International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 06, 2020
ISSN: 1475-7192

Personality traits and work-related compulsive technology use: An organizational perspective

[1]Dr Basil John Thomas

ABSTRACT--*The development of technology has led to the expansion of automatic and complex technology-usage behavior. As a result, individuals are likely to feel compelled to interact with the system, which is referred as a compulsive technology use. The current study attempts to find whether in organizational context employees who frequently engage in work-related compulsive technology use have common personality traits, while also investigates whether work-related compulsive technology use leads to positive firm performance. Data was originated from online survey conducted with 332 employees of 8 construction companies in the Middle East and then used in multiple hierarchical regression analysis. The findings reveal that among the personality factors, Extraversion, Agreeableness, and Openness positively predict Task CTU, while Neuroticism is negatively related to it. Conversely, Consciousness does not have an influence on Task CTU. As an external variable, Computer Self-Efficacy positively and strongly predicts Task CTU. Finally, Task CTU is positively related to firm performance, but not employee performance. The other findings are discussed further.*

Keywords--*Work-related compulsive technology use, personality trait, firm performance*

I. INTRODUCTION

The growing adoption rate of personal mobile devices enhances their non-work-related usage (e.g., aimless Internet surfing, personal use) hat possesses a new threat to firms (Jamaluddin et al., 2015). One of the former studies identified that employees spent minimum one hour using Internet for non-work-related activities such as personal reasons during a regular work day (Vitak et al., 2011), while another research stated that roughly 30 to 50% of Internet usage for non-work-related usage at work causes up to US$ 1 billion annual loss for firms (Restubog et al., 2011). According to Carter et al. (2011), technology involvement is often intended, while at the same time activated by an organizational directive to switch to a new system. Although the majority of previous studies have solely based on individuals' behavioral intention to use a compulsory information system (IS) related to their occupation, technology engagement is less likely to be an outcome of directive coming from organization for a new system implementation (Clements & Boyle, 2018; Clements & Bush, 2011). Conversely, many technologies nowadays are used outside the organizational borders, which are not obligatory (Clements & Boyle, 2018), leading to the need for understanding the factors that trigger technology engagement for personal reasons (Ang, 2017). According to Chan et al. (2017), technology engagement can be an outcome of technology characteristics that elicit certain behaviors freestanding form an individual's awareness. Clements and Boyle (2018) has addressed the gap, which is related to an understanding the determinants and consequences of these

[1] *Assistant Professor, Sur University College, Sultanate of Oman*

automatic, unintended behaviors that are also out of control. They referred the above-mentioned behavior as "Compulsive technology use."

The workplace usage of personal mobile Internet devices has become omnipresent since 2012, through which employees can experience the comfort of performing their tasks during working and post-working hours (Disterer & Kleiner, 2013). According to O'Neil (2017), nearly forty million Americans are closely related to compulsive use of technology in the context of chatting, texting, social media updating, mindless app using, and web surfing. It is defined as "spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient." (Clements & Boyle, 2018). Fiorenza (2014) stated that mobile Internet use at the workplace could produce productivity, comfort, and cost saving. However, Small (2009) stressed that compulsive behaviors may product destructive outcomes such as traditional addictions (e.g., alcohol and substance use). Moreover, it is unclear what would be the outcomes of compulsive technology use. Clements and Boyle (2018) investigated the antecedents of compulsive technology use. It was revealed that technology habit, technology complexity, and technology-enabled triggers positively influence the compulsive technology behavior. Although the characteristics that affect the compulsive technology use are well addressed, it still remains unclear whether personality characteristics would change the compulsive technology behavior. It is added that different personalities are differently affected by components of technology design (Clements & Boyle, 2018). Another study suggested the worthiness to explore the effect of compulsive technology use on performance (Klobas et al., 2018). Hence, it is necessary to understand the consequence of compulsive technology use, such as firm performance in an organizational context.

1.2 Research aim

The current study addresses the above-mentioned research gaps and aims to answer the following research questions:

RQ1. Do employees who frequently engage in compulsive technology as part of their jobs use have common personality traits?

RQ2. Does compulsive technology use at the workplace result in positive firm performance?

RQ3. Does compulsive technology use at the workplace result in positive employee job performance?

In the empirical part of the study, to conceptualize the personality characteristics, the Big Five traits theory is employed (John & Srivastava, 1999; Barrick & Mount, 1991), characterizing individual personality in terms of five behavioral clusters: Agreeableness, Conscientiousness, Extraversion, Openness, and Emotional stability (Stajkovic et al., 2018). Clements and Boyle (2018) added that people who possess a highly impulsive personality would be highly influenced by technology compare to people with more conscientious personality. Therefore, the Big Five trait theory can help us identifying the personality difference in work-related compulsive technology use.

Although the Big Five traits and Self-efficacy (SE) autonomously relate to distinctive outcomes in different domains, less number of studies have examined them together in a single conceptual model (Stajkovic et al., 2018). In the academic domain, SE was found to be a strong determinant of academic performance (Schneider & Preckel, 2017). It has been defined as a "belief in one's capabilities to organize and execute the courses of action required to produce given attainments." (Bandura, 1997). SE is a predictor of creative productivity as individuals who have higher self-efficacy are more persistent, while they put more efforts to cope with puzzling situations and explore creative solutions. (Hallak et al., 2018). Therefore, in the current study, SE or so-called computer self-efficacy (CSE) is added as an external variable to test how it affects the work-related compulsive technology use of employees. Finally, firm performance is measured with turnover development, profitability, and employment development (Koellinger, 2008).

II. THEORETICAL DEVELOPMENT

2.1 Compulsive technology use

Compulsive technology use is explained to the extent where a person is involved in a use of certain technology for comfort, relief, and(or) inspiration, which if discontinued to use, results in discomfort or anxiety (Porter & Kakabadse, 2006). In the literature, the terms “problematic Internet use” and “Internet addition” are used, which are defined as an excessive use of Internet (Thatcher et al., 2008; Davis et al., 2002). They derive from several motives, such as relational problems, abandonment anxiety, introversion, and loss of control (Johnson & Indvik, 2003). In addition, those who have problematic Internet use behavior, are more likely to spend more time using emails, and surfing the web. Similarly, compulsive technology use occurs without alertness, attention, and control of an individual (Bayer & Campbell, 2012).

In their study, Clements and Boyle (2018) explored non-work related compulsive technology use in educational context. However, De Guinea and Markus (2009) suggested that goal-driven intended habits are likely to lead to even more spontaneous and unplanned behavior. Instead of using the theories representing the technology acceptance behavior (e.g., theory of planned behavior (TPB) and theory of reasoned action (TRA)), it is worthy to investigate unplanned behavior as well as unreasoned action. Therefore, the current study particularly focuses on work-related compulsive technology use, which can also be referred as goal-oriented use of technology by employees as part of their jobs.

