebook and Internet addiction. Based on two studies with samples of undergraduate, they found that conscientiousness, openness to experience, positive orientation and emotional steadiness are linked to the addictive use of Facebook and Internet. Moreover, agreeableness and extraversion are associated with Internet addiction. Nevertheless, the study engaged hierarchical multiple regression analyses without firstly evaluating the multivariate assumptions of normality, linearity, homoscedasticity and multicollinearity. More importantly, there were no assessments of common method bias (CMB), non-response bias, discriminant and convergent validity of the measures. The study was not theory driven and moreover, it was confined to only undergraduate students in a specific context of social media addiction (i.e., Facebook addiction). Owing to these deficiencies, the validity and generalizability of the findings are unconvincing.

Hong et al. (2014a,b) studied on the effects of psychological traits towards Facebook addiction amongst undergraduates. They found that neuroticism, depressive character and self-inferiority have significant correlations with Facebook addiction. However, there is an insignificant association between social extraversion and Facebook addiction. The study did not engage all personality traits and it was not built on any established IS theory. Besides, there were no evaluations concerning CMB and non-response bias as well as the multivariate assumptions. Finally, the study drew samples from two northern Taiwan universities using convenience sampling. Due to these shortcomings, there are issues of validity and generalizability pertaining to the study's outcomes.

Ifinedo (2016) applied UGT and social influence processes to study undergraduates' pervasive use of SNSs. The findings revealed that the internalization and identification from social influence process and UGT categories of entertainment value, need to maintain interpersonal connectivity, social enhancement and self-discovery have substantial effects on the pervasive use of SNSs. The study found that individualism-collectivism has significant effect on the pervasive use of SNSs too. Even though the study applied UGT in developing the model, it focused only at the pervasive adoption of SNSs. Ifinedo (2016) asserted that the term "pervasive" (i.e., prevalent, profound and extensive) refers to an adjective that emphasizes the depth of use. Turel and Serenko (2012) used the terms of "*high engagement*" and "*immersion*" to describe the pervasive use of SNSs. Ifinedo (2016) stressed that the pervasive adoption is different from addiction as it is not an uncontrollable pathological behavior and in fact it is controlled by the users and no medical intervention is needed. Since the research was intended to investigate the impacts of UGT on behavioral intention and pervasive adoption of SNSs only, the effects of UGT on social media addiction deserve further investigation. Furthermore, the study did not engage procedural remedy to address the CMB, while the multivariate assumptions of normality, linearity and homoscedasticity were omitted. On top of these, non-response bias was not examined and the findings based on undergraduates may not be generalized to all social media adopters. Consequently, the outcomes from the study may be invalid and unreliable.

Huang et al. (2014) studied the role of flow and gratifications in SNSs use. Their findings revealed that arousal has full mediating effect on the association between social gratifications and pathological SNSs use. Arousal and interaction have also partial mediating effects on the association between social gratifications and revisit intentions towards SNSs. Nonetheless, since the study did not investigate the direct impacts of UGT categories on problematic SNSs use, further examination is needed to identify the direct effects of UGT on social media addiction. Moreover, as their survey was administered in two phases, anonymity of the respondents was compromised. We believe that this might subsequently lead to CMB. Further, no statistical remedy was taken in their study, thus CMB issue cannot be ruled out appropriately. Moreover, as the sample of their study was drawn entirely from Facebook users at ICT exhibitions, therefore the sample might not be representative. Besides, the non-response bias and multivariate assumptions have also been ignored, which render the validity and reliability of the findings unconvincing.

In terms of microblog, Wang, Lee, and Hua (2015) used the Theory of Rational Addiction through the theoretical lens of cognitive-affective-behavioral modeling in examining the development of psychological dependence. It was found that habit has positive influence on maladaptive cognition (i.e., perceived enjoyment, usefulness and ease-of-use). Furthermore, ease-of-use influences perceived enjoyment and usefulness while perceived enjoyment influences perceived irreplaceability. Even though perceived usefulness has no significant effect on perceived irreplaceability; perceived irreplaceability has significant effect on negative affect anticipation. Psychological dependence is significantly affected by negative affect anticipation and deficient in self-regulation. Nonetheless, since the study has focused only on microblog users, the findings may not be generalized to represent the universal social media users. In addition, the study examined psychological dependence, which is referred to as a psychological state that is different from users' addictive behaviors. Finally, CMB and non-response bias were overlooked while tests on multivariate assumptions were missing too. Hence, the study's contributions are arguable and further investigation on social media addiction is necessary.

Tang et al. (2016a,b) investigated the influences of online social support, interpersonal relationships and personality traits on Facebook addiction. Applying hierarchical regression analysis with college students as a sample, the study found that online social support and interpersonal relationships have positive associations with Facebook addiction, whereas conscientiousness, agreeableness and neuroticism have negative associations with Facebook addiction. The study further outlined that neuroticism and interpersonal relationships are the main antecedents of Facebook addiction, and there were insignificant impacts from control variables (i.e., gender, grade and school type). However, the study was not developed based on any IS theory and remains as an exploratory and descriptive study. Furthermore, the study has confined its focus to only Facebook addiction with college students as the respondents and there was no reporting on CMB and non-response bias as well as the multivariate assumptions. Hence, generalizability and implications of the study are believed to be compromised.

Andreassen et al. (2013) examined the associations between BFM and behavioral addictions (i.e., compulsive buying; Facebook, Internet, video game, mobile phone, exercise and study addiction). Using hierarchical regression analysis with undergraduates as the sample, they found that extraversion has positive effect on Facebook addiction, whereas conscientiousness and openness to experience have negative effects on Facebook addiction. Since the study was not supported by any IS theory, has examined Facebook addiction only, did not address CMB issue and non-response bias, therefore the validity and generalizability of the findings are questionable.

Last but not least, Błachnio et al. (2017) studied personality traits' impacts on Internet and Facebook addictions. The study revealed that conscientiousness, extraversion and emotional stability have negative associations with Internet addiction, which ultimately influences Facebook addiction. Similar to the above-mentioned studies, CMB, non-response bias, as well as the multivariate assumptions were overlooked. Further, the study was not anchored on any IS theory and the direct effects of BFM on Facebook addiction were not examined. Hence, there is indeed a necessity to investigate the influences of BFM and UGT on social media addiction.

3. Research model and hypothesis development

From a comprehensive literature review, it was found that the existing studies have largely concentrated on the adoption of a specific SNS and behavioral addictions. Most of them were relying on undergraduates as the sample, not theory driven, and generating inconsistent or mixed results of personality traits. Moreover, the issues of CMB and non-response bias were ignored and there were no validations on the multivariate assumptions before conducting further statistical analyses. Hence, the theoretical and practical contributions of these studies were questionable. In view of these shortcomings, this study is theory driven by integration of UGT and BFM as well as inclusion of two control variables (i.e. age and gender) together with a moderating variable (i.e. hours spent on social media. Additionally, multivariate assumptions were conducted to verify the existence of linear and non-linear associations among the variables. In Fig. 1, we propose a non-linear and

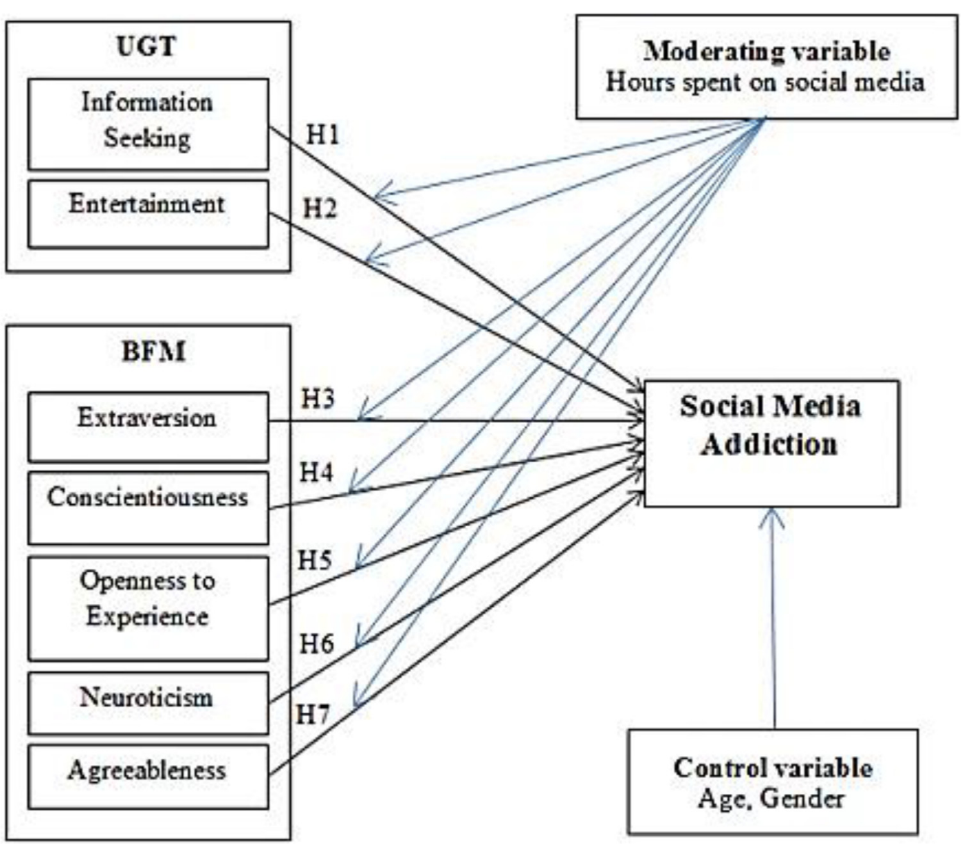

Fig. 1. Research model.

non-compensatory model, which we believe to have a high level prediction power towards social media addiction.

