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The perceptions of social media users of digital detox apps considering personality traits

Vinh T. Nguyen[1,2]

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Abstract
The purpose of this study was to investigate the perceptions of users about using digital detox applications and to display relationships among personality traits and technology-related variables. This study was designed using survey approach and employed Generalized Structured Component Analysis (GSCA). As such, 11 hypotheses were constructed and tested. The study recruited 263 participants who utilize detox applications to avoid social media distractions. Data were collected through Google Form and analyzed using GSCA Pro 1.1 to better understand whether the proposed conceptual model fits the data. The results of the study indicated that behavioral intention predicted usage behavior significantly; performance expectancy, effort expectancy, and social influence positively affected behavioral intention; in turn, agreeableness and extroversion positively influenced performance expectancy, and extroversion affected effort expectancy; finally, neuroticism had a statistically significant and negatively associated with effort expectancy of using social media detox apps. The significant exceptions were that facilitating conditions were not predictive of behavioral intention, openness to experience did not influence performance expectancy, and conscientiousness was not linked to effort expectancy. The proposed conceptual model explained 56.68% of the amount of variation, indicating that instructors, policy makers and software designers should consider personal factors for preparing practical intervention approaches to mitigate learning issues related to social media distraction.

Keywords Personality traits · Social media detox apps · Generalized structured component analysis · Covid-19 · Education issues · utaut

✉ Vinh T. Nguyen
vinhnt@ictu.edu.vn

1 TNU - University of Information and Communication Technology, Thai Nguyen, Vietnam

2 FPT University, Ha Noi, Vietnam

1 Introduction

Social media are interactive technologies that enable the creation and sharing of information, ideas, hobbies, and other kinds of expression throughout digital environments (Kietzmann et al., 2011; Obar & Wildman, 2015). Having developed digital devices, especially the iPhone and other similar gadgets with large screens, social media gave rise to a new way of studying, working, interacting, and socializing (Ahmed et al., 2019). In just a few steps, smartphone owners can surf the web, upload photos, live stream, and participate in social networking discussions. Statista Research Department (2021) reported that the number of smartphone users in 2021 is expected to be 6.378 billion, with a predicted growth to 7.516 billion by 2026. This is a significant proportion, accounting for 80.69 percent of the world's population. The number of smartphone owners has increased significantly since 2016, when there were only 3.668 billion users, accounting for 49.40 percent of the population at the time. In accordance with the number of smartphone owners, 4.48 billion people are currently using social media, with an average time spent on social media of around 2 hours and 24 minutes per day (Statista Research Department, 2021). What that mean is that a large proportion of users, particularly adolescents, spend substantial amount of time on social media activities (Jarman et al., 2021).

As a means of facilitating the exchange of information, social media has proven to be useful in many contexts, including but not limited to socializing (Chuang and Liao, 2021), academic work (Klar et al., 2020), mental health, and healthcare (Abdelguiom & Iahad, 2020; Naslund et al., 2020). As a site for socializing, social media offers new opportunities for self-expression and connectivity (Abdelguiom & Iahad, 2020). Users may develop and improve their social capital by exploiting the inter-connectivity. Through improved self-esteem and improved quality of life, social media can benefit users' psychological well-being. As a result, social media has grown more interwoven in people's everyday lives (Chuang & Liao, 2021). In terms of academic work, students benefit from social media in a variety of ways, including acquiring the most up-to-date material for their assignments, preparing for examinations, improving note-taking and learning abilities, and deciding on a vocation (Klar et al., 2020; Chugh et al., 2021).

With regards to mental health and healthcare support, social media can benefit patients in a variety of ways (as illustrated in Fig. 1), such as emotional, informational, esteem-building, networking, social comparison, and self-expression (Beaunoyer et al., 2017; Smailhodzic et al., 2016; Schønning et al., 2020; Skogen et al., 2021). Lederman et al. (2014) presented a synergistic positive psychology model which aims to encourage long-term social and functional rehabilitation of children with mental health problems. The key objective of this model is to capitalize on the interest young people have in social media, while addressing and minimizing the potential downsides of commercial social networking, thereby maximising the opportunity for therapeutic benefit while minimizing negative consequences (Valentine et al., 2019).

Despite the benefits provided by social media, the downsides of its excessive use also need to be considered. Results from (Schønning et al., 2020; Valkenburg