2.2 Factors influencing Compulsive technology use

This research devised the previous studies associated with the compulsive technology use, its antecedents and consequences in different settings. It is shown in Table 1 that the compulsive technology use is mainly explored in academic/educational field and non-work related context. Klobas et al. (2018) discovered that entertainment motivation creates more compulsive use, compare to information motivation, whereas personality factors distinctively affect compulsive use. Such that, higher agreeableness and conscientiousness cause lower compulsive use in comparison with higher neuroticism. Another study found that openness, conscientiousness, extraversion, and agreeableness influence compulsive smartphone use of students (Panda & Jain, 2018). Quinones et al. (2016) investigated compulsive technology use in work-related context in the market research firm and found that both neuroticism and conscientiousness significantly impact compulsive technology use, which in its turn leads to working compulsively and longer hours of technology use. However, the authors did not emphasize how the employee or firm performance is affected by employee’s stronger engagement in technology use at the workplace. Henceforth, the impact of compulsive technology use on the performance has been given less consideration in the literature.

Drawing on the assumption from personality difference of employees and its distinctive impact on the compulsive technology use at the workplace, we propose that two key dimensions positively and significantly influence work-related compulsive technology use—the dimensions of the Big Five personality traits and computer self-efficacy.

Table 1: Overview of the studies related to compulsive technology use

Antecedents of compulsive technology use	**Consequences of compulsive technology use**	**Context**	**Area**	**Insights from studies**	**Source**	**Journal**
Technology habit Craving	N/A	Non-work related	Education	This study mainly explored technology-enabled factors that affect technology usage. However, major portion of tech adoption is categorized as personal and voluntary use, which has not been fully explored yet. Hence, personal and organizational context can be further studied.	Clements and Boyle (2018)	Computers in Human Behavior
Informational motivation (lower compulsive use) Entertaining motivation (higher compulsive use) Higher agreeableness (lower compulsive use) Higher conscientiousness (lower compulsive use)	Academic motivation	Non-work related	Academic	The study inspected the impact of compulsive use of YouTube on academic motivation, while not academic performance	Klobas et al. (2018)	Computers in Human Behavior

Higher neuroticism (higher compulsive use)						
Openness Conscientiousness Extraversion Agreeableness	Emotional Ill-being Physical Ill-being	Non-work related	Education	In this study, emotional and physical states of respondents have been tested and again their educational performance has not been considered.	Panda and Jain (2018)	Telematics and Informatics
Flow (Enjoyment and concentration)	N/A	Non-work related	Education	This study tested compulsive smartphone use for general purpose without specific function or application	Chen et al. (2017)	International Journal of Information Management
Extraversion Agreeableness Neuroticism	Technostress	Non-work related	Academic	Academic performance is considered with an inclusion of academic self-perception and course grade variables. However, only social apps are taken into consideration by considering that this study is in the non-work related context. The authors suggest to test self-efficacy.	Hsiao et al. (2017)	Telematics and Informatics

International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 06, 2020
ISSN: 1475-7192

Social pressure self-efficacy (less compulsive use of SNS) Perceived increased activity by peers (more compulsive use of SNS)	N/A	Non-work related	N/A	Not including specific group (e.g., students, employees, or others) of SNS users may reduce the generalizability of the study. In addition, the impact of self-characteristics of the SNS user has not been considered.	Turel and Osatuyi (2017)	Computers in Human Behavior
Self-esteem Interaction anxiousness	Problematic learning outcome	Non-work related	Education	Academic outcomes, such as academic stress and academic dissatisfaction have not been considered	Aladwani and Almarzouq (2016)	Computers in Human Behavior
Neuroticism Conscientiousness	Working compulsively Hours of use	Work-related	Market research	This study tested the relationship between CIU and compulsive working particularly. It was found that employees who use Internet for job, can cope with conflict regarding the excessive online behavior by socially acceptable behavior (work). Hence, it can be extended to examine the impact of CIU on work performance	Quinones et al. (2016)	Computers in Human Behavior
Introversion	Social connectedness	Non-work related	Education	Personality traits have not been considered in the study	McIntyre et al. (2015)	Computers in Human Behavior
Locus of control Social interaction anxiety Need for Touch Materialism	Technostress	Non-work related	Different	Non-inclusion of personality traits. However, it was suggested that psychological traits	Lee et al. (2014)	Computers in Human Behavior

Received: 22 Sep 2019 | Revised: 13 Oct 2019 | Accepted: 15 Jan 2020

		could facilitate compulsive usage of smartphone and lead to technostress.

Note: Only 5-years studies (2014-2018) have been reviewed

2.2.1 The Big Five traits and compulsive technology use

Although the consequences of SE are known in the literature as personality traits in the domains of education, organization, managerial behavior, and psychology remain unexplored in the information technology (IT) literature (Saleem et al., 2011).

H1a. Extraversion positively and significantly predicts compulsive technology use

H1b. Agreeableness positively and significantly predicts compulsive technology use

H1c. Conscientiousness positively and significantly predicts compulsive technology use

H1d. Neuroticism positively and significantly predicts compulsive technology use

H1e. Openness positively and significantly predicts compulsive technology use

2.2.2 Computer self-efficacy

Perceived SE is found to be positively associated with achievement-based behaviors, such as motivation, effectiveness, and positive attitude (Liaw, 2008; Bandura, 1986). The frequent interaction with the computer leads to a higher level of confidence of an employee in handling computer at the workplace (Achim & Al Kassim, 2015). While general SE positively influences performance and motivation, it is argued that the prognostic capacity of SE is stronger and more precise while it is determined by specific domain-related measures instead of general measures (Saleem et al., 2011). Hence, in the Internet-based environment, CSE is referred as a "judgement of one's capability to use a computer." (Compeau & Higgins, 1995, p. 192). Empirical evidence also reveals that a higher CSE leads to a more frequent use of IT applications (Compeau et al., 1999). In addition to SE and CSE, general computer self-efficacy (GCSE) is proposed (Hasan, 2006), which is described as individual's efficacy towards to multiple computer domains. On the contrary, system-specific computer self-efficacy (SCSE) is referred by Hasan (2006) as a belief of an individual in accomplishing specific task with the use of specific computer application. By considering that the current study is strongly related to work-related compulsive technology use, it can be assumed that employees are required to use specific computer application in their workplace as well. Moreover, the SCSE is given a more consideration in this study and the further hypothesis is proposed as following:

H2. CSE positively and significantly influences compulsive technology use

2.3 The Big Five traits and computer self-efficacy

Previous studies have emphasized the link between Big Five traits and self-efficacy (Stajkovic et al., 2018; Shaw & Rich, 2007). Extraversion amplifies positive feedbacks from others that increases self-efficacy (Judge et al., 2002). In addition, agreeableness leads to the engagement in new activities, which in its turn upsurges self-efficacy (Caprara et al., 2009). Conscientiousness also fosters higher level of self-efficacy (Brown et al., 2011) along with openness (Sanchez-Cardona et al., 2012). On the contrary, neuroticism leads to anxiety that creates lower level of self-efficacy (Shmitt, 2008). Stajkovic et al. (2018) found that among the 5 personality traits, conscientiousness is the only factor that significantly and positively impact self-efficacy in academic context. Saleem et al. (2011) highlighted the negative effect of neuroticism and agreeableness on CSE, while the positive influence of including extraversion, conscientiousness, and openness on CSE. It was found that extraversion, openness, and conscientiousness positively and significantly affected the CSE, while agreeableness negatively affected the CSE. Conversely, neuroticism was not a significant predictor for all respondents. Drawn from the findings of the previous studies, we hypothesize that,

H3a. Extraversion positively and significantly predicts computer self-efficacy

H3b. Agreeableness positively and significantly predicts computer self-efficacy

H3c. Conscientiousness positively and significantly predicts computer self-efficacy

H3d. Neuroticism positively and significantly predicts computer self-efficacy

H3e. Openness positively and significantly predicts computer self-efficacy

Other hypotheses are defined as following:

H4. Compulsive technology use positively and significantly predicts employee job performance

H5. Compulsive technology use positively and significantly predicts firm performance

III. RESEARCH METHODOLOGY

In this study, the conceptual model (see Fig. 1) is proposed by extensively reviewing the literature, with particular emphasis on the most recent studies association with compulsive technology use. Initially the antecedents of it were identified as personality traits characterized by the Big Five traits (Barrick & Mount, 1991) and CSE (Compeau & Higgins, 1995). As former studies suggested to test the influence of compulsive technology use on the performance (Clements & Boyle, 2018; Klobas et al., 2018), the proposed conceptual model of the current study differentiation two kinds of performance: (1) firm performance; and (2) employee job performance, which could help to recognize whether the compulsory use of technology at the workplace will have similar or different influence on them.

A quantitative method with purposive sampling technique is used to collect the data. An online survey was administered due to the fact that it ensures a broad geographical distribution with relatively less cost and efficient timeliness (Chang et al., 2017; Kurfali et al., 2017). The target audience of the sampling was employees with experience interacting with online messaging and task-related mobile applications in the construction companies in Middle East, for the job purpose. An initial survey was translated into Arabic and then refined with the use of pre-test that was done with 11 respondents. The results allowed constructing the final version of the survey questionnaire with exclusion of 4 items. Cronbach's Alpha (α) was employed for reliability assessment of the survey items and results indicate that the alpha values of study variables are higher than 0.7, meaning that the final questionnaire is reliable. Hence, the final questionnaire is given in Appendix A.

Construct validity is assessed by confirmatory factor analysis (CFA) (Anderson & Gerbing, 1988). Moreover, convergent validity is tested by the relationship between scores on the independent variables and on constructs suggested by the theory. Discriminant validity is measured with the use of square root of AVE for each study construct (Fornell & Larcker, 1981). Reliability assessment determines the accuracy and consistency between measurements of each variable (Hair et al., 2010). This study employed Cronbach's Alpha (α) to measure internal consistency of the constructs.

Finally, AMOS 23 software package is processed for the evaluation of the structural model with structural equation modelling (SEM) technique, following the measurement model testing as mentioned above.

IV. INSTRUMENTS

3.1.1. Self-reported vs. peer-reported survey

Former studies related to compulsive technology use and personality traits tackled to the suitability of self-reported survey. According to Aladwani & Almarzouq (2016), regardless of self-reported scales being useful, data precision issues could have an impact on the reliability of findings. For instance, Panda and Jain (2018) inserted that measuring compulsive technology, emotional and physical ill-beings could be perceived as socially and contextually unfavorable, which could in its turn lead to bias (Elmes et al., 2011). The same problem is considered as one of the limitations of another study as well (Chen et al., 2017). Self-reporting is to ask an individual what they are like instead of assume (Paulhaus & Vazire, 2007). In personality psychology, self and peer reporting methods are employed to measure personality from the perspective of a subject. The main goal is to identify how personal behavior is influenced by the personality (Friedman & Schustack, 2011). On the contrary, peer-reporting data is collected from the members of the client firm whose knowledge and expertise can be valuable for understanding the personality of a subject. Therefore, in data collection process, people, so-called informants who know about the subject must be taken into consideration (Martel et al., 2016). The main characteristics of self- and peer-reporting are described in Table 2.

Table 2: Self-reporting vs. peer-reporting

Self-reporting	Source	Peer reporting	Source
Introspective: If respondents are not able to understand themselves, while personality test asking for honest and objective self-evaluation	Paulhaus and Vazire (2007)	Observation: As one of the methods of peer-reporting, which however would be unreliable based on experience and bias of informant	Martel et al. (2016)
Self-representation can be an issue when including self-esteem and self-confidence in a personality study	Friedman and Schustack (2011)	However, it is considered reliable due to the combination of judgements from several informants	Martel et al. (2016)
Although some people are honest in their answers, others might not strive for social acceptance or feel threatened/challenges while being asked questions	Paulhaus and Vazire (2007)	Peer-reporting can be advantageous and instrumental in complementing self-reporting	McDonald (2008)

Received: 22 Sep 2019 | Revised: 13 Oct 2019 | Accepted: 15 Jan 2020

By looking at the difference between self- and peer-reporting in literature, it can be seen that both have advantages and disadvantages. In the context of this study, both of the methods are combined in order for self-assessment of respondents regarding their personality traits and compulsive technology use behavior as well as their assessment by informants. To ensure the reliability of informants, the demographic survey included the question regarding how many years do employees work in the same firm, due to the fact that the longer the year, the more familiarity will be among coworkers.

3.1.2. Measurement development

The instruments aimed to measure the Big Five traits, computer self-efficacy, compulsive technology use, and firm performance. Moreover, demographic variables, including gender, age, education, position at the firm, years of employment, and internet usage frequency were added in the online questionnaire. Respondents were asked to state the approximate time spent online at the workplace. Additionally, they were asked to specify how much time they spend on the 5 work-related internet tasks, namely, checking email, information searching, chatting, downloading files, and sending files, and 5 non-work-related functions including web surfing, gaming, forum reading, videos, as well as dating.