To accomplish the objective of this study, a hybrid SEM-neural network algorithm was employed. Firstly, Partial Least Square (PLS) SEM is engaged to validate the suggested hypotheses. Secondly, the significant predictors are included as the input neurons under the neural network analysis. PLS is applicable for linear and compensatory models, while neural network is suitable for both linear/non-linear and compensatory/non-compensatory models. Nevertheless, due to ANN's "black-box" operations, it is inappropriate for hypotheses testing. Similarly, PLS is inappropriate in the event of non-linear relationships. Therefore, to complement each other, the SEM-neural network approach was used. In a compensatory model, a decrease in a dependent variable can be compensated by an increase in another dependent variable. However, the personality traits of BFM are non-compensatory as a drop in one trait (e.g., agreeableness) cannot be compensated by a surge in another trait (e.g., neuroticism). These personality traits can't be controlled or altered by the users as they are innate in nature.

Information seeking is defined as users' behaviors in searching for information in social media to boost awareness, knowledge of an individual' personality, other and the world (Shao, 2009). Studies have revealed that information seeking and entertainment are the fundamental drivers in surfing the Internet. Li et al. (2013a,b) defined information seeking as gratification to explore relevant situations and events in users' immediate surroundings, community and the world; to look for recommendations, opinions and decision on concerned matters; to fulfill interests and curiosities; to be constantly acquiring knowledge; to seek and provide information. Masur, Reinecke, Ziegele, and Quiring (2014) found that the feeling of low competence among users can be fulfilled by acquiring knowledge that is positively linked to SNS addiction. Moreover, Chen and Kim (2013) opined that information seeking is a strong predictor of SNS use and this factor can satisfy the needs for competence. Moreover, users who learn novel ideas from playing video games tend to get addicted to video games (Khang, Kim, & Kim, 2013). Similarly, Baek, Cho, and Kim (2014) found that information utility drives SNS addiction among anxious and fearful groups. Hence, we posit the succeeding hypothesis:

H1. Information seeking positively influences social media addiction.

Entertainment is defined as "an intrinsic motivation linked to playfulness and fun inherent to the adoption decision processes" (Luo, Chea, & Chen, 2011 p. 184). Simsek and Sali (2014) found that majority of the Internet addicts use Internet for entertainment. This is also supported by Çiçekoğlu, Durualp, and Durualp (2014), who found that the adolescents who have spent four to six hours daily on Internet for entertainment attained high scores in Internet addiction. Leung (2014) asserted that adolescents have frequently lost control in using Internet due to entertainment escape. Among the primary reasons for the use of SNSs is entertainment (Hsu, Tien, Lin, & Chang, 2015; Zolkepli & Kamarulzaman, 2015). Users will not be actively participating in SNSs if they find them to be boring (Ifinedo, 2016). Therefore, we expect that a higher extent of entertainment will cause a higher extent of social media addiction and the next hypothesis is formed:

H2. Entertainment positively influences social media addiction

Extraversion is referred to the users' intensity and depth of interpersonal relations (Ho et al., 2017). Users with strong extraversion are extroverts, sociable, chatty and outgoing, whereas those who are less extraversion are introverts and shy. Extroverts possess positive mood and affectivity towards external events and preferences on interpersonal relationships. Studies have shown that extraverted users have larger online social network, participate more in Facebook groups and spend more time on SNSs in order to fulfill their needs for social enhancement and socialization, which might eventually develop a risk of overdependence or addictive tendencies towards SNSs over time (Ho, Lwin, & Lee, 2017). Extraversion was found to have significant effect on Internet addiction (Bulut Serin, 2011; Gnisci et al., 2011; Stieger, Burger, Bohn, & Voracek, 2013), pathological mobile phone adoption (Augner & Hacker, 2012; Bianchi & Phillips, 2005), Facebook addiction (Andreassen et al., 2012, 2013) and social media usage (Tang et al., 2016a,b). The extant literature e.g., Müller et al. (2016) has proposed that users with high scores in extraversion are prone to excessive SNSs use and addiction. Wang et al. (2015) opined that extraverts possess higher usage frequencies on SNSs to fulfill their communication needs. Wilson et al. (2010), who noticed that a higher degree of extraversion triggers higher propensity towards SNSs.

H3. Extraversion positively influences social media addiction.

Mahmood and Farooq (2014 p. 57) defined conscientiousness as "traits of being disciplined, cautious and having strong willpower and show restraint over their desires and are structured and hard working to achieve their goal". Users who have high score in conscientiousness show tendencies for achievements, responsibility, self-dependence, strong will and diligence and are more risk averse, reliable, and organized and search for long-term relationships. Wilson et al. (2010) found that the low conscientiousness users are spending more time on SNSs and like to procrastinate the tasks assigned to them. Similarly, Buckner, Castille, and Sheets (2012) found that the low conscientiousness scorers have higher risk towards being disorderly, disorganized, negligence and are prone to the overuse of Internet.

In contrary, users with high degree of conscientiousness are more dependable and disciplined; hence have a stronger negative association towards Internet addiction (Çelik, Atak, & Başal, 2012). Conscientiousness has been shown to have substantial effects on Internet addiction (Andreassen et al., 2012; Błachnio et al., 2017; Gnisci et al., 2011; Stieger et al., 2013) and Facebook addiction (Andreassen et al., 2013; Błachnio & Przepiorka, 2016; Tang et al., 2016a,b). Hence, it can be theorized that the users with higher conscientiousness scores have lower degree of social media addiction and the hypothesis is stated as:

H4. Conscientiousness negatively influences social media addiction.

Openness refers to the trait in users who are broad-minded, creative, unconventional, imaginative, insightful and curious. These users prefer to get new experiences and try out new ideas. Papastylianou (2013) found that openness is the main personal predictor of Internet use while Mostafaei and Khalili (2012) found that users with high openness scores are more associated with Internet dependency. In addition, openness has direct effect on social media adoption (Wang, Jackson, Zhang, & Su, 2012), Internet addiction (Andreassen et al., 2013; Błachnio & Przepiorka, 2016; Stieger et al., 2013) and addiction in Facebook (Andreassen et al., 2013; Błachnio & Przepiorka, 2016; Błachnio et al., 2017; Tang et al., 2016a,b). Thus, we hypothesize that the users with higher extent of openness tend to possess a higher degree of social media addiction. Thus, the hypothesis is established as:

H5. Openness to experience positively influences social media addiction.

Neuroticism is defined as "individuals' levels of emotional stability and adjustment, in which those with high neuroticism are less likely to keep their emotions in check and are extremely sensitive with a propensity to worry" (Ho et al., 2017 p. 634). Neurotic users demonstrate the tendency of anxiousness, fearfulness, depression, sadness, poor emotional stability and tend to isolate themselves from events that need taking control. Neurotics are anxious, moody, insecure and easily nervous. Users with strong neuroticism tend to respond more intensely to stimuli and therefore will be more engross when surfing the Internet. Therefore, neurotic users will use more time on social media and are more probable to become social media addicts (Ho et al., 2017). This happens as users with strong neuroticism will turn to social media to minimize their dysphonic moods as well as a surrogate for communication.

Moreover, Seidman (2013) opined that the neurotic users are frequently accessing Internet to portray their opinions, feelings and hidden skills. Neuroticism is related to Internet addiction (Andreassen et al., 2013; Hong et al., 2014a,b; Yao, He, Ko, & Pang, 2014), SNS addiction (Ho et al., 2017; La Barbera, La Paglia, & Valsavoia, 2009; Müller et al., 2016) and Facebook addiction (Andreassen et al., 2012; Tang et al., 2016a,b). Users with instable emotion are more vulnerable to pathological Internet usage (Yao et al., 2014). Finally, Şenormanci et al. (2014) asserts that the degree of neuroticism is higher among addicted groups. Hence, we argue that a stronger degree of neuroticism is associated with a stronger extent of social media addiction. The following hypothesis is then offered as:

H6. Neuroticism positively influences social media addiction.

Agreeableness is referred to as the tendency to be altruistic and cooperative with other individuals (Huang, Cheng, Huang, & Teng, 2018). Individuals with high scores in agreeableness are courteous, emphatic to others, forgiving, caring, sympathetic, kind, altruistic and trusting. They have respectfulness, modesty, trustable and tender-mindedness attributes. Abadi et al. (2014) asserted that individuals with high agreeableness have lower rate of becoming Internet addicts. Likewise, Randler, Horzum, and Vollmer (2014) opined that the students with high agreeableness are less probable to become Internet addicts. Agreeableness is negatively linked with mobile phone addiction (Andreassen et al., 2013), problematic Internet use (Błachnio & Przepiorka, 2016), Internet addiction (Andreassen et al., 2013; Servidio, 2014) and Facebook addiction (Błachnio et al., 2017; Tang et al., 2016a,b). Therefore, we anticipate users with a greater degree of agreeableness will show a lower tendency towards social media addiction and consequently the next hypothesis is formulated:

H7. Agreeableness negatively influences social media addiction.