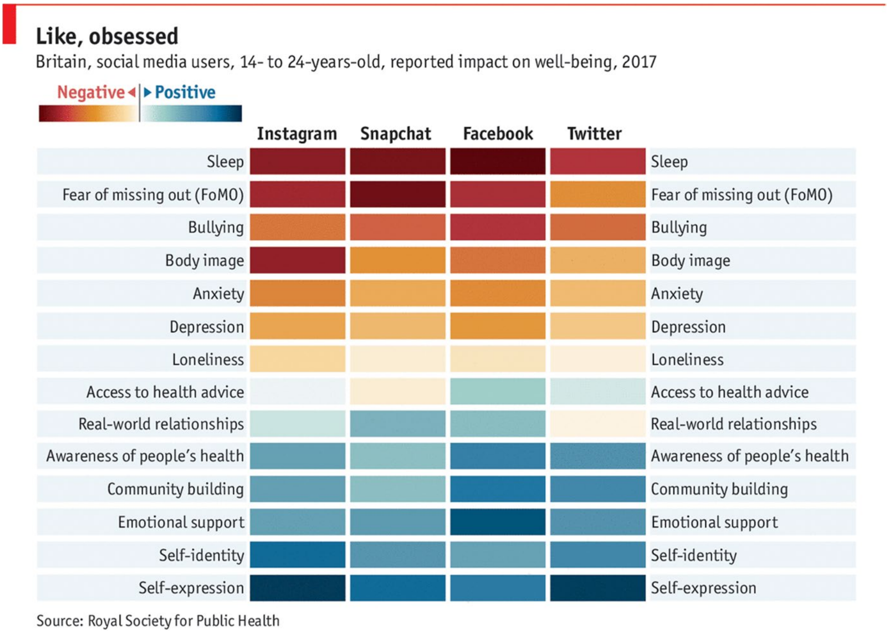

Fig. 1 Effects of social media on mental health. Source: Royal Society of Public Health

et al., 2021) reported that many existing studies had a focus on different negative aspects of mental health, such as life satisfaction, happiness, self-esteem, anxiety, depression, stress, and loneliness, sleep, fear of missing out (FOMO) (as depicted in Fig. 1). In addition to impairing the body's ability to function in the short-term, this has long-term consequences (e.g., such as vision problem, self-harm and suicidal behavior (Ellis and Goggin, 2013; Schønning et al., 2020)). In education settings, excessive use of social media while teaching and learning would also lead to distracted thinking and superficial learning (Lesch, 2014) - a critical issue that needs to be addressed in the context of covid-19 pandemic (Dontre, 2021). Taking into account the aforementioned problems, minimizing the role and impact of social media as well as digital devices in daily life has captured the attention of users, parents, and governments worldwide (Yu et al., 2018).

In recent years, researchers in a variety of fields have focused attention on an emerging trend pertaining to digital detox - a method of combating technology addiction (Ugur & Koc, 2015; Syvertsen & Enli, 2020; Radtke et al., 2021). A digital detox, according to the Oxford Dictionary, is a "period of time during which a person refrains from using electronic gadgets, such as their smartphone, as a chance to relieve stress or focus on social connection in the real world." On top of the preceding notion, (Meier & Reinecke, 2020) added elements such as device type (laptop, smartphone, tablet), application type, branding (e.g., Facebook, Instagram), properties (e.g., detached from chat), interactions, and messages. A number of assertions have been made over decades about the impact of digital communication on mental health and recent studies on this phenomenon have focused on social media substantially (Meier & Reinecke, 2020; Turel & Vaghefi, 2019; White, 2013). A significant portion of the aforementioned issue may be linked to the COVID-19 epidemic, in which remote working (e.g., e-learning) has become the primary strategy for maintaining social distance (Chuang & Liao, 2021; Beaunoyer et al., 2020). On the one hand, this approach appears to limit the hazards of face-to-face interaction; but, it also permits individuals to increase their exposure to digital gadgets, leading to social media use as a "double-edged sword" (Nazir et al., 2020; Guitton, 2021).

Many strategies have been proposed to help users get rid of digital devices or maintain an appropriate balance in their usage (Cao & Sun, 2018; Schmuck, 2020; Chuang & Liao, 2021). Moment, Flipd, AntiSocial App, Forest, OffTime, QualityTime, Digital Detox, etc., are all apps that aim to help users balance their lives. Yet, little is known about how users adopt this technology or what causal relationships exist among factors that influence their behavior. A recent attempt made by Schmuck (2020) to tackle the aforementioned issue showed that the usage of digital detox applications seemed to lower the chance of youths getting reliant on their cellphones by reducing adverse consequences associated with social media use. However, only three variables (e.g., problematic smartphone use, social networking sites and well-being) were taken into account in the study, and the author suggested that future research should look into if and how key determinants are associated to the usage of digital detox apps.

Given the emergence of Covid-19 variants, the persistence of lockdowns in many countries, and the necessity "to better understand the difficulties in remote learning, to investigate more effective delivery of education contents, and to find ways to improve remote-learning outcomes" (Abdel-Hameed et al., 2021), the purpose of this article was to better understand the factors that influence users' intention to use detox applications at the individual level. In another word, this research attempts to evaluate a conceptual framework that integrates personal traits and technology-related variables that affect usage behavior of social media detox applications. The current study also meets the call by Schmuck (2020) as to "investigate if and how [other] factors are related to digital detox app use". The findings of this study are intended to provide instructors and educational policymakers with indications to alleviate the difficulties of social media distraction in online teaching, which leads to distracted and superficial learning.