Initially, the compulsive technology use was measured with the compulsive Internet use scale (CIUS), which consists of fourteen items on a 7-point Likert scale ("strongly disagree" to "strongly agree"). According to Meerkerk et al. (2010). The CIUS is believed to have a high internal consistency. The items of the CIUS are taken from Meerkerk et al. (2009). This study hypothesized an association between personality traits and compulsive technology use at the workplace. The adjusted NEO personality inventory (NEO-PI-R) is an effective framework to assess the personality traits, which is developed by Costa and McCrae (1992). It has been translated into more than 30 languages (McCrae, 2001). It complies with the 20-item mini international personality item pool (IPIP) scale, suggested by Donnellan et al. (2006), which also evaluates the Big Five traits. Moreover, both NEO-PI-R and IPIP contain of the five personality traits. Since, NEO-PI-R allows self-reported and peer-reported surveying, this study mainly focused on this scale and its facets as the questionnaire items in order to address both employees for self-reporting and managers for peer-reporting. Alike IPIP scale, the personality traits scale comprised of 20 items in total.

CSE that is the employee's self-judgement on the ability to use a computer was assessed with 4 items, which were taken from Saleem et al. (2011) and Compeau and Higgins (1995). Finally, in assessing firm performance, employees were asked to weigh how successful their firms have performed in regard to financial and employment indicators, namely profit, turnover, and employment (Hallak et al., 2018; Koellinger, 2018). The qualitative information about firm performance mainly included the items such as "Your firm has been profitable over the past 12 months", "The turnover of my firm has increased this year compare to the last year", and "The number of employees in my firm has increased during the past 12 months." Since self-assessment of firm performance as a means of obtaining financial evidences from firms is challenging with non-response bias (Runyan et al., 2008), we collected the financial and employment information from the Government database of Middle East[2] to match the

[2] https://data.gov.tw/en

qualitative and quantitative data. The results have been shown in Figure. Finally, employee job performance was measured with 3 items taken from Buil et al. (2018).

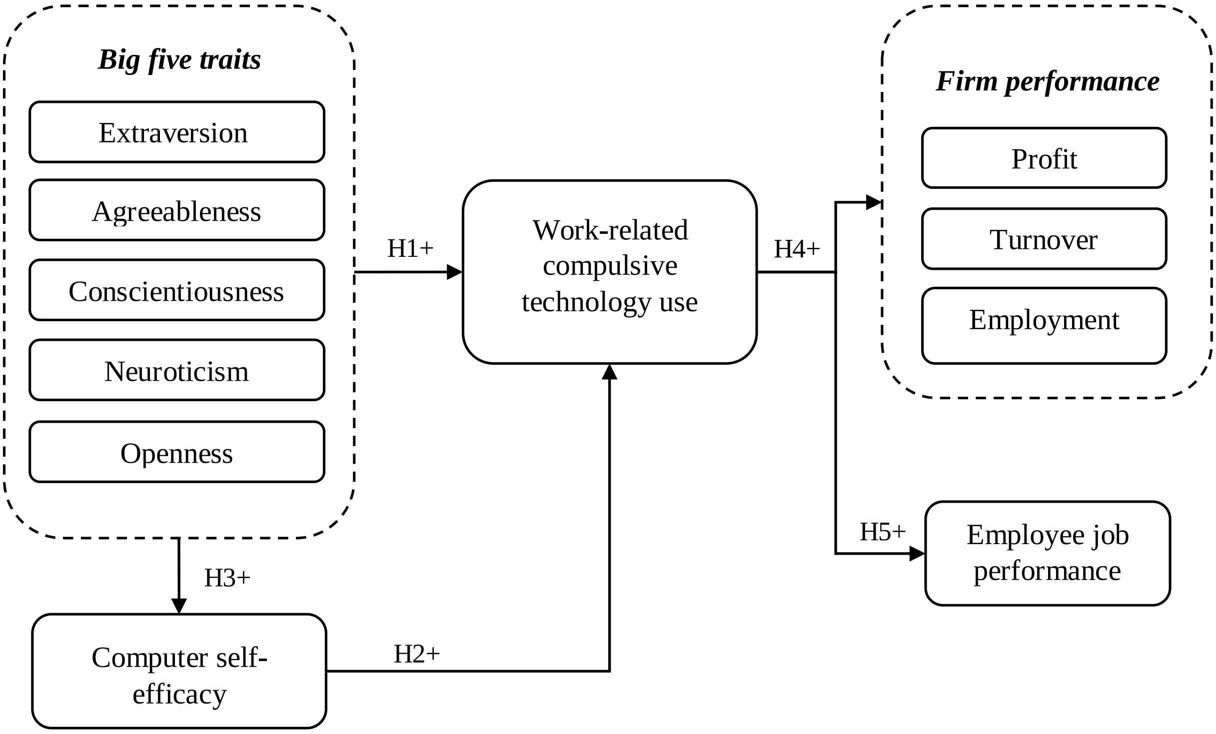

Figure 1: Conceptual model

V. DATA ANALYSIS AND RESULTS

4.1. Demographic analysis of respondents

Overall, 386 survey questionnaires were obtained. However, 54 of them were delisted from the final analysis as they were incomplete. Hence, 332 questionnaires were processed in the analysis. The details are given in Table 3.

Table 3: Respondent demographics

Profile	Item	Frequency	%
Gender	Male	217	65.4
	Female	115	34.6
Age	<20	14	4.2
	20-22	93	28.0
	22-24	104	31.3
	>24	121	36.4
Education degree	High school	32	9.6
	Bachelor	67	20.2
	Master	132	39.8
	Ph.D.	101	30.4
Device type to access to Internet	Smartphone	95	28.6

	Tablet	135	40.7
	Desktop	102	30.7
Excessive Internet usage frequency - work purpose	<1 hour	21	6.3
	1-2 hours	43	13.0
	2-3 hours	76	22.9
	3-4 hours	113	34.0
	>4 hours	79	23.8
Excessive Internet usage frequency - non-work purpose	<1 hour	27	8.1
	1-2 hours	72	21.7
	2-3 hours	98	29.5
	3-4 hours	79	23.8
	>4 hours	56	16.9

4.2. Analysis of measurement model

The descriptive statistics findings are given in Table 4. Besides that, the measurement model included the analysis of standardized factor loadings for measuring the scale validity, as suggested by Anderson and Gerbing (1988) in line with confirmatory factor analysis, where item loading must be higher than 0.5 acceptance level according to Hair et al. (2006); composite reliability that must be over 0.6, while average variance extracted must be higher than 0.5 levels, respectively. The analysis also included reliability testing with the consideration of Cronbach alpha (α), where α values are considered excellently reliable if higher than 0.90, highly reliable if between 0.70 and 0.90, moderately reliable if between 0.50 and 0.70, and finally lowly reliable if less than 0.50 (Hinton et al., 2004).