3.1. Control variables

Gender and age were engaged as control variable in the studies of e-Government portal usage (Venkatesh, Sykes, & Venkatraman, 2014) and Internet addiction (Chak & Leung, 2004). Further, problematic gaming, problematic SNSs use and Internet addiction are influenced by age and gender (Andreassen et al., 2016; Li et al., 2013a,b; Siomos, Dafouli, Braimiotis, Mouzas, & Angelopoulos, 2008). Toker and Baturay (2016), together with van Rooij, Ferguson, van de Mheen, and Schoenmakers (2017) also found that gender is associated with game addiction and problematic gaming. Besides, Chen et al. (2017) and Shi, Wang, and Zou (2017) discovered that there are gender differences in smartphone and Internet addictions. Therefore, we anticipate that age and gender would have confounding effects on social media addiction.

3.2. Moderating variable of hours spent on social media

Study has shown that smartphone addiction is related to the increase in time used on the smartphone (Duke & Montag, 2017). Similarly, Saquib et al. (2017) opined that the time spent on video game and Internet would lead to video game addiction. Similarly, Lin et al. (2015) asserted that the day-to-day use count and frequency trend are related to smartphone addiction. Jang, Hwang, and Choi (2008) further stressed that the duration of Internet use is a determinant that differentiates non-dependents groups from the at-risk groups and the daily duration of Internet usage is an antecedent that can distinguish at-risk groups from the dependent groups in Internet addiction. In addition, Laconi, Tricard, and Chabrol (2015) discovered that the time spent online is associated to specific problematic use of Internet video while Khang et al. (2013) opined that the duration spent in social media is linked to addictive media usages (e.g., Internet, video game and mobile phone). Besides, Aljomaa, Mohammad, Albursan, Bakhiet, and Abduljabbar (2016) found that the smartphone addiction is varied with daily hours of smartphone use. Here, we theorize that the more the time spent on social media would make the effects of information seeking and entertainment become stronger due to the higher propensity for users to search for more info and entertainment. Similarly, we also anticipate that as the time spent on social media increases, the association between the five BFM dimensions and social media addiction would become stronger as the tendency to get highly immerse with the social media becomes inevitably higher compared to users who spent just a little time surfing the social media. Hence, we expect that hours spent on social media will have some moderating effects on addiction in social media.

H8. Time spent moderates the relationships between BFM, UGT and social media addiction.

4. Methods

4.1. Population, sample and data gathering

As reported by Statista (2018), the total of Malaysian Facebook users in 2019 is anticipated to reach 13.57 million compared to 2016′s 11.04 million and continue to grow to 15.87 million in 2022. Owing to the non-existence of sampling frame, purposive sampling was adopted to gather 633 samples that were drawn from three states in the country with the highest percentage in the distribution of Internet users as reported by MCMC (2017). Out of the 633 samples, 18 samples were discarded due to their incompleteness, and this leaves a final usable sample of 615 in further statistical analyses. It shall be noted that the sample size of 615 is more than ten-fold that of the arrows directed to an endogenous variable and therefore is adequate for PLS analysis (Hair, Ringle, & Sarstedt, 2011).

4.2. Operationalization of measures, pretest and pilot test

To maintain the face and construct validities of the measures, all measures were revised from published works. The complete list of the constructs and their sources are shown in Appendix A. Except for the demographic variables that were measured by using nominal and categorical scales, all other variables were measured using 5-point Likert scales. Information seeking and entertainment were adapted from Kim et al. (2011), while the BFM measures were modified from Donnellan, Oswald, Baird, and Lucas (2006). The measures for social media addiction were altered from Young (1998). In the pre-test, the survey instrument was sent for review to a prominent IS professor. The professor was satisfied

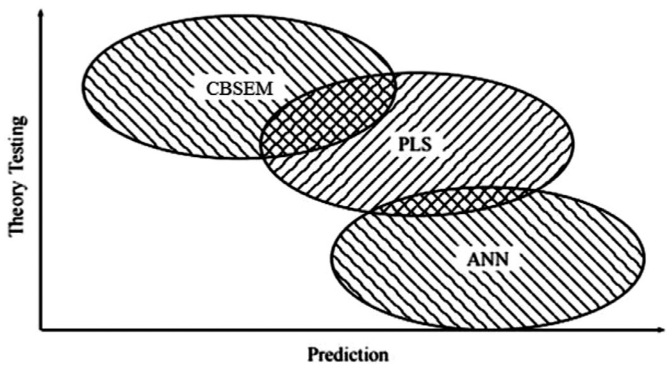

Fig. 2. Types of analytical approaches.

with the instrument's content validity as well as the face validity. During the pilot test, the survey instrument was distributed to 40 social media users and minor amendments were performed based on their inputs. The construct reliability (i.e., Cronbach's alpha) of the instrument during the pilot test fulfilled the minimum threshold of 0.70.

4.3. Comparison of SEM and ANN modeling techniques

Basically there are two types of SEM analysis namely the covariance-based SEM (CBSEM) and variance-based SEM (VBSEM) (Henseler, Ringle, & Sinkovics, 2009). Examples of CBSEM are AMOS, LISREL, EQS, MPLUS and etc. while examples of VBSEM are SmartPLS, PLS-Graph, VisualPLS and etc. In addition to CBSEM and VBSEM, researchers can also use Artificial Neural Network (ANN) as an alternative approach. Fig. 2 shows these three types of analytical approaches.

According to Henseler et al. (2009), CBSEM is suitable for theory testing and development while VBSEM is more suitable for theory prediction. In addition, for causal models with strong prior theory and further theory development and testing is the goal then CMSEM would be the best choice. This is because CBSEM enables hypothesis testing and assessment of goodness-of-fit that emphasize theory testing rather than theory building. Nevertheless, CBSEM requires the adherence of multivariate assumptions (e.g. normality in distribution, linearity of relationships, homoscedasticity of variance and no multicollinearity issues) before the causal relationships can be tested (Hew & Kadir, 2016a). In addition, CBSEM also requires absence of outliers and a minimum sample size of at least 100 (Hair, Matthews, Matthews, & Sarstedt, 2017).

On the other hand, VBSEM is more suitable for causal modeling with the aim of theory building. It assumes that all measured variance is useful for explanation of the hypotheses therefore the parameter estimates are based on the ability to minimize the residual variances of the dependent variables. PLS algorithm maximizes the explained variance of all dependent variables and therefore supports prediction-oriented goals. However, the prerequisites for VBSEM are less stringent than CBSEM as it is robust against non-normal data distribution (Hew & Kadir, 2017). In addition, the minimum sample size for VBSEM can be determined using the ten time rule of thumb i.e. 10 times the maximum arrows pointing to an endogenous variable (Hair, Risher, Sarstedt, & Ringle, 2018a,b). If CBSEM prerequisites (e.g. normal distribution, minimum sample size, maximum model complexity etc.) are violated then VBSEM will be a reasonable analytical alternative for CBSEM.

However, for research setting with predictive scope, weak theory and no requirement of the understanding of the underlying relationships then ANN is the suitable choice. ANN is the most flexible analytical approach as it does not require all the multivariate assumptions imposed by CBSEM and VBSEM and no hypotheses are required (Hew, Leong, Tan, Ooi, & Lee, 2017a,b). The minimum sample size for ANN can be determined using the 50 time rule of thumb i.e. 50 times the number of adjustable parameters in the neural network (Alwosheel, van Cranenburgh, & Chorus, 2018). The ANN approach uses artificial neurons and their interrelationships in the hidden layers that link the input and output data to improve predictivity without having to create a theoretical model. A comparison between CBSEM, VBSEM and ANN is given in Table 1.

As can been seen from Table 1, each analytical approach has its own strengths and weaknesses, therefore, the application of a hybrid SEM-ANN approach would be able to provide the best research methodology as both SEM and ANN are able to complement each other rather than competing against each other. This is because while SEM is able to test hypotheses of causal relationships, however, it cannot detect non-linear relationships in non-compensatory model. On the other hand, due to the "black-box" operation of the ANN algorithm, hypothesis testing is impossible. Nevertheless, ANN has the advantages of detecting linear and non-linear relationships and can "learn" through its artificial intelligence feature. Hence, the integration of SEM and ANN would be a good match so that we can perform hypotheses testing while detecting nonlinear relationships in a non-compensatory model at the same time. With the inclusion of IPMA that can analyze the importance and performance of the constructs, we have offered a new SEM-IPMA-ANN approach that is even better than the existing SEM-ANN approach and thus have provided new methodological contribution to the expert systems and artificial intelligence literature.

5. Results

5.1. Multivariate assumptions

Prior to further multivariate analyses, we have firstly tested the multivariate assumptions to ensure that the outcomes from the study are valid and reliable (Hew and Kadir 2016b).