The rest of this article is organized as follows: Section 2 will briefly review existing studies along with theoretical framework and hypothesis development. Section 3 is attributed to materials and method. Section 4 will report findings. Discussions are presented in Section 5. Finally, the study is concluded in Section 6

2 Literature review

2.1 Digital and social media detox

In recent years, a growing body of research has focused on digital detox (Wilcockson et al., 2019; Schmuck, 2020; Syvertsen and Enli, 2020; Radtke et al., 2021). (Wilcockson et al., 2019) studied the effects of smartphone abstention on three variables (i.e., mood, anxiety, and craving). In their research, participants were required to refrain from using their smartphones for 24 hours. Their findings revealed that craving levels increased after abstaining from smartphones. Mood and anxiety, on the other hand, were unaffected by the absence of smartphones. Similarly, Schmuck (2020) explored the associations between the use of social network sites, problematic smartphone use and well-being in a sample of 500 young individuals aged 18 to 35. Results showed that using social networking sites was positively correlated with problematic smartphone usage, which was adversely related to well-being among individuals who did not use such applications. However, the study did not find such a relationship amongst digital detox app users. Radtke et al. (2021) conducted a comprehensive study on 21 publications to determine if digital detox interventions are helpful in improving outcomes (e.g., health, well-being, social connections, self-control or performance). The research found that the impact of digital detox interventions on health and well-being, social interactions, self-control, and performance differed between experiments. Some publications, for example, revealed favorable intervention results, but others found no effect or even negative repercussions for well-being. In line with previous studies, Schmitt et al. (2021) examined factors that influence work performance and well-being. In this regard, for users who employ digital tools, the number of digital detox measures moderates the association between cognitive overload and the level of job expectations. Because of the disparity in reported results in the literature on the impact of personality traits on social media detoxification, there is still an opportunity for researchers to delve deeper into this topic.

In accordance with digital detox, social media detoxification has recently attracted scientific interest (Keles et al., 2020; Booker et al., 2018; El-Khoury et al., 2021). There are several benefits to detoxification, including enhanced mental wellbeing, social connections, and heightened productivity (Osterberg, 2021). (Booker et al., 2018) discovered that among teenagers who use the Internet, social media profiles may have a detrimental influence on well-being later in adolescence and maybe into adulthood. Studying with 68 university students, El-Khoury et al. (2021), during and after the detoxification period, the majority of students reported improved moods, reduced anxiety, and better sleep. What it means is that university students understand and employ “social media detoxification” to control their social media use. In contrast to previous findings, Przybylski et al. (2021) did not support the existing literature’s claim that avoiding social media has a favorable influence on daily well-being. Social media users and non-users reported similar feelings of well-being.

In summary, the focus of existing research has either been on human well-being views or on social media cognitive overload as a basis for detoxification. There is insufficient evidence that examines the causal link between human factors and technological adoption. As a result, the current study contributes to the body of knowledge by situating itself as a bridge between human factors and technological adoption .

2.2 Theoretical framework and hypothesis development

Since the development of computers, several applications and technology have been developed to aid users in enhancing labor efficiency, lowering calculation time, and streamlining industrial and manufacturing processes. However, not all software meets its initial expectations. In part, the problem may be concerned with technology affordances, which represent a negotiation between a user, their context, and the specifics of the technology (Hammond, 2010). Because technology has many dimensions, and its use is not determined by creators or designers, but by the opportunities it offers. As such, technology has its constraints which may also affect why and how users decide to use it. The term "affordance" was coined by Gibson and then revised by (Hammond, 2010) to describe how ICT can be used in education and it was adopted in different contexts (Krouska et al., 2021; Hanney and Skirkeviciutey, 2020; Humble, 2021). In the case of digital and social media detox, the question that both practitioners and scholars have is why users adopt new technology (i.e., detox app). By addressing this issue, they may be able to better create, analyze, and predict user reactions to new technology (Taherdoost, 2018). A number of models and frameworks have been developed to explain user adoption of new technologies and these models introduce factors that can affect the user acceptance (e.g., Technology Acceptance Model (Davis, 1989), Theory of Reasoned Action (Ajzen, 1985), Diffusion of Innovation Theory (Rogers, 2010), Social Cognitive Theory (Teasdale, 1978), Motivation Model (Davis et al., 1992), Theory of Reasoned Action (Fishbein, 1979), or Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2016)). Technology Acceptance Model (TAM) theorizes that a person's intent to use an information system depends on two beliefs: perceived usefulness, or the belief that the system improves his or her performance, and perceived ease of use, or the belief that using the system will be effortless (Davis, 1989). The TAM model was refined throughout time to include additional theoretical constructs such as intrinsic/extrinsic factors (Maheshwari, 2021), and cognitive instrumental processes (e.g., job relevance, output quality, outcome demonstrability) (Venkatesh & Davis, 2000), extended (Mailizar et al., 2021), or incorporates with other models (Alshurafat et al., 2021). Although the Theory of Reasoned Action (TRA) model was originally intended for sociological and psychological studies, it has lately been used to analyze individuals' IT usage behavior (Kuo et al., 2015). The TRA model theorizes that an individual's behavioral intention to use an information system is determined by two beliefs: attitudes and subjective norms. A refined and expanded TRA model was also developed which now includes a Theory of Planned Behavior (Ajzen, 1985) and a Reasoned Action Approach (Fishbein & Ajzen, 2011). Diffusion of Innovation Theory (DOI) studies a diverse array of innovations by incorporating four aspects such as innovation, communication channel, time, and social system to describe how a new idea or innovation spreads in a social system (Rogers, 2010). Social Cognitive Theory (SCT) is built on three primary factors: behavior, personal, and environment, all of which interact bi-directionally to predict both group and individual behavior (Teasdale, 1978). Motivation Model (MM) theorizes that system utilization is driven by two beliefs: internal incentive and extrinsic motivation (Davis et al., 1992). The availability of multiple models, as well as the incorporation of countless more factors, has created considerable obstacles for researchers who do not specialize in social behavior. To address the issue, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was developed after eight existing models were integrated and polished into a single model to describe user behavior with an IT system (Venkatesh et al., 2016). In this regard, the model retained four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions.