Finally, discriminant validity, which takes into consideration the correlations among the study constructs, refers that the square root of AVE values must be higher than the coefficients of correlations themselves (Fornell & Larcker, 1981) (Table 5).

Table 4: Measurement model results

Construct item	Mean	SD	Loadings	Cronbach's α	CR	AVE
Task-related CTU				0.71	0.89	0.61
Task CTU1	2.34	0.98	0.74			
Task CTU2	2.43	0.99	0.78			
Task CTU3	2.11	1.02	0.82			
Task CTU4	2.76	0.89	0.88			
Task CTU5	2.44	0.83	0.84			
Task CTU7	2.35	1.12	0.83			
Task CTU9	2.13	1.08	0.89			
Task CTU11	2.03	1.04	0.86			
Task CTU14	2.38	0.84	0.77			

Big Five traits						
EXT				0.69	0.84	0.58
EXT1	2.34	0.94	0.79			
EXT2	2.43	0.86	0.81			
EXT4	2.22	1.04	0.78			
AGR				0.72	0.87	0.62
AGR1	2.89	1.07	0.83			
AGR2	3.09	1.13	0.87			
AGR3	3.01	1.22	0.79			
CON				0.71	0.83	0.59
CON1	2.87	1.08	0.82			
CON2	2.65	0.99	0.75			
CON3	2.58	0.84	0.77			
CON4	2.71	0.91	0.72			
NEU				0.68	0.91	0.65
NEU1	2.84	0.83	0.81			
NEU2	3.09	0.92	0.82			
NEU4	2.67	0.95	0.88			
OPEN				0.82	0.88	0.63
OPEN1	2.48	1.14	0.79			
OPEN2	2.74	0.96	0.84			
OPEN3	2.45	0.76	0.78			
OPEN4	2.78	0.83	0.76			
CSE				0.79	0.85	0.59
CSE1	2.24	0.92	0.75			
CSE2	2.41	0.78	0.77			
CSE3	2.56	0.72	0.78			
CSE4	2.49	1.02	0.83			
PROF				0.72	0.87	0.61
PROF1	3.11	0.89	0.75			
PROF2	2.98	0.85	0.72			
TURN	3.05	0.83	0.69	0.71	0.84	0.57
TURN1	2.79	0.96	0.73			
TURN2	2.83	0.93	0.68			
EMPLOY	2.74	0.95	0.79	0.72	0.85	0.62
EMPLOY1	2.91	1.06	0.76			
EMPLOY2	3.02	0.75	0.68			
PERF				0.69	0.86	0.63
PERF1	2.89	1.04	0.73			
PREF2	2.74	0.95	0.81			

Received: 22 Sep 2019 | Revised: 13 Oct 2019 | Accepted: 15 Jan 2020

PERF3	2.93	0.86	0.77

Table 5: Discriminant validity results

	CTU	EXT	AGR	CON	NEU	OPEN	CSE	PROF	TURN	EMPLOY	PERF
Task CTU	**0.781**										
EXT	0.23	**0.762**									
AGR	0.11	0.23	**0.787**								
CON	0.05	0.31	-0.02	**0.768**							
NEU	0.32	-0.09	0.13	-0.21	**0.806**						
OPEN	0.41	-0.13	0.22	-0.08	-0.09	**0.794**					
CSE	0.29	-0.04	0.27	0.16	0.16	0.42	**0.768**				
PROF	0.32	0.05	0.25	0.13	0.17	0.18	0.21	**0.781**			
TURN	0.37	0.11	0.31	0.32	0.29	0.21	0.37	0.32	**0.755**		
EMPLOY	0.22	0.32	0.38	-0.09	0.21	0.23	0.18	0.41	0.31	**0.787**	
PERF	0.09	0.41	0.05	0.08	0.18	0.07	-0.09	0.16	0.26	0.14	**0.794**

4.3. Testing of hypotheses

The testing of hypotheses was conducted initially between Work CTU and its antecedents (Big five traits and CSE). The results show that among Big five traits, EXT (β=0.215*, p<0.05); OPEN (β=0.167*, p<0.05); and AGREE (β=0.252**, p<0.01) are significantly and positively associated with Work CTU. On the contrary, NEU (β=-0.146*, p<0.05) and CON (β=0.007, p=0.388) are negatively and not significantly related to Work CTU, respectively. Moreover, Hypotheses designated as H1a, H1b, and H1e are supported, whereas H1c and H1d are rejected.

In addition, it is revealed that CSE (β=0.370***, p<0.001) positively and significantly predicts Work CTU in an organizational context. Hence, H2 is supported as well.

The second stage of SEM analysis of structural model testing included the relationship between Work CTU and performance-related outcome variables, namely employee performance and firm performance. It is discovered that Work CTU positively and slightly impacts firm performance as following:

- Work CTU to PROF (β=0.112*, p<0.05)
- Work CTU to TURN (β=0.103*, p<0.05)
- Work CTU to EMPLOY (β=0.146*, p<0.05)

Conversely, it is found that Work CTU negatively predicts PERF (β=-0.108*, p<0.05). Henceforth, H4a, H4b and H4c are supported, while H5 is rejected.