5.1.1. Normality

Table 2 illustrates that all the variables in the research model are not distributed normally as all *p*-values of the Kolmogorov-Smirnov statistics are less than 0.05 (Tan, Ooi, Chong, & Hew, 2014). Hence, the variance-based PLS which is robust against non-normal distribution was used in this study.

5.1.2. Linearity

To evaluate the linear relationships between the dependent and independent variables, ANOVA test was performed. Table 3 shows that the hours spent on social media, information seeking, entertainment, conscientiousness and agreeableness have linear relationships only with social media addiction, while age has non-linear relationship only with social media addiction. On the other hand, extraversion, openness and neuroticism have both linear and non-linear relationships with social media addiction. Linearity for gender was assessed based on a simple regression analysis because it contains of less than three categories. Table 4 depicts that gender has only linear relationship with social media addiction.

5.1.3. Multicollinearity

Table 5 shows that all variance inflation factors are below 10 (Sim, Tan, Wong, Ooi, & Hew, 2014) and the tolerances are all above 0.10. Therefore, the concern of multicollinearity has been ruled out.

5.1.4. Homoscedasticity

Fig. 3 depicts the scatter plot of the standardized residuals regression. Similar to Hew and Kadir (2017 p. 886), it is clear that all

Table 1
Comparison between CBSEM, VBSEM and ANN.

	CBSEM	VBSEM	ANN
Goal of study	Theory testing	Theory building	Prediction
Objective	Maximize model fit	Maximize variance explained	Minimize predictive error
Theory dependency	Strong	Moderate to strong	Weak
Algorithm	Covariance-based	Variance-based	Artificial intelligence
Measurement philosophy	Common variance	Total variance	Prediction accuracy
Model specification	Only reflective model	Reflective and formative model	Not applicable
Model complexity	Low to moderate	Low to high	Low
Data type	Metric	Metric and non-metric	Metric and non-metric
Normal distribution	Required	Optional	Not required
Linearity	Required	Required	Optional
Homoscedasticity	Required	Optional	Not required
Absence of multicollinearity	Required	Required	Not required
Absence of outliers	Required	Optional	Not required
Sample size	At least 100[a]	10-time rule[b]	50-time rule[c]
Hypothesis development	Required	Required	Not required
Predictive power measurement	Beta coefficient	Beta coefficient	Normalized importance
Strengths	Provided model fit indices Theory confirmation Test common factor model	Can test formative model Robust against non-normal data Can test small sample Robust against outliers Can test non-normal data Provide predictive relevance Provide effect size Theory building Test composite model	Can detect both linear and nonlinear relationships Can test non-compensatory model Robust against noises No hypothesis required No theoretical foundation is required High predictive accuracy Able to “learn” No multivariate assumptions required Robust against outliers
Weaknesses	Cannot detect nonlinear relationships Unable to “learn” Cannot test formative model Hypothesis is a must Large sample size Subject to outliers Needs strong theoretical foundation Cannot test non-compensatory model No normalized importance	Cannot detect nonlinear relationships Unable to “learn” Hypothesis is a must Needs moderate theoretical foundation Cannot test non-compensatory model No normalized importance	Cannot test hypotheses Cannot test moderation and mediation effect No parameter estimates No model fit indices No effect size

Note:
[a] Hair et al. (2017).
[b] Hair et al. (2018).
[c] Alwosheel et al. (2018).

Table 2
One-sample Kolmogorov–Smirnov test.

	N	Normal parameters[a,b]		Most extreme differences			Kolmogorov–Smirnov Z	Asymp. sig. (2-tailed)
		Mean	Std. deviation	Absolute	Positive	Negative		
GDR	615	1.4400	0.49600	0.373	0.373	−0.309	9.261	0.000
AGE	615	1.7400	0.72900	0.273	0.273	−0.211	6.776	0.000
INF	615	4.0740	0.70119	0.115	0.114	−0.115	2.849	0.000
ENT	615	3.8967	0.74831	0.101	0.070	−0.101	2.510	0.000
EXT	615	3.8744	0.62437	0.090	0.090	−0.089	2.237	0.000
CON	615	4.0228	0.59423	0.125	0.076	−0.125	3.109	0.000
OPN	615	3.5191	0.71990	0.089	0.081	−0.089	2.209	0.000
NEU	615	3.5191	0.71990	0.089	0.081	−0.089	2.209	0.000
AGR	615	3.7004	0.61352	0.129	0.129	−0.076	3.195	0.000
SMA	615	3.0972	0.82627	0.081	0.044	−0.081	1.998	0.001

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, GDR = Gender, HR = Hours spent, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMA = Social Media Addiction.
[a] Test distribution is Normal.
[b] Calculated from data.

the residuals are uniformly distributed near a straight line. Therefore, the presence of homoscedasticity in the data could be concluded.

5.2. CMB analysis

CMB was addressed by both procedural and statistical remedies. Procedurally, the respondents were told that their identities are obscured and there are no absolute right or wrong responses whereby they just need to response candidly (Hew et al., 2017a, b). In addition, different types of scale were used in the instrument. For example, gender was measured by using nominal scale, whereas age, location, occupation, hours spent on social media, social media connection and uses were measured by using categorical scale. All attitudinal measures were captured using 6-point Likert interval scales. Finally, CMB was assessed through Harman’s single factor (Wong, Tan, Tan, & Ooi, 2015) and common latent factor analysis.

5.2.1. Harman’s single factor

The single factor extraction implies that the individual factor contributes just 18.92% of the total variance explained. As the

Table 3
ANOVA.

			Sum of squares	df	Mean square	F	Sig.
SMA * AGE	Between groups	(Combined)	0.703	2	0.351	0.514	0.599
		Linearity	0.138	1	0.138	0.201	0.654
		Deviation from Linearity	0.565	1	0.565	0.826	0.364
	Within groups		418.485	612	0.684		
SMA * HR	Between groups	(Combined)	26.305	3	8.768	13.636	0.000
		Linearity	24.679	1	24.679	38.381	0.000
		Deviation from Linearity	1.625	2	0.813	1.264	0.283
	Within groups		392.883	611	0.643		
SMA * INF	Between groups	(Combined)	33.194	15	2.213	3.434	0.000
		Linearity	18.517	1	18.517	28.736	0.000
		Deviation from Linearity	14.677	14	1.048	1.627	0.068
	Within groups		385.994	599	0.644		
SMA * ENT	Between groups	(Combined)	81.745	15	5.450	9.674	0.000
		Linearity	73.880	1	73.880	131.145	0.000
		Deviation from Linearity	7.865	14	0.562	0.997	0.454
	Within groups		337.443	599	0.563		
SMA * EXT	Between groups	(Combined)	31.439	12	2.620	4.068	0.000
		Linearity	14.576	1	14.576	22.631	0.000
		Deviation from Linearity	16.863	11	1.533	2.380	0.007
	Within groups		387.749	602	0.644		
SMA * CON	Between groups	(Combined)	7.737	12	0.645	.943	0.503
		Linearity	1.223	1	1.223	1.790	0.181
		Deviation from Linearity	6.514	11	0.592	0.866	0.573
	Within groups		411.451	602	0.683		
SMA * OPN	Between groups	(Combined)	51.492	15	3.433	5.592	0.000
		Linearity	19.522	1	19.522	31.802	0.000
		Deviation from Linearity	31.971	14	2.284	3.720	0.000
	Within groups		367.696	599	0.614		
SMA * NEU	Between groups	(Combined)	51.492	15	3.433	5.592	0.000
		Linearity	19.522	1	19.522	31.802	0.000
		Deviation from Linearity	31.971	14	2.284	3.720	0.000
	Within groups		367.696	599	.614		
SMA * AGR	Between groups	(Combined)	52.682	13	4.052	6.645	0.000
		Linearity	43.997	1	43.997	72.147	0.000
		Deviation from Linearity	8.685	12	0.724	1.187	0.289
	Within groups		366.506	601	0.610		

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, HR = Hours spent, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMA = Social Media Addiction.

Table 4
ANOVA[a].

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	12.522	1	12.522	18.875	0.000[b]
	Residual	406.666	613	0.663		
	Total	419.188	614			

[a] Dependent Variable: Social Media Addiction.
[b] Predictors: (Constant), Gender.

percentage is below 50%, CMB should not be a major concern in this study (Lin, Fan, & Chau, 2014). Such claim is further proven based on a common method factor analysis.

5.2.2. Common method factor analysis

Common method factor was created by changing all indicators into single-indicator constructs, thus making all the key constructs and common method factor as second-order variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Table 6 indicates that all substantive loadings are significant and substantially greater than their method loadings, which are mostly insignificant and having very small and negative values. The substantive variance is significantly higher than the method variance with a ratio of 34:1. Therefore, we again conclude that CMB shall not be a major concern.

5.3. Non-response bias

Even though there are various methods to address non-response bias including comparing the respondents to the population or to non-respondents, dropping of non-respondents, “double-dipping” non-respondents or comparing the late and early respondents (Tajudeen, Jaafar, & Ainin, 2018); however, we chose to engage the last method. The *t*-test statistics indicate no significant variances in the mean values of the major constructs, such as information seeking ($t = 0.975$), entertainment ($t = -1.400$), extraversion ($t = 0.810$), conscientiousness ($t = -0.682$) and agreeableness ($t = 0.215$). Hence, we conclude that the non-response bias is inconsequential.