UTAUT has been widely utilized in the literature to understand human behavior of technology acceptance in various fields (e.g., virtual/augmented reality (González Bravo et al., 2020; Jung et al., 2021), education (Abbad, 2021; Yee & Abdullah, 2021), social media (Khechine et al., 2020; Williams et al., 2021). However, UTAUT has been criticized for taking a narrow perspective (Shachak et al., 2019) by focusing only few factors, thus, providing little insight on actual IT usage. One of the approaches to mitigate the aforementioned issues was to incorporate personal traits into the model. As (Barnett et al., 2015) suggested, more study is needed to uncover potentially beneficial individual variations. TAM2 and UTAUT are two feasible possibilities for reintroducing dispositional personal characteristics into models of technology use and adoption. (Devaraj et al., 2008) emphasized that recent breakthroughs in personality psychology imply that adopting the five-factor model (FFM (Barnett et al., 2015)), a concise and comprehensive framework of personality, would be a useful method to incorporate individual traits into IS models and theories.

In this research, an interactional psychology approach was adopted to connect FFM components (neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness) to technology usage within the UTAUT conceptual framework. As such, the questionaires were also modified and justified for this study.

Use behavior The concept of use behavior refers to continual commitment to the product (Black, 1983). The amount of use is equally as significant as the first adoption of a technology. In the context of this study, use behavior is defined as the degree to which a person utilizes a digital detox app in order to abstain from social media. Three questions were used to assess use behavior including: 1) I use a digital detox app whenever I have a chance to use it, 2) I use a digital detox app only when I need to, 3) I use a digital detox app once a day (e.g., before or after work).

Behavioral intention The vast majority of behavioral theories and models, such as the TAM, Reasoned Action Theory (TRA), or UTAUT, seek to investigate the factors that influence individuals' willingness to accept technology (Khechine et al., 2020). Behavioral intention was defined as "a person's subjective probability that he/she will perform some behavior" (Fishbein & Ajzen, 1977). In the context of this study, behavioral intention is defined as the likelihood that a person will utilize a digital detox app in order to abstain from social media. Three questions were used to assess behavioral intention including: 1) I intend to use a digital detox app in the next six months for social media abstinence, 2) I predict I will use a digital detox app in the next six months, 3) I plan to use a digital detox app each time I need it for social media abstinence. The following hypothesis was proposed:

Hypothesis 1 (H1). Behavioral Intention has a positive effect on Use Behavior.

Performance expectancy Performance Expectancy is defined as an individual's perception that using the system would enable individuals to meet their work performance objectives (Venkatesh et al., 2003). A variety of models has identified five factors linked to performance expectations, namely perceived usefulness, intrinsic motivation, job fit, relative advantage, and outcome expectations (Venkatesh et al., 2003). Three questions were used in this study to estimate performance expectation: 1) I would find the digital detox app useful for my social media abstinence, 2) I think using a digital detox app will help me abstain from social media, 3) I think using a digital detox app will help me avoid time spent on social media usage. Thus, the following hypothesis was proposed:

Hypothesis 2 (H2). Performance Expectancy has a positive effect on Behavioral Intention.

Effort expectancy The ease with which the system may be utilized is defined as Effort Expectancy (Venkatesh et al., 2003), and it is a critical prediction in the UTAUT model. Perceived ease of use, complexity, and ease of use are three criteria related with effort expectations from various models (Davis, 1989; Thompson et al., 1994; Karahanna & Straub, 1999). In the context of this study, effort expectancy refers to users' perceptions of how easy a digital detox app might be to use. We employed four questions to measure effort expectancy, which are as follows: 1) I would find the digital detox app easy to use, 2) I would not take me long to learn how to use the digital detox app, 3) My interaction with the digital detox app would be clear and understandable, and 4) It would be easy for me to become skillful at using the digital detox app. Thus, the following hypothesis was proposed:

Hypothesis 3 (H3). Effort Expectancy has a positive effect on Behavioral Intention

Social influence An individual's perception of how influential people feel about him or her using a particular technology is considered to be social influence (Venkatesh et al., 2003). UTAUT asserts that social influence has a direct influence on behavioral intentions since it alters the attitudes of potential users. For the purpose of this study, social influence has been defined as friends, family members, and colleagues persuading people to adopt new technologies. As part of our effort expectancy assessment, we used the following four questions: 1) People who influence my behavior think that I should use a digital detox app for for social media abstinence, 2) I think I am more likely to use a digital detox app if my friends and my family use it, and 3) I use a digital detox app if it is widely used by people in my community. Thus, the following hypothesis was proposed:

Hypothesis 4 (H4). Social Influence has a positive influence on Behavioral Intention.