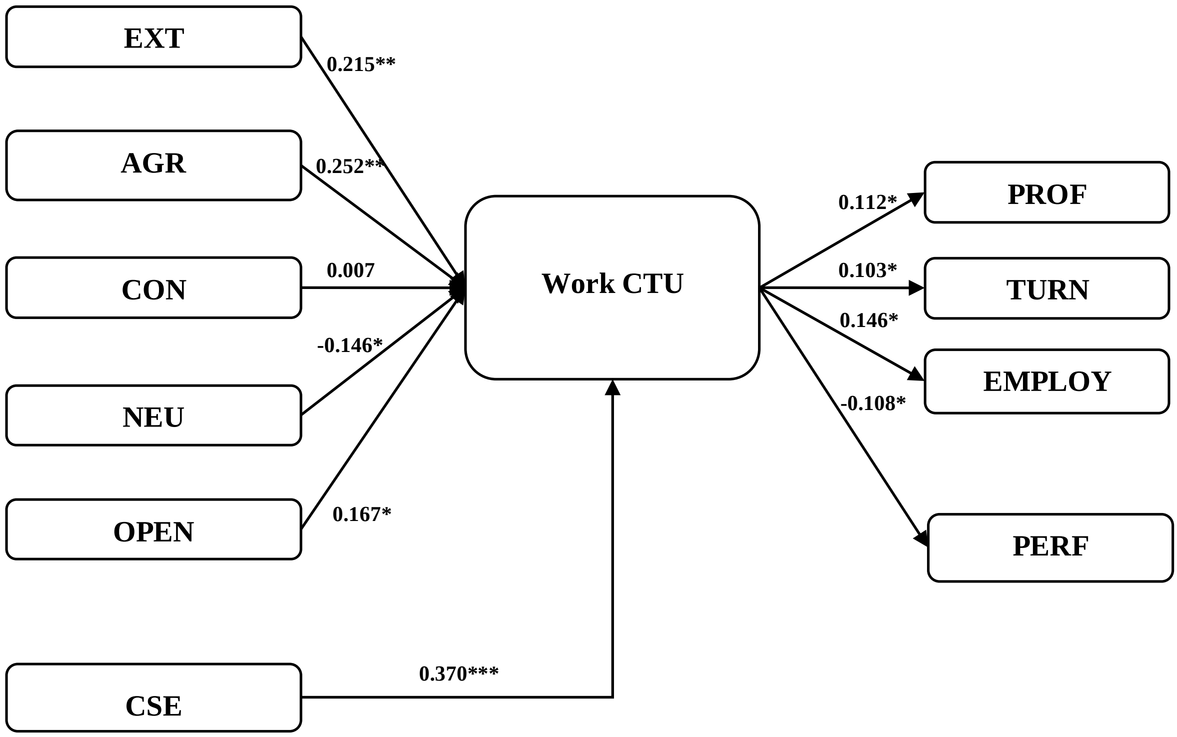

Figure 2: Results of the hypotheses

VI. DISCUSSION OF STUDY FINDINGS

The current research mainly investigated what drives the work-related excessive use of technology at workplace, and in its turn how it influences the performance indicators in a firm. The performance is measured in two directions: employee performance and firm performance. As an external variable, Computer Self-Efficacy is considered

The results of hypotheses testing showed that among the Big five traits, Extraversion, Agreeableness, and Openness are significant and positive determinants of Work CTU. It is more likely that firm employees who are involved in technology use while working, do not miss any information or message related to any specific task as part of their job, and immediately respond to it. The findings are not adjacent with that of several other scholars (Servidio 2014; Kuss et al., 2013). They had discovered that actually Agreeableness negatively predicts compulsive use of Internet. In another study, it was found that Openness, Agreeableness and Consciousness are critical factors that help to raise awareness on the potential consequences of excessive Internet use, such as data breach, cybersecurity and information security risks. Moreover, in the current study, it is revealed that Openness is also an important determinant of Work CTU. It can be explained in the organizational context to the extent that organizational members are well aware of cybersecurity rules and the internal system might be well-protected against any outer cybersecurity attack, as well as data breach risks, and therefore they are comfortable in overuse of technology for work purposes. The results are also adjoining the findings of Hadlington (2017). Conversely, Consciousness does not predict Work CTU in an organizational context. Uebelacker and Quiel (2014) had found that high level of Consciousness creates higher data breach risk in an educational setting, where students with also higher Openness and Agreeableness are more likely to be vulnerable to the cybersecurity attack. In the current research, the relationship between Consciousness and Work CTU can be justified to the extent employees with higher consciousness regarding their technology usage behavior could make them more confident that their technology usage will not create a problem for their firms. In addition, as their excessive use of internal technology is purely work-related, they may be allowed to use it unlimitedly. On the other hand, their firms may be result-oriented, such as more concentration on the performance of the firm, revenue growth and thereby motivate employees to work hard to reach goals and use all potential tools of technology in a work process.

NEU is found to negatively impact Task CTU. In former studies, it was discovered that NEU is a positive determinant of compulsive SNS usage and social apps Hughes et al. (2012). It is explained to the extent that highly neurotic individuals seek for social interaction online, regardless of feeling anxious in a real communication. Hsiao et al. (2017) revealed that neuroticism is positively related to compulsive social app usage. On the contrary, in the present study it is suggested that task-related use of Internet at workplace is not same as non-task usage to make friends and interact with others in online environment. Hence, employees with higher neuroticism may comprehend that although Internet is highly useful to deal with stress, task-related usage must not be considered as a means for reducing stress at workplace.

The frequent interaction with the computer leads to a higher level of confidence of an employee in handling computer at the workplace. While general CSE positively influences performance and motivation, it is argued that the prognostic capacity of CSE is stronger and more precise when it is determined by specific domain-related measures instead of general measures (Saleem et al., 2011). Hence, the findings of the present study also confirm that CSE strongly predicts the compulsive use of technology at workplace, if it is related to accomplishing the tasks. Finally, Task CTU was found to positively determines the performance of firm in terms of making profit, increasing turnover and attracting new employees, while it slightly reduces employees' self-performance. It can be explained to the extent that probably employees are mostly using their times to accomplish firm tasks rather than using technology for personal development, such as taking online courses, looking for Internet sources for learning new skills and so on. In this case, it is suggested that this kind of overuse of technology only for the benefits of a firm is not useful for both employees and a firm in a long-run, as employees may sometime feel frustrated and leave their firms, which may ultimately downgrade the firm performance as well.

VII. CONCLUSION AND FUTURE RESEARCH

The present study investigates the relationship between the personality and the technology usage behavior in an organizational setting. In this regard, Big five traits are selected as the determinants of Task CTU to know which personality type is positively and negatively related to Task CTU. The personalities that are open to the world and curious in trying out new things are believed to be positive about using the technology excessively. In addition, it is recommended to firms that they must take into account that the technology usage at workplace must be proportional for both job accomplishment and personal development of organizational members, as they learn more and reduce stress more, will ultimately contribute to the performance more. Although firm performance might be increased in a short-run, it might not be promising in a long-run. Because, firm performance relies on employee performance to some extent.

Future research would better be focused on including cultural variables to test personality and culture (e.g., organizational, national) interchangeably. In addition, the sample size could be increased, or longitudinal study could be done to observe the employee behavior change over time.