5.4. Construct reliability and validity

Table 7 depicts that all composite reliabilities are more than 0.70 (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017), implying

Table 5
Test for multicollinearity.

Coefficients[a]								
Model		Unstandardized coefficients		Standardized coefficients			Collinearity statistics	
		B	Std. error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	−0.090	0.311		−0.289	0.773		
	HR	0.119	0.031	0.142	3.813	0.000	0.882	1.134
	INF	−0.027	0.048	−0.023	−0.557	0.578	0.742	1.347
	ENT	0.351	0.045	0.318	7.873	0.000	0.746	1.341
	EXT	0.064	0.049	0.049	1.307	0.192	0.882	1.134
	CON	−0.037	0.050	−0.027	−0.746	0.456	0.961	1.040
	NEU	0.102	0.042	0.089	2.434	0.015	0.908	1.101
	AGR	0.293	0.050	0.218	5.853	0.000	0.881	1.135

[a] Dependent Variable: Social Media Addiction; b Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, HR = Hours spent, INF = Information Seeking, NEU = Neuroticism, OPN = Openness.

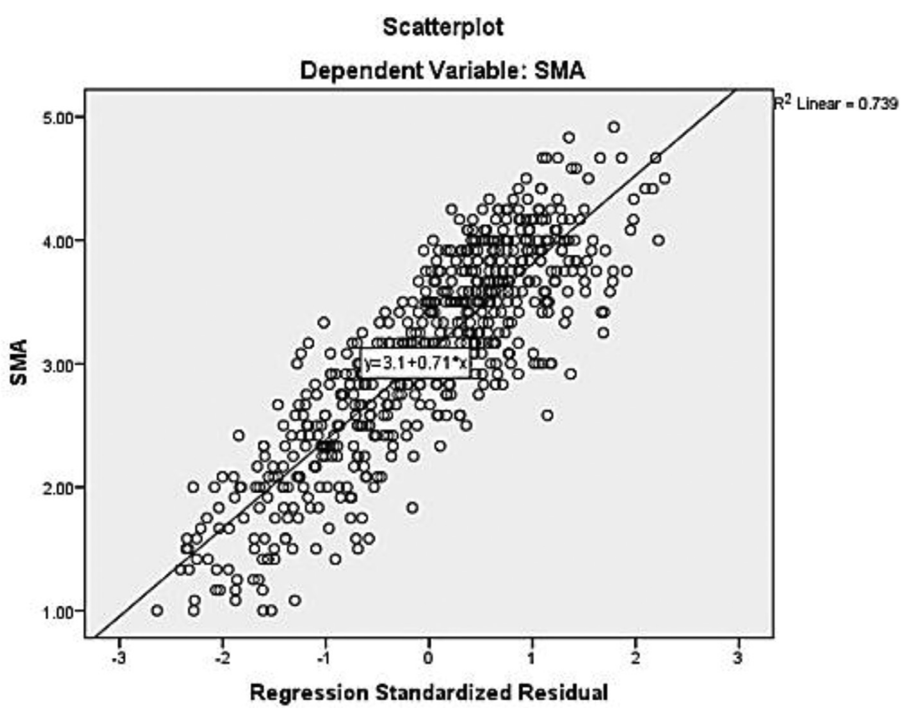

Fig. 3. Test of homoscedasticity.

that the constructs are reliable. Moreover, since all AVE values are above 0.50, convergent validity of the measures is formed. Table 8 indicates that each square-root of AVE is higher than the relevant inter-correlation coefficients, suggesting that discriminant validity is achieved.

5.5. Model fit and effect size

Following the Standardized Root Mean Square Residual (SRMR) of 0.071 (<0.08) and the discrepancy distances of d_{ULS} and d_G that are less than HI95% bootstrapped quantiles, we conclude that the dataset satisfactorily fits the model. The full analysis of the structural path testing is shown in Table 9. Entertainment (β = 0.289, $p < 0.001$), agreeableness (β = 0.191, $p < 0.001$), neuroticism (β = 0.190, $p < 0.001$) and hours spent on social media (β = 0.190, $p < 0.001$) have significant effects on social media addiction. Hence, H2, H6 and H7 were supported. Nevertheless, information seeking (β = −0.030, p = 0.460), extraversion (β = 0.068, p = 0.065), conscientiousness (β = 0.031, p = 0.403) and openness (β = −0.039, p = 0.201) have no significant effects. Therefore, H1, H3, H4 and H5 were unsupported. Further, the effect size is shown in Table 10. An effect size of 0.02, 0.15 and 0.35 is considered as marginal, moderate and huge (Palimaka, Blackhouse, & Goeree, 2015). Agreeableness, entertainment, neuroticism and hours spent on social media have a marginal to moderate effect size whereas the effect size for age, conscientiousness, extraversion, information seeking and openness is less than the marginal threshold. Surprisingly, we found that there is no moderating effect from the hours spent on social media.

5.6. Importance-Performance Map Analysis (IPMA)

IPMA was further performed to breakdown the importance and performance of latent variables (i.e., constructs). Fig. 4 shows the percentage of performance on vertical axis and the level of importance on horizontal axis with average values of 64.678% and 0.101 respectively. Of the five significant predictors, four (hours spent, entertainment, agreeableness and neuroticism) have between 63% and 73% performance, while gender has only a 43% of performance. However, entertainment has the highest importance followed by

Table 6
Substantive and method variance.

Construct	Item	Substantive loading	Substantive variance	Method loading	Method variance
AGR	Ag1	0.876**	0.767	0.023	0.001
	Ag2	0.894**	0.799	−0.024	0.001
CON	Con1	0.783**	0.614	0.106**	0.011
	Con2	0.816**	0.666	−0.055*	0.003
	Con4	0.659**	0.434	−0.065	0.004
EXT	Ex1	0.688**	0.473	0.187**	0.035
	Ex3	0.856**	0.733	−0.130**	0.017
	Ex4	0.759**	0.576	−0.055	0.003
NEU	Nr1	0.769**	0.591	0.082*	0.007
	Nr3	0.797**	0.635	−0.090*	0.008
OPN	Op2	0.814**	0.662	0.007	0.000
	Op3	0.872**	0.760	−0.013	0.000
	Op4	0.839**	0.704	0.006	0.000
ENT	En1	0.729**	0.532	−0.053	0.003
	En2	0.795**	0.632	−0.002	0.000
	En3	0.830**	0.689	−0.039	0.001
	En4	0.693**	0.480	0.091**	0.008
INF	IS1	0.792**	0.627	0.008	0.000
	IS2	0.827**	0.684	−0.017	0.000
	IS3	0.825**	0.680	−0.024	0.001
	IS4	0.753**	0.568	0.035	0.001
SMA	SMA1	0.563**	0.317	0.251**	0.063
	SMA2	0.747**	0.557	0.049	0.002
	SMA3	0.995**	0.989	−0.271**	0.073
	SMA4	0.850**	0.722	−0.137	0.019
	SMA5	0.523**	0.274	0.173	0.030
	SMA6	0.448**	0.201	0.253**	0.064
	SMA8	0.964**	0.929	−0.290**	0.084
	SMA9	0.959**	0.920	−0.281**	0.079
	SMA11	0.567**	0.321	0.189*	0.036
	SMA12	0.702**	0.493	0.046	0.002
	Mean	0.774	0.614	−0.001	0.018

Note: $^{**}p < 0.01$, $^{*}p < 0.05$; AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMA = Social Media Addiction.

Table 7
Reliability and validity.

	Composite reliability	Average Variance Extracted (AVE)
AGR	0.877	0.781
CON	0.795	0.672
ENT	0.847	0.581
EXT	0.785	0.556
INF	0.876	0.638
NEU	0.720	0.584
OPN	0.878	0.706
SMAddict	0.919	0.533

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMAddict = Social Media Addiction.

agreeableness, neuroticism, gender and hours spent on social media. Therefore, there is still a 27–57% of potential improvement in the performance of these predictors. Similar to Ooi, Hew, and Lee (2018), we partitioned the IPMA chart into four sectors with sectors upper-right as sector 1, lower-right as sector 2, lower-left as sector 3 and upper-left as sector 4. Attention is given to sector 2 since these constructs are highly important but of low performance which is followed by those in sector 1, 3 and 4. Hence, focus should be given to neuroticism and gender first followed by entertainment, agreeableness and hours spent on social media.

5.7. Neural network results

In neural network analysis, every neuron computes its output according to the number of stimulations derived from an input vector, x. The weights linking input component-i to the hidden neuron-j are designated by W_{ji}, whereas the weights linking the hidden neuron-j to the output neuron-k are represented by V_{kj}. The neuron's real input is computed as the weighted-sum of its

Table 8
Fornell-Larcker's test of discriminant validity.