Facilitating condition A person's perception of whether there is an organizational and technological environment to support the utilization of a system is called facilitating conditions (Venkatesh et al., 2003). We employed four questions to measure facilitating condition in this study, which are as follows: 1) I have the resources necessary to use the digital detox app, 2) I have the knowledge necessary to use the digital detox app, 3) The digital detox app is compatible with my devices, and 4) If I have problem using the digital detox app, I can get help from the service provider. Thus, the following hypothesis was proposed:

Hypothesis 5 (H5). Facilitating Conditions have a positive effect on Use Behavior.

Agreeableness Politeness, flexibility, trustworthiness, good-naturedness, forgiveness, co-operation, and tolerance are common attributes associated with this personal traits (Barrick & Mount, 1991). A person whose personality is more agreeable is more likely to see social media detox technology as beneficial, since it will help strengthen their relationships. (Devaraj et al., 2008) revealed that agreeableness is related to Perceived Usefulness, which is embodied in Performance Expectancy. Three questions were employed to measure Agreeableness in this study, which are as follows: 1) I like to take time out for others, 2) I like to cooperate with others in person, and 3) When I'm present, I believe I'm helpful and unselfish to others. Thus, the following hypothesis was proposed:

Hypothesis 6 (H6). Agreeableness have a positive effect on Performance Expectancy.

Openness Openness to experiencing new things, which is associated with qualities such as creativity, culture, curiosity, innovation, sharpness, and aesthetic sense, helps differentiate individuals who are creative from others who are not (Barrick & Mount, 1991). In the context of technology adoption and usage, open to experience individuals would thus be keen to test new technologies and appreciate their use. (Devaraj et al., 2008) found no relationship between openness and Perceived Usefulness. This study tries to investigate the assumption that attitudes about the perceived usefulness of technology are positively associated to openness to experience. Three questions were employed to measure Openness, which are as follows: 1) I'm curious about trying new technologies, 2) I prefer to do something that I haven't done in a long time, and 3) I like to be independent from social media. Thus, the following hypothesis was proposed:

Hypothesis 7 (H7): Openness to experience is positively associated with the Performance Expectancy of the digital detox app.

Extroversion Extroverts are frequently characterized as "sociable, gregarious, assertive, talkative, and active" (Barrick & Mount, 1991). People with this personality tend to be optimistic, and self-motivated. Existing studies (Devaraj et al., 2008; Svendsen et al., 2013) found that extroversion is positively associated with perceived usefulness and perceived ease of use. This study employed three questions to measure extroversion, including: 1) I enjoy being active, 2) I am an assertive person, and 3) I am friendly with strangers. Thus, the following hypotheses was proposed:

Hypothesis 8 (H8): Extroversion is positively associated with Performance Expectancy of the digital detox technology.

Hypothesis 9 (H9): Extroversion is positively associated with Effort Expectancy of social media detox technology

Conscientiousness Conscientious personalities are self-controlled individuals who are efficient, organized, and tend to search for different methods to use technologies to allow them to improve their level of performance at work (Costa P.T. Jr et al., 1991; Devaraj et al., 2008). Conscientiousness was shown to be related to perceived ease of use of technology (Rosen & Kluemper, 2008). Three questions were employed to measure Conscientiousness, which are as follows: 1) I enjoy doing things meticulously, 2) I adhere to a strict schedule at work, and 3) I take responsibility for my actions. Thus, the following hypothesis was proposed:

Hypothesis 10 (H10): Conscientiousness is positively associated with Effort Expectancy of social media detox technology

Neuroticism Neuroticism is characterized by a person's proclivity to experience unpleasant emotions such as fear, guilt, wrath, shame, discomfort, anxiety, grief, and guilt (Barrick & Mount, 1991). A neurotic individual might see a digital deteox app as an opportunity to avoid social interactions. Authors from studies in (Terzis et al., 2012; Devaraj et al., 2008) found that Neuroticism has significant negative effect on Perceived Usefulness. This study employed three questions to measure Neuroticism, including: 1) I am easily disturbed, 2) I am easily stressed, and 3) I am far more nervous than most individuals. Thus, the following hypothesis was proposed:

Hypothesis 11 (H11): Neuroticism is negatively associated with Effort Expectancy of the social media detox app.

These assumptions guided the development of the study and were converted into the conceptual model as illustrated in Fig. 2. The ellipses represent constructs (also known as latent variables) evaluated by a series of items, and the arrows represent hypotheses numbered 1 to 11.

3 Materials and methods

The following subsections describe how data is collected, measured and analysed to evaluate the conceptual research model presented in Fig. 2.