Table 6: APPENDIX A

Construct	Items	Source
Task CTU	*"Task CTU" denotes all task-related activities*	Meerkerk et al. (2009)
CTU1	I find it difficult to stop using the Internet for my work when I am online	
CTU2	I continue to use the Internet for my work despite my intention to stop	
CTU3	My colleagues say I should use the Internet less	
CTU4	I prefer to use the Internet for my work instead of spending time with colleagues	
CTU5	I am short of sleep because of the Internet	
CTU6	I think about the Internet, even when not online	
CTU7	I look forward to my next Internet session during work	
CTU8	I think I should use the Internet less often for work	
CTU9	I have unsuccessfully tried to spend less time on the Internet	
CTU10	I rush through my assignments in order to go on the Internet	
CTU11	I check for messages and work-related discussions online when I am awake	
CTU12	I go on the Internet when I am feeling down	
CTU13	I use the Internet to escape from my sorrows or get relief from negative feelings at work	
CTU14	I feel restless, frustrated, or irritated when cannot use the Internet at work	
Big Five traits	***Self-reported***	Wu et al. (2008); Costa and McCrae (2008)
Extraversion (EXT)	*I am often…*	
EXT1	Assertive	
EXT2	Active	
EXT3	Seeking excitement	
EXT4	Gregarious	
Agreeableness (AGR)	*I am often…*	
AGR1	Straightforward	
AGR2	Altruistic	
AGR3	Modest	

AGR4	Tended-minded	
Conscientiousness (CON)	*I am often…*	
CON1	Competent	
CON2	Striving for achievement	
CON3	Self-disciplined	
CON4	Deliberate	
Neuroticism (NEU)	*I am often…*	
NEU1	Anxious	
NEU2	Depressive	
NEU3	Self-conscious	
NEU4	Vulnerable	
Openness (OPEN)	*I am often…*	
OPEN1	Imaginative	
OPEN2	Interested in aesthetics	
OPEN3	Emotional in feelings	
OPEN4	Adventurous	
Computer self-efficacy		Lee et al., (2014); Sapp and Harrod (1993)
CSE1	I am confident about my computer skills	
CSE2	My computer usage is chiefly controlled by powerful others	
CSE3	I have not taken instructions from others when I use technology	
Profit		Hadlington (2017)
PROF1	Our firm has made big profit in the past few years	
PROF2	Our firm's profit growth is greatly relied on task-oriented employees' majority	
Turnover		
TURN1	Our firm's turnover has exceeded the previous years	
TURN2	Technology use for purely task purposes helps our firm to track changes in turnover trend	
Employment		
EMPLOY1	Employment rate has grown in the past few years	
EMPLOY2	Many employees prefer to maintain as parts of the firm currently	
Employee job performance		Kim et al. (2016)

PERF1	Firm's business growth also affected employee performance in the past few years
PERF2	Employees use Technology excessively for self-improvement
PERF3	Employees use Technology excessively for job improvement

VIII. ACKNOWLEDGMENT

The author is thankful to the management and staff of Sur University College for their full support and cooperation in getting this research work accomplished in time.

REFERENCES

1. Achim, N., & Al Kassim, A. (2015). Computer usage: The impact of computer anxiety and computer self-efficacy. Procedia – Social and Behavioral Sciences, 172, 701-708.
2. Ajzen, I., & Fishbein, M. (2000). Attitudes and the attitude-behavior Relation: Reasoned and automatic processes. European Review of Social Psychology, 11, 1–33.
3. Aladwani, A. M., & Almarzouq, M. (2016). Understanding compulsive social media use: The premise of complementing self-conceptions mismatch with technology. Computers in Human Behavior, 60, 575-581.
4. Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 10(3), 411-423.
5. Ang, C. (2017). Internet habit strength and online communication: Exploring gender differences. Computers in Human Behavior, 66, 1–6.
6. Bandura, A. (1997). Self-efficacy: The exercise of control. New York: Freeman & Company.
7. Barrick, M. R., & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. Personnel Psychology, 44, 1–26.
8. Buil, I., Martinez, E., & Matute, J. (2018). Transformational leadership and employee performance: The role of identification, engagement and proactive personality. International Journal of Hospitality Management, 77, 64-75.
9. Carter, M., Clements, J. A., Thatcher, J., & George, J. (2011). Unraveling the "paradox of the active user": Determinants of individuals' innovation with it-based work routines. AMCIS 2011 proceedings, paper 41.
10. Chan, T. K., Cheung, C. M., & Lee, Z. W. (2017). The state of online impulse-buying research: A literature analysis. Information & Management, 54(2), 204–217.
11. Ching-Ter Chang, Chang-Shu Tu, Jeyhun Hajiyev.(2019) "Integrating academic type of social media activity with perceived academic performance: A role of task-related and nontask-related compulsive Internet use", Computers & Education.
12. Chang, C.-T., Hajiyev, J., & Su, C.-R. (2017). Examining the students' behavioral intention to use e-learning in Azerbaijan? The General Extended Technology Acceptance Model for E-learning approach. Computers & Education, 111, 128-143.
13. Clements, J. A., & Boyle, R. (2018). Compulsive technology use: Compulsive use of mobile applications. Computers in Human Behavior, 87, 34-48.