	AGR	CON	ENT	EXT	INF	NEU	OPN	SMAddict
AGR	0.884							
CON	0.081	0.820						
ENT	0.275	0.227	0.762					
EXT	0.214	0.200	0.317	0.746				
INF	0.179	0.232	0.433	0.305	0.799			
NEU	0.225	0.069	0.232	0.180	0.163	0.764		
OPN	0.141	0.049	0.136	0.128	0.100	0.498	0.840	
SMAddict	0.345	0.152	0.445	0.271	0.228	0.320	0.153	0.730

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMAddict = Social Media Addiction; diagonal elements are square roots of variance.

Table 9
Full path analysis result.

Hypothesis	Structural path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H1	INF → SMA	−0.030	−0.027	0.041	0.739	0.460
H2	ENT → SMA	0.289	0.290	0.042	6.916	0.000
H3	EXT → SMA	0.068	0.068	0.037	1.848	0.065
H4	CON → SMA	0.031	0.036	0.037	0.837	0.403
H5	OPN → SMA	−0.039	−0.034	0.031	1.280	0.201
H6	NEU → SMA	0.190	0.190	0.043	4.452	0.000
H7	AGR → SMA	0.191	0.185	0.036	5.228	0.000
Moderator	HR → SMA	0.190	0.190	0.040	4.767	0.000
	HR x AGR → SMA	−0.002	−0.011	0.041	0.045	0.964
	HR x CON → SMA	0.029	0.010	0.049	0.592	0.554
	HR x ENT → SMA	0.033	0.058	0.060	0.548	0.584
	HR x EXT→ SMA	0.060	0.053	0.050	1.201	0.230
	HR x INF → SMA	0.067	0.029	0.064	1.044	0.297
	HR x NEU → SMA	0.032	0.018	0.047	0.678	0.498
	HR x OPN → SMA	0.009	0.011	0.048	0.197	0.844
Control	GDR → SMA	0.106	0.104	0.033	3.236	0.001
	AGE→ SMA	0.019	0.020	0.033	0.559	0.576

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, GDR = Gender, HR = Hours Spent, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMA = Social Media Addiction.

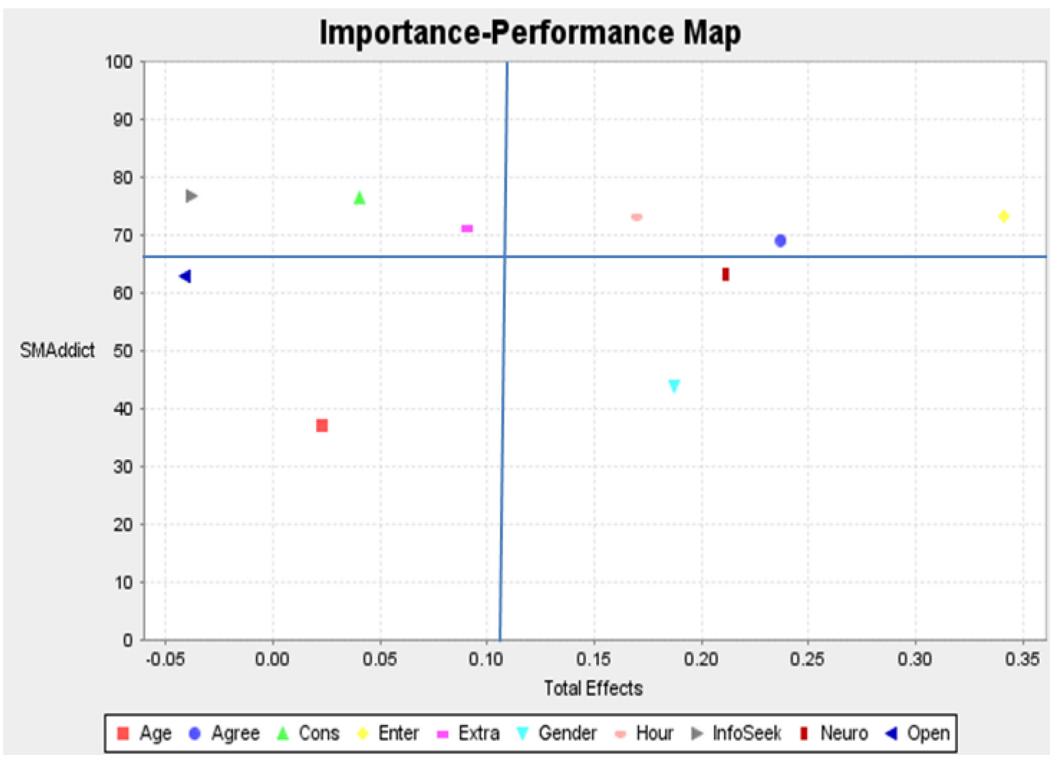

Fig. 4. Importance-Performance Map Analysis (IPMA).

Table 10
Effect size.

Structural path	Effect size (f^2)
AGR → SMA	0.045
CON → SMA	0.001
ENT → SMA	0.086
EXT → SMA	0.006
HR → SMA	0.045
INF → SMA	0.001
NEU → SMA	0.038
OPN → SMA	0.002
AGE → SMA	0.001
GDR → SMA	0.016

Note: AGR = Agreeableness, CON = Conscientiousness, ENT = Entertainment, EXT = Extraversion, GDR = Gender, HR = Hours spent, INF = Information Seeking, NEU = Neuroticism, OPN = Openness, SMA = Social Media Addiction.

inputs and the output of the neuron (y_i) is calculated with a sigmoid function (Sharma, Gaur, Saddikuti, & Rastogi, 2017). More precisely, for the jth hidden neuron,

$$net_j^h = \sum_{i=1}^{N} W_{ji} x_i \text{ and } y_i = f\left(net_j^h\right) \tag{5-1}$$

For the kth output neuron,

$$net_k^o = \sum_{j=1}^{J+1} V_{kj} y_j \text{ and } o_k = f\left(net_k^o\right) \tag{5-2}$$

A sigmoid function (Eq. (5-3)) with parameter λ is engaged to control the slope of the function (Lee, Ooi, Chong, & Seow, 2014). During the training process, for a particular input pattern, an output o_k will be generated and matched to the preferred response of

Table 11
RMSE values.

Training			Testing			Total samples
N1	SSE	RMSE	N2	SSE	RMSE	N1 + N2
552	9.664	0.1323	63	1.103	0.1323	615
552	8.987	0.1276	63	0.883	0.1184	615
555	9.154	0.1284	60	0.923	0.1240	615
553	8.768	0.1259	62	0.775	0.1118	615
551	8.915	0.1272	64	0.922	0.1200	615
553	8.673	0.1252	62	0.962	0.1246	615
556	8.799	0.1258	59	0.976	0.1286	615
559	8.888	0.1261	56	0.800	0.1195	615
551	8.717	0.1258	64	0.965	0.1228	615
553	8.954	0.1272	62	0.829	0.1156	615
Mean	8.952	0.1272	mean	0.914	0.1218	
Sd	0.2877	0.0021	sd	0.0972	0.0060	

Note: N = Number of samples, SSE = Sum square of errors, RMSE = Root mean square of errors.

Table 12
Sensitivity analysis with normalized importance.

Neural networks	GDR	AGR	ENT	HR	NEU
1st	0.073	0.234	0.400	0.148	0.145
2nd	0.086	0.324	0.331	0.079	0.178
3rd	0.097	0.214	0.397	0.110	0.182
4th	0.064	0.256	0.415	0.134	0.131
5th	0.088	0.222	0.367	0.117	0.206
6th	0.067	0.319	0.392	0.127	0.096
7th	0.031	0.298	0.379	0.120	0.173
8th	0.072	0.232	0.425	0.117	0.154
9th	0.066	0.285	0.382	0.149	0.118
10th	0.091	0.269	0.436	0.071	0.133
Mean importance	0.074	0.265	0.392	0.117	0.152
Normalized importance	18.7	67.6	100.0	29.9	38.6

Note: AGR = Agreeableness, ENT = Entertainment, GDR = Gender, HR = Hours spent, NEU = Neuroticism.

each neuron d_k. Later, the weights will be adjusted to minimize the error and the next pattern will be forwarded (Priyadarshinee, Raut, Jha, & Gardas, 2017). The weight adjustment formula for output layer weights V is calculated with Eq. (5-4) while the hidden layer weights W is calculated with Eq. (5-5) where d_{pk} denotes the preferred output of neuron-k while o_{pk} denotes the actual output of neuron-k for input pattern-p. These weights will be constantly adjusted in this way till the sum square of error, SSE (Eq. (5-6)) across all training patterns is minimized (Foo, Lee, Tan, & Ooi, 2018).

$$f(net) = \frac{1}{1 + e^{-\lambda \times net}} \tag{5-3}$$

$$V_{kj}(t+1) = v_{kj}(t) + c\lambda(d_k - o_k)o_k(1 - o_k)y_i(t) \tag{5-4}$$

$$W_{ji}(t+1) = w_{ji}(t) + c\lambda^2 y_i x_i(t)\left[\sum_{k=1}^{K}(d_k - o_k)o_k(1 - o_k)v_{kj}\right] \tag{5-5}$$

$$SSE = \frac{1}{2p}\sum_{p=1}^{P}\sum_{k=1}^{K}\left(d_{pk} - o_{pk}\right)^2 \tag{5-6}$$