3.1 Data collection

The study employed a non-probability, purposive sampling approach to collect data. Google Form was used to develop and distribute the online survey to participants. Users were sent an invitation message by email and social media channels (e.g., Facebook, Twitter), along with a link to the Google Form. Participants of interest are individuals who utilize applications to avoid social media. The snowball sampling technique was utilized to reach participants, starting from the author's networking channel. The author asked peers/friends to disseminate the survey. Based on the preliminary estimate given by the author's peers, about 520 users are expected to participate. Qualified individuals are those who use at least one digital detox method indicated in the questionnaires to avoid social media distraction during the Covid-19

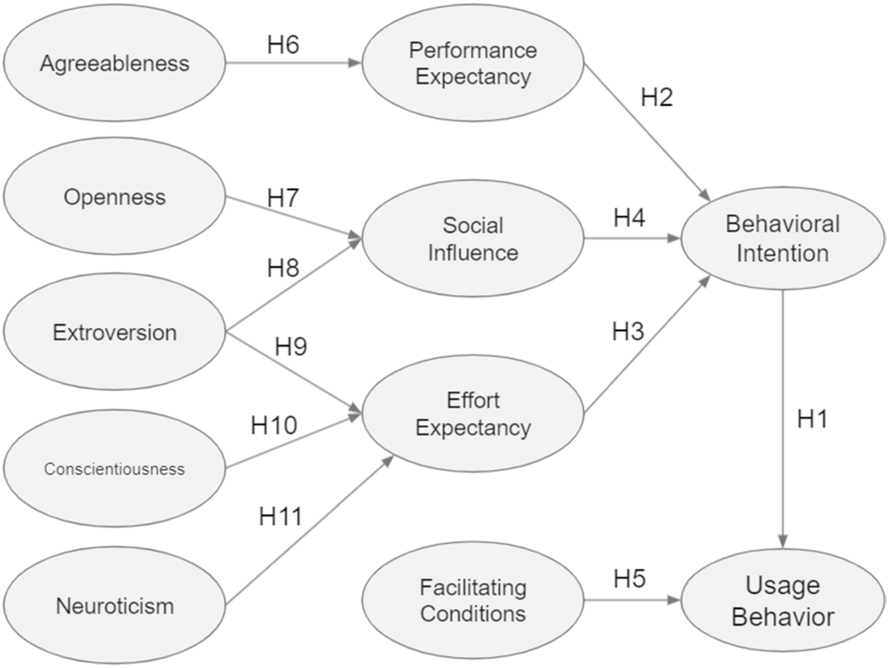

Fig. 2 The conceptual model to examine factors that predict usage behavior of using social media detox apps taking into account of personal traits and UTAUT

pandemic. The survey was divided into two parts (a) 4 questions to gather general information, (b) 35 Likert-type questions for various points of view utilizing a digital detox app.

The sample size is a contentious subject in the literature, and it varies to date. Some academia advocates for a minimum sample size of 100-200 subjects per study (Kock & Hadaya, 2018) or the appropriate sample size for the test may range between 300 and 500 (Kock & Hadaya, 2018), or 5 samples per free parameter (Kock & Hadaya, 2018). For factors with 3 or more indications, (Anderson & Gerbing, 1984) argued that a sample size of 100 is usually sufficient for convergence, and that a sample size of 150 is usually sufficient for convergence and accuracy. The sample size in this study was guided by Kline (2015) who suggested a tool to estimate an appropriate sample size (Soper, 2016). In the tool, the following settings were adjusted: anticipated effect size: 0.3, desired statistical power level: 0.8, number of latent variables: 11, number of observed variables: 35, probability level: 0.05. Consequently, the recommended minimum sample size was 195.

3.2 Measures

A review of the survey questions using the research methodologies led to the selection of 35 questions for the study (see Table 1). A five-point Likert scale (1

Table 1 Construct and items

Performance Expectancy (Venkatesh et al., 2003)

(PE1) I would find the digital detox app useful for my social media abstinence.

(PE2) I think using a digital detox app will help me abstain from social media.

(PE3) I think using a digital detox app will help me avoid time spent on social media usage.

Effort Expectancy (Venkatesh et al., 2003)

(EE1) I would find the digital detox app easy to use.

(EE2) I would not take me long to learn how to use the digital detox app,

(EE3) My interaction with the digital detox app would be clear and understandable.

(EE4) It would be easy for me to become skillful at using the digital detox app.

Social Influence (Venkatesh et al., 2003)

(SI1) People who influence my behavior think that I should use a digital detox app for for social media abstinence.

(SI2) I think I am more likely to use a digital detox app if my friends and my family use it.

(SI3) I use a digital detox app if it is widely used by people in my community.

Facilitating Conditions (Venkatesh et al., 2003)

(FC1) I have the resources necessary to use the digital detox app.

(FC2) I have the knowledge necessary to use the digital detox app.

(FC3) The digital detox app is compatible with my devices.

(FC4) If I have problem using the digital detox app, I can get help from the service provider.

Agreeableness (John et al., 1999)

(AG1) I like to take time out for others.

(AG2) I like to cooperate with others in person.

(AG3) When I'm present, I believe I'm helpful and unselfish to others.

Openness (John et al., 1999)

(OP1) I'm curious about trying new technologies.

(OP2) I prefer to do something that I haven't done in a long time.