14. Clements, J. A., & Bush, A. A. (2011a). Habitual IS use and continuance. Proceedings of the southern association for information systems conference, Atlanta, GA, US.
15. Compeau, D., Higgins, C. A., & Huff, S. (1999). Social Cognitive Theory and individual reactions to computing technology: A longitudinal study. MIS Quarterly, 23(2), 145-158.
16. Compeau, D. R., & Higgins, C. A. (1995). Application of Social Cognitive Theory to Training for Computer Skills. Information Systems Research, 6(2), 118-143.
17. Costa, P. T., & McCrae, R. R. (1992). Revised NEO personality inventory (NEO-PI-R) and the NEO five-factor inventory (NEO-FFI) professional manual. Odessa, FL: Psychological Assessment Resources, Inc.
18. Davis, R. A., Flett, G. L., & Besser, A. (2002). Validation of a new scale for measuring problematic Internet use: implications for pre-employment screening. CyberPsychology Behavior, 5, 331–345.
19. De Guinea, A. O., & Markus, M. L. (2009). Why break the habit of lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. MIS Quarterly, 33(4), 434-444.
20. Disterer, G., & Kleiner, C. (2013). BYOD Bring Your Own Device. Procedia Technology, 9, pp.43–53.
21. Fiorenza, P. (2014). Mobile Technology Forces Study of Bring Your Own Device. Public Manager, pp.12–15.
22. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.
23. Friedman, H. S., & Schustack, M. W. (2011). Personality: Classic theories and modern research (5th Ed.). Boston: Allyn & Bacon.
24. Goodall Jr., H.L., 1992. Empowerment, culture, and postmodern organizing: Deconstructing the Nordstrom employee handbook. Journal of Organizational Change Management, 5 (2), 25–30.
25. Jamaluddin, H., Ahmad, Z., Alias, M., & Simun, M. (2015). Personal Internet use: The use of personal mobile devices at the workplace. Procedia – Social and Behavioral Sciences, 172, 495-502.
26. John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin, & O. P. John (Eds.). Handbook of personality: Theory and research (pp. 102–138). (2nd ed.). New York, NY: Guilford Press.
27. Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct? Journal of Personality and Social Psychology, 83, 693–710.
28. Hadlington, L. (2017). Human factors in cybersecurity; examining the link between Internet addiction, impulsivity, attitudes towards cybersecurity, and risky cybersecurity behaviors. Heliyon, 3.
29. Hair, J. R., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data anlysis (6th ed.). Upper Saddle River, NJ: Pearson-Prentice Hall.
30. Hallak, R., Assaker, G., O'Connor, P., & Lee, C. (2018). Firm performance in the upscale restaurant sector: The effects of resilience, creative self-efficacy, innovation and industry experience. Journal of Retailing and Consumer Services, 40, 229-240.
31. Hinton, P. R., Brownlow, C., McMurray, I., & Cozens, B. (2004). SPSS explained. London, UK: Routledge.
32. Hsiao, K.-L., Shu, Y., & Huang, T.-C. (2017). Exploring the effect of compulsive social app usage on technostress and academic performance: Perspectives from personality traits. Telematics and Informatics, 34, 679-690.

33. Hughes, D. J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and personality factors of social media use. Computers in Human Behavior, 28, 561-569.
34. Klobas, J. E., McGill, T. J., Moghavvemi, S., & Paramanathan, T. (2018). Compulsive YouTube usage: A comparison of use motivation and personality effects. Computers in Human Behavior, 87, 129-139.
35. Koellinger, P. (2008). The relationship between technology, innovation, and firm performance – Empirical evidence from e-business in Europe. Research Policy, 37, 1317-1328.
36. Kurfali, M., Arifoğlu, A., Tokdemir, G., & Pacin, Y. (2017). Adoption of e-government services in Turkey. Computers in Human Behavior, 66, 168-178.
37. Kuss, D. J., Griffiths, M. D., & Binder, J. F. (2013). Internet addiction in students: Prevalence and risk factors. Computers in Human Behavior, 29, 959-966.
38. Lee, Y-K., Chang, C-T., Lin, Y., & Cheng, Z-H. (2014). The dark side of smartphone usage: Psyhcological traits, compulsive behavior and technostress. Computers in Human Behavior, 31, 373-383.
39. Leephaijaroen, S. (2016). Effects of the big-five personality traits and organizational commitments on organizational citizenship behavior of support staff at Ubon Ratchathani Rajabhat University, Thailand. Kasetsart Journal of Social Sciences, 37, 104-111.
40. Martel, M. M., Markon, K., & Smith, G. T. (2016). Research Review: Multi-informant integration in child and adolescent psychopathology diagnosis. Journal of Child Psychology and Psychiatry.
41. McCrae, R. R. (2001). Trait psychology and culture: Exploring intercultural comparisons. Journal of Personality, 69, 819–846.
42. McDonald, J. D. (2008). Measuring personality constructs: The advantages and disadvantages of self-reports, informant reports and behavioral assessments. Enquire, 1(1), 1-18.
43. McIntyre, E., Wiener, K. K. K., & Saliba, A. J. (2015). Compulsive Internet use and relations between social connectedness, and introversion. Computers in Human Behavior, 48, 569–574.
44. Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., Franken, I. H. A., & Garretsen, H. F. L. (2010). Is compulsive internet use related to sensitivity to reward and punishment, and impulsivity? Computers in Human Behavior, 26, 729-735.
45. Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., Vermulst, A. A., & Garretsen, H. F. L. (2009). The compulsive internet use scale (CIUS): Some psychometric properties. Cyber Psychology and Behavior, 12 (1), 1–6.
46. O'Neil, T. D. (2017). Cyber wellness: A liberal studies course in higher education. Proceedings of the EDSIG conference, 2473.
47. Panda, A., & Jain, N. K. (2018). Compulsive smartphone usage and users' ill-being among young Indians: Does personality matter? Telematics and Informatics, 35, 1355-1372.
48. Paulhaus, D. L., & Vazire, S. (2007). The self-report method. Handbook of research methods in personality psychology, 224-239.
49. Restubog, S. L. D., Garcia, P. R. J. M., Toledano, L. S., Amarnani, R. K., Tolentino, L. R., & Tang, R. L. (2011). Yielding to cyber temptation: Exploring the buffering role of self-control in the relationship between organizational justice and cyberloafing behavior in the workplace. Journal of Research in Personality, 45 (2), 247–251.
50. Robbins, S. P., & Judge, T. A. (2009). Organizational behavior (13th ed.). Upper Saddle, NJ: Pearson Prentice Hall.

51. Runyan, R., Droge, C., & Swinney, J. (2008). Entrepreneurial orientation versus small business orientation: what are their relationships to firm performance? Journal of Small Business Management, 46 (4), 567–588.
52. Servidio, R. (2014). Exploring the effects of demographic factors, Internet usage and personality traits on Internet addiction in a sample of Italian university students. Computers in Human Behavior, 35, 85–92.
53. Small, G. (2009). Brain bootcamp, exercising your most important organ. Psychology Today.
54. Stajkovic, A. D., Bandura, A., Locke, E. A., Lee, Dongseop., & Sergent, K. (2018). Test of three conceptual models of influence of the big five personality traits and self-efficacy on academic performance: A meta-analytic path-analysis. Personality and Individual Differences, 120, 238-245.
55. Turel, O., & Osatuyi, B. (2017). A peer-influence perspective on compulsive social networking site use: Trait mindfulness as a double-edged sword. Computers in Human Behavior, 77, 47-53.
56. Uebelacker, S., & Quiel, S. (2014). The Social Engineering Personality Framework. Workshop on Socio-Technical Aspects in Security and Trust, 24–30.
57. Vitak, J., Crouse, J., & LaRose, R. (2011). Personal Internet use at work: Understanding cyberslacking. Computers in Human Behavior, 27 (5), 1751–1759.
58. Wu, K., Lindsted, K. D., Tsai, S-Y., & Lee, J. W. (2008). Chinese NEO-PI-R in Middle Eastese adolescents, Personality and Individual Differences, 44, 656-667.