Similar to Leong, Hew, Tan, and Ooi (2013), the significant paths from the structural path testing, agreeableness, entertainment, gender, hours spent on social media and neuroticism were taken into the neural network analysis as input neurons. Sigmoid functions were engaged as the activation functions for the input and hidden layers (Sharma, Joshi, & Sharma, 2016). Using a ten-fold cross-validation routine to evade over-fitting (Ooi et al., 2018), the root mean squares of errors (RMSE) were obtained from the training and testing processes (Lee, Foo, Leong, & Ooi, 2016a,b). Since the mean value of RMSE for both processes are relatively small (Table 11), therefore we conclude that the dataset does fit the model (Chong, 2013). To estimate the percentage of variance explained by the neural network model, we engaged the similar approach by Leong et al. (2018) based on the formula $R^2 = 1 - \frac{RMSE}{S^2}$ where S^2 is the variance of the desired output. The result shows that 86.67% of the variance in social media addiction is predicted by the input neurons. Based on the sensitivity analysis (Table 12) that calculates the normalized importance (NI) of all input neurons by dividing the mean importance with the highest importance and express in percentage (Leong, Hew, Lee, & Ooi, 2015), it was found that entertainment is the most powerful predictor for social media addiction tailed by agreeableness (NI = 67.6%), neuroticism (NI = 38.6%), hours spent on social media (NI = 29.9%) and gender (NI = 18.7%). This is further supported by the total contribution of the input neurons (Table 13).

6. Discussion

The PLS-neural network analysis revealed that gender, hours spent on social media, agreeableness, neuroticism and entertainment are significant predictors of social media addiction. The significant effect of gender is consistent to Chak and Leung (2004), Li et al. (2013a,b) and van Rooij et al. (2017). This is because social media and Internet addictions belong to the same category of human addictive behavior and therefore the consistent results are expected. A new relationship between hours spent and social media addiction is an interesting finding. Although a similar relationship has been validated in various different contexts (Duke & Montag, 2017; Khang et al., 2013; Laconi et al., 2015; Lin et al., 2015;

Table 13
Total contribution of hidden layer.

Predictor		Predicted				
		Hidden layer 1			Output layer	Total contribution
		H(1:1)	H(1:2)	H(1:3)	SMA	
Input layer	(Bias)	−0.073	−0.005	−0.091		0.170
	GDR	0.191	0.228	0.173		0.592
	AGR	0.501	0.159	0.204		0.864
	ENT	0.217	0.447	0.634		1.299
	HR	−0.170	0.159	0.403		0.732
	NEU	0.000	0.000	0.000		0.000
Hidden layer 1	(Bias)				−0.343	
	H(1:1)				0.647	
	H(1:2)				0.339	
	H(1:3)				0.199	

Note: AGR = Agreeableness, ENT = Entertainment, GDR = Gender, HR = Hours spent, NEU = Neuroticism, SMA=Social Media Addiction.

Saquib et al., 2017), this is perhaps the first time that empirical evidence has been found to support the new finding specifically from the context of social media addiction.

Surprisingly, hours spent has no moderating effect on social media addiction. This unexpected result shows that regardless of how long the users have spent time on social media, the relationships between the significant predictors from UGT and BFM and social media addiction remain the same. This may be accounted by the fact that Malaysians are spending a relatively large amount of time in social media. On average, Malaysians spend 159 min viewing videos on social media and this is 55% higher than the worldwide mean of 102 min. Therefore, the differences in social media addiction in association with time spent on social media are negligible.

Among the BFM factors, agreeableness has the strongest predictive power. This outcome is consistent with several scholars (Andreassen et al., 2013; Błachnio & Przepiorka, 2016; Błachnio et al., 2017; Randler et al., 2014; Servidio, 2014; Tang et al., 2016a,b). However, it contradicts with Abadi et al. (2014), who discovered a negative relationship between agreeableness and Internet addiction. It happens because of the variances in the contexts of Internet and social media addictions. This further proves that individuals who are highly altruistic, trusting, caring, forgiving, kind and sympathetic are more probable to become obsessed to social media. This is an interesting new finding and it has proffered empirical evidences to support the theory that the higher the degree of agreeableness among social media users, the lower the level of addiction would be. This theoretical finding will further propel the current literature of social media addiction to a new frontier.

Neuroticism is the second strongest BFM predictor and this is similar to some scholars (Ho et al., 2017; Hong et al., 2014a,b; La Barbera et al., 2009; Müller et al., 2016; Tang et al., 2016a,b; Yao et al., 2014). Nevertheless, this may perhaps the first time that empirical evidence was found to support the effect of neuroticism specifically in the perspective of social media addiction. This outcome further indicates that individuals who are nervous, anxious, fearful, sad, introvert and with poor emotional stability are easily subjected to social media addiction. This is because they tend to reduce their dysphonic moods and use social media as a surrogate for interpersonal communication.

Interestingly, extraversion, conscientiousness and openness have insignificant impacts on social media addiction. The insignificant impact of extraversion is inconsistent to several past studies (Andreassen et al., 2012, 2013; Augner & Hacker, 2012; Bianchi & Phillips, 2005; Bulut Serin, 2011; Gnisci et al., 2011; Müller et al., 2016; Servidio, 2014; Stieger et al., 2013; Tang et al., 2016a,b). One possible justification is that extroverts are sociable, outgoing and possess positive moods, therefore unlike neurotic individuals they do not need to address their dysphonic moods or use social media as a surrogate for interpersonal communications. Hence, the level of extraversion will have no effect on tendency towards social media addiction.

Equally astonishing is the insignificant effect of conscientiousness on social media addiction. This may be attributed to the traits of being disciplined, structured and the ability to restraint over the desires (Mahmood & Farooq, 2014) have prevented the users with a high level of conscientiousness from becoming addicted to social media. Therefore, these users will not be easily addicted to social media even they are heavy users. This has proffered empirical proof to support that the extent of conscientiousness is irrelevant and regardless of it, users' tendencies toward social media addiction are not affected at all.

The insignificant effect of openness is beyond our expectation. It shows that empirically, users who are imaginative, innovative, creative and broad-minded do not seem to be subjected to social media addiction. This new empirical discovery implies that regardless of the level of openness, the level of social media addiction will not be changed.

In terms of UGT, only entertainment has positive effect on social media addiction but not information seeking. The effect of entertainment is similar to Hsu et al. (2015), Simsek and Sali (2014) and Zolkepli and Kamarulzaman (2015). This empirical finding shows that the stronger the degree of entertainment among users, the stronger the level of social media addiction. This is understandable, as when users are immersed in entertainment activities, they are likely to be carried away and lost their power to control their behaviors and therefore becoming addicted to social media. Surprisingly, information seeking has no effect as theorized. This finding is contradictory to Chen and Kim (2013). This may be justified by the fact that information seeking is a type of utilitarian motivation which requires rational thinking. Compared to entertainment which is a type of hedonic motivation, information seeking requires users to think rationally and this would provide a protective wall for social media addiction as users are always conscious on what they are doing. Hence, empirically, we may say that regardless of the level of information seeking, the degree of social media addiction is not affected.

As for control variables, only gender has significant influence on social media addiction and not age. This is inconsistent to Andreassen et al. (2016), Li et al. (2013) and Siomos et al. (2008) due to the proliferation of social media among Malaysian users across different age brackets. Hence, no matter old or young, the level of social media addiction is not influenced by age.

6.1. Methodological contributions

Unlike existing social media addiction studies (Dhaha, 2013; Hong et al., 2014a; Kircaburun et al., 2019; Maati et al., 2018; Moretta & Buodo, 2018; Pontes, 2017; Wegmann et al., 2015) that are limited to applications of linear and compensatory models (e.g. SEM, MLR and etc.), we used a hybrid SEM-ANN approach with additional IPMA analysis. Though there are some studies that used SEM-ANN (Lee et al., 2016a,b; Leong et al., 2015; Liébana-Cabanillas, Marinkovic, Ramos de Luna, & Kalinic, 2018; Ooi & Tan, 2016; Ooi et al., 2018; Priyadarshinee et al., 2017), however, the use of IPMA is perhaps the first of its kind and with this new SEM-IPMA-ANN approach, we were able to advance the existing methodologies as IPMA is able to extends the results of SEM analysis by considering both performance and importance of each of the independent variables. Existing SEM analyses are limited to conclusions using information on the relative importance of the independent variables in explaining other variables in the structural model and this cannot provide a holistic and comprehensive conclusion to researchers (Hair, Sarstedt, Ringle, & Gudergan, 2018). With the conclusion drawn from the two dimensions (i.e. importance and performance), it will provide useful information with regards to the prioritization of managerial actions as primary focus can be given to improve performance of variables that exhibit huge importance but with relatively low performance (Ringle & Sarstedt, 2016).