(OP3) I like to be independent from social media.

Extroversion (John et al., 1999)

(ET1) I enjoy being active.

(ET2) I am an assertive person.

(ET3) I am friendly with strangers.

Conscientiousness (John et al., 1999)

(CT1) I enjoy doing things meticulously.

(CT2) I adhere to a strict schedule at work.

(CT3) I take responsibility for my actions.

Neuroticism (John et al., 1999)

(NT1) I am easily disturbed.

(NT2) I am easily stressed.

(NT3) I am far more nervous than most individuals.

Behavioral Intention (Venkatesh et al., 2003)

(BI1) I intend to use a digital detox app in the next six months for social media abstinence.

(BI2) I predict I will use a digital detox app in the next six months.

Table 1 (continued)

(BI3) I plan to use a digital detox app each time I need it for social media abstinence.
Use Behavior (Venkatesh et al., 2003)
(UB1) I use a digital detox app whenever I have a chance to use it.
(UB2) I use a digital detox app only when I need to.
(UB3) I use a digital detox app once a day (e.g., before or after work).

= Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree) was used to measure users' traits and the level of technology acceptance.

3.3 Data analysis

Structural Equation Modeling (SEM) is a popular approach that has been utilized in the literature to better understand the complex relationship among factors (Calaguas and Consunji, 2022; Eksail & Afari, 2020; Lavidas et al., 2020). The use of SEM in the social sciences is commonly justified by the fact that it enables us to determine latent variables that are supposed to exist but cannot be immediately identified in reality. There are two type of SEM including covariance-based (CB-SEM) and component-based (PLS-SEM). The Generalized Structured Component Analysis (GSCA) was employed, an alternative to PLS-SEM, to evaluate the proposed study model due to its ability to work with small samples without requiring a rigid normal distribution (Hwang & Takane, 2014). It is a method for modeling structural equations based on components of observed variables as proxy for latent variables and an examination of the direction of relationships between them. In addition to the benefits of PLS-SEM, GSCA should have less limits on distributional assumptions (multivariate normality of observed variables is not required for parameter estimation), unique component score estimates, and avoidance of improper solutions in small samples. Although GSCA has been criticized (Henseler, 2012), it has gained attention and utilized in a variety of domains (e.g., education (Lemay et al., 2018), VR/AR (Jung et al., 2021; Nguyen et al., 2020), tourism (Manosuthi et al., 2020; Jung et al., 2020))

4 Results

Upon collecting data,inappropriate responses were excluded (122 invalid answers due to picking just one option, 97 responses due to missing values). The total number of observations remained in the study was 263 (accounted for 54.56% of 482 responses). As the actual sample size of the present study was 263, exceeding the previous threshold of 195, the present study met its sample size requirements.

Table 2 General information about the participants

Variable	Item	No	%
Gender	Male	87	33.08
	Female	176	66.92
Age	18 - 25	132	50.20
	26 - 35	78	29.65
	36 - 45	41	15.59
	Over 45	12	4.56
Working Sector	Public	119	45.25
	Private	53	20.15
	Student	91	34.60
Digital detox methods	Turn to silent/ sleep mode	175	66.54
	Customize notifications	83	31.56
	Use third-party apps	5	1.90
Total		**263**	**100**

4.1 Demographic characteristics

Data from the survey is shown in Table 2, with males accounting for 33.08%, while females account for 66.92%. Half of the respondents are under the age of 25 (50.20%), 29.65% are between the ages of 26 and 35, and 15.59% are between the ages of 36 and 45 and 4.56 percent over 45. In terms of working sector, 45.25% are working in the public sector, followed by being students (34.60%), the remaining subjects stay in private firms (20.15%).The majority of participants (66.54%) reported turning their smartphones to mute or sleep mode to minimize disruption from social media messages, one-third of respondents (31.56%) changed notification settings to retain business connections, and only 5 individuals installed third-party applications.

4.2 Quantitative analysis

The descriptive statistics for the construct items were shown in Table 3. Means are larger than the average point of 2.5 and standard deviations ranged from 0.4422 to 1.0521

Table 4 reported the internal consistency and convergent validity metrics for each construct. Dillon–Goldstein‘s rho was utilized to measure the internal consistency and reliability requirements of each construct. All values were greater than 0.7, exceeding the recommended reliability estimate (Hwang & Takane, 2014). Average Variance Extracted (AVE) was examined to determine whether it was convergent. AVE’s values were greater than 0.5, suggesting convergent validity (Hwang & Takane, 2014).