In general, the strength of the new methodological approach lies on its ability in optimizing the benefits of the SEM, IPMA and ANN while at the same time minimizing the weaknesses of these approaches. The weakness of the hybrid SEM-ANN approach is that it is not a perfect approach that can address all the weaknesses in SEM and ANN totally. Instead, it is just a balanced statistically approach that takes the middle way in obtaining the best results for researchers. Furthermore, there are many other activation functions for ANN (e.g. hyperbolic tangent, sigmoid, identify, softmax) and in this study, sigmoid function was used as the activation function for the hidden and output layer. Therefore, this may not be the best activation function and more experimental studies are needed to further fine tune the proposed SEM-IPMA-ANN approach.

6.2. Theoretical contributions

The first theoretical contribution refers to the successful integration of UGT and BFM in predicting social media addiction. This is perhaps the first study that integrates personality theory with consumer theory. This has further extended the existing literature of social media addiction as the model is both theory and data driven. With the newly validated integrated model, more understanding on social media addiction from the perspective of BFM and UGT was obtained. This has path the way for scholars to further extend the integrated theory to other contexts of study in future.

Secondly, the present study is among the first from the context of social media addiction as prior studies have mostly concentrated on online game addiction, Internet addiction, smartphone addiction and Facebook addiction. The general context of social media addiction may provide a wider perspective to scholars as it is not limited to any specific context. This will enable scholars to gain a more holistic and in-depth understanding with regards to not just a specific social media platform but a more general social media addiction across various social media platforms. Therefore, the findings will provide greater generalizability and impacts to the extant literature on social media addiction.

Third, unlike prior works that did not include any moderator; this study incorporates hours spent on social media as a moderator. In addition, two control variables (i.e., age and gender) were incorporated into the research model. This is a new perspective as previously there were no studies that examined the moderating effect of hours spent on social media addiction. Thus, the study has provided empirical evidence for scholars to further pursue the moderating effect of hours spent in the context of social media addiction. On top of that, IPMA was used to measure the level of performance and importance of each of the latent variables. This is a relatively new technique in PLS analysis that was not found in existing studies. The IPMA enable us to illustrate graphically the order of importance and performance so that scholars may have a better visualization and understanding about the predictors of social media addiction. With the IPMA, scholars are able to determine which constructs should be given more attention and which are less important. Thus, the use of IPMA will enable scholars to plan their future studies based on the priority of the constructs.

Forth, dissimilar to existing studies that did not address for multivariate assumptions; this study found non-linear relationships between extraversion, openness and neuroticism with social media addiction. This is perhaps the first ever study that has investigated non-linear relationships from the social media addiction context. In order to recognize the linear and non-linear associations in our newly proposed non-compensatory model, the SEM-neural network analysis, which is a novel approach in social media addiction studies, was engaged. By applying a machine learning technique and artificial intelligence (i.e., ANN) that can learn from the data and is robust against noise in dataset, better predictions can be obtained. The discovery of nonlinear relationships is a breakthrough in the literature of social media addiction that may serve as an eye opener for scholars to further pursue the subject matter.

Finally, several new relationships that were not found in prior studies emerged in the perspective of social media addiction. These include the direct effects of agreeableness, entertainment, gender, hours spent on social media and neuroticism on addiction in social media. The study has also discovered the insignificant roles of age, information seeking, extraversion, conscientiousness and openness under the context of social media addiction. Moreover, the study has empirically verified that there is no moderating effect of hours spent on social media. With these findings, scholars are able to gain more understanding about social media addiction and therefore are able to apply these findings in future studies that can further extend their knowledge about social media addiction.

6.3. Practical contributions

Practically, since entertainment has the highest normalized importance, social media service providers (e.g., Facebook, Twitter, Instagram, etc.) should put more attention and effort in reducing the level of entertainment contents of the social media. As responsible social media service providers with social consciousness, it is important that appropriate measures are taken to reduce the extent of social media addiction. In terms of corporate social responsibility (CSR), they may incorporate some circuit-breaker features in social media games so that users will not be easily addicted to these games. For examples, timers may be used to temporary stop users from continue playing the game for a long period or warning messages may be displayed to acknowledge users that they have been playing for too long. These features may also be applied to other forms of entertainment like video clips, movies and music. Besides, online test on social media addiction may also be provided for users to evaluate whether they are social media addicts so that they are aware of it and may restraint themselves from being further addicted.

Secondly, based on the second highest normalized importance, social media service providers may track the number of hours spent by users so that warning messages can be displayed onscreen to alert users on the time spent and should temporarily take a break. For hard-core addicts, they may be blocked from accessing the social media temporarily and resume after certain intervals. Another alternative is to let hard-core addicts continue using the social media but with limited functions. For examples, functions that are addicted by users may be disabled and only functions that are of immediate importance are allowed to be used for a stipulated time until the users regained normal usage pattern.

Third, the personality of users may be ascertained through short online personality test e.g. Psyc Central website ("http://psychcentral.com/quizzes/personality.htm") when users register themselves with the social media for the first time. Based on the outcomes of the test, social media providers may provide different treatments to users with different scores in agreeableness. Since users' personality traits cannot be altered, therefore the service providers need to tailor the social media content to reduce the level of addiction. For high scorers, since they are very emphatic, sympathetic, courteous and altruistic, limits may be imposed when they try to excessively access to charity and sympathetic news in the social media. For low scorers, their access to these news links may be recorded and tracked so that in case they are getting addicted in future similar measure can be implemented.

Fourth, since neurotic users are emotionally not stable, moody, nervous, anxious, insure and respond strongly to stimuli hence social media providers may trace the activities of the highly neurotic users and provide the emotional support through encouraging messages from time to time. In addition to that, they may also offer online companions via online chat so that highly neurotic users do not need to access social media as a surrogate for face-to-face communication. Through the online chats, they will feel more secure, supported and listened to by a good listener thus reducing their dysphonic moods.

In terms of gender, since males are having higher tendency towards social media addiction, therefore their usage on social media should be tracked and controlled. Once the level is getting addictive, warning messages may be displayed to alert them about the prospective of becoming a social media addict. Advice may be given to them on how to avoid from becoming an addict to social media. An alternative is to divert their attention by diverting them to other non-social websites that are of their interest based on their track record. This will temporarily avoid them from keep on surfing the social media for long duration of time.

Finally, since it is quite hard for social media users to have self-control and self-regulation on the adoption of social media especially for youths, therefore the Ministry of Education and educators (e.g. teachers, lecturers and parents) may play their roles in educating the youngsters on the potential of becoming social media addicts. The government through its campaigns in printed and online media can disseminate the dark side of social media usage to the society while the Curriculum Development Center may include the relevant information in text books other teaching materials. Parents may also need to monitor the usage of social media among their kids and advice may be given from time to time to remind the kids to abstain from becoming an addict to social media.

7. Conclusions, limitations and future research directions

The current study has managed to unveil the impacts of BFM and UGT theories on social media addiction. The use of PLS-neural network analysis has also detected not only the linear but the non-linear and non-compensatory relationships within the model. Nevertheless, the study is limited to a certain time frame as a cross-sectional approach was used. In addition, since the study was conducted in the Malaysia therefore the findings are limited to the Malaysian context and cannot be generalized to other nations or geographical regions. Furthermore, the current study integrated BFM with UGT and this has limited the predictive power of the research model as there may be other factors that contribute to social media addiction. In addition, we have limited the activation function to sigmoid function and this has limited the results of the ANN analysis as there are other types of activation function available (e.g. hyperbolic tangent, softmax, identity) that may produce better results. The last limitation is that we only examined the moderating effect of hours spent. This has limited the explanatory power of the study in terms of moderating effect by other potential moderators.

Therefore, for future research directions, upcoming studies may use a longitudinal approach to examine the effect of time. Besides, other relevant factors (e.g. situational, psychological, environmental etc.) may be included in order to increase the overall predictive power of the research model. Furthermore, future studies may also include other theories such as social presence theory, theory of rational addiction or social support theory in the theoretical model. Moreover, as the context of this study was restricted to Asian country, future studies could be conducted in other geographical areas in order to study the effects of cultural differences. Methodologically, future studies may use other types of activation function (e.g. identity, softmax, hyperbolic tangent) in experimental studies to identify the best activation function for the hybrid SEM-ANN approach. Finally, since we have only examined the moderating effects of hours spent on social media, future studies may investigate the moderating effects of other variables that are associated to social media addiction, for example, the number of social media friends, gender or age differences.

Credit authorship contribution statement

Lai-Ying Leong: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Teck-Soon Hew:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Keng-Boon Ooi:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Project administration. **Voon-Hsien Lee:** Conceptualization, Methodology, Validation, Investigation, Writing - original draft, Writing - review & editing. **Jun-Jie Hew:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing.

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Conflict of interest

None.

Appendix A. Constructs and their sources

Construct	Number of items	Source
Information seeking	4	Kim et al. (2011)
Entertainment	4	Kim et al. (2011)
Agreeableness	4	Donnellan et al. (2006)
Conscientiousness	4	Donnellan et al. (2006)
Extraversion	4	Donnellan et al. (2006)
Neuroticism	4	Donnellan et al. (2006)
Openness to experience	4	Donnellan et al. (2006)
Social media addiction	12	Young (1998)

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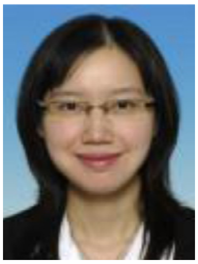

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