Based on the item loading estimates simulation, Table 5 shows their standard errors (SEs) and 95 percent bootstrap percentile confidence intervals (CIs), including the lower and upper bounds (LB and UB, respectively). The confidence intervals

Table 3 Means and standard deviations of the personal traits and UTAUT's measures (N = 263)

Construct	Item	Mean	SD
Performance Expectancy	PE1	4.3384	0.8061
	PE2	4.0913	0.7892
	PE3	3.8099	0.8238
Effort Expectancy	EE1	3.8061	0.8206
	EE2	4.2662	0.6793
	EE3	4.2624	0.8061
	EE4	3.5856	0.9225
Social Influence	SI1	3.0456	0.8665
	SI2	3.0494	0.8142
	SI3	3.2167	0.8334
Facilitating Conditions	FC1	3.8099	0.8238
	FC2	4.2700	0.6806
	FC3	4.2624	0.8061
	FC4	4.0913	0.7892
Agreeableness	AG1	3.8365	0.7896
	AG2	4.2814	0.6675
	AG3	3.9658	0.7719
Openness	OP1	3.9392	0.8064
	OP2	3.5817	0.9270
	OP3	3.4525	0.9615
Extroversion	ET1	4.2395	0.8038
	ET2	3.9049	0.7960
	ET3	3.7529	0.8156
Conscientiousness	CT1	3.9125	0.8110
	CT2	3.7452	0.8587
	CT3	4.1521	0.7499
Neuroticism	NT1	3.5856	0.9225
	NT2	3.4487	0.9613
	NT3	3.6692	0.8278
Behavioral Intention	BI1	3.9620	0.7742
	BI2	3.6274	0.8443
	BI3	3.5247	0.8490
Use Behavior	UB1	3.9506	0.7808
	UB2	3.6236	0.8538
	UB3	3.5095	0.8627

were estimated using 100 bootstrap samples (CIs). Here, parameter estimates were considered statistically significant if the 95 percent confidence interval did not include zero at the 0.05 level. There was statistical significance for all loading estimates, indicating that all items were reliable predictors of constructs.

Table 6 presented that GSCA provided FIT = 0.5668 (SE = 0.0125, 95% CIs = 0.5434 – 0.595), AFIT = 0.5629 (SE = 0.0126, 95% CI = 0.5393 – 0.5914),

Table 4 Internal consistency and convergent validity

Construct	Items	Dillon-Goldstein's Rho	AVE
Performance Expectancy	3	0.8897	0.7293
Effort Expectancy	4	0.7933	0.4899
Social Influence	3	0.8547	0.6624
Facilitating Conditions	4	0.8888	0.6666
Agreeableness	3	0.7483	0.5267
Openness	3	0.8575	0.6704
Extroversion	3	0.8804	0.711
Conscientiousness	3	0.9108	0.7729
Neuroticism	3	0.8842	0.7192
Behavioral Intention	3	0.8386	0.6413
Use Behavior	3	0.8461	0.652

GFI = 0.9788 (SE = 0.0072, 95% CI = 0.961 – 0.9868), and SRMR = 0.3697 (SE = 0.0146, 95% CI = 0.3488–0.4078). The variation of the data explained by a particular model specification was examined by both FIT and Adjusted FIT (AFIT). The FIT value ranges from 0 to 1 and may be understood as a measure of the variance explained by the model specification. The higher the number, the greater the variance explained, as in linear regression. Thus, the model accounted for about 56.68 percent and 56.29 percent of the total variance of all variables. The statistical difference between FIT and AFIT was significantly different from zero. Following that, the goodness-of-fit index (GFI) and standardized root mean square residual (SRMR) indicate the closeness between sample covariance and covariance as additional measure of overall model fit. The values GFI around 1 and SRMR near 0 may be regarded an indication of excellent fit. The GFI value was extremely close to one, and the SRMR value was relatively close to zero.

Table 7 shows the estimates of path coefficients in the structural model, together with their standard errors and 95% confidence intervals. The results indicated that the influence of behavioral intention on usage behavior was statistically significant and positive (H1 = 0.9878*, SE = 0.0054, 95% CI = 0.9768 – 0.9977). Performance Expectancy had a statistically significant and positive effect on Behavioral Intention (H2 = 0.5418*, SE = 0.1083, 95% CI = 0.333 – 0.7389). Effort Expectancy had a statistically significant and positive influence on Behavioral Intention (H3 = 0.9948*, SE = 0.1323, 95% CI = 0.7574 – 0.1.2211). In addition, Social Influence had a statistically significant and positive influence on Behavioral Intention (H4 = 0.1597*, SE = 0.0796, 95% CI = 0.0485 – 0.3225). In turn, Agreeableness had a a statistically significant and positive effect on Performance Expectancy (H6 = 0.6824*, SE = 0.0553, 95% CI = 0.5796 – 0.7982). Moreover, Extroversion had a statistically significant and positive influence on Performance Expectancy (H8 = 0.285*, SE = 0.0566, 95% CI = 0.1603 – 0.3915)) as well as Effort Expectancy of social media detox technology (H9 = 0.6057*, SE = 0.1206, 95% CI = 0.3946 – 0.8632). Finally, Neuroticism had a statistically

Table 5 Estimates of loadings

	Estimate	Std.Error	95%CI_LB	95%CI_UB
PE1	0.7933	0.0363	0.7042	0.8543
PE2	0.8829	0.0141	0.8527	0.9109
PE3	0.8826	0.0146	0.859	0.9159
EE1	0.7318	0.0413	0.6499	0.8106
EE2	0.6934	0.0537	0.5752	0.7943
EE3	0.6806	0.0555	0.5677	0.7816
EE4	0.693	0.0611	0.5281	0.779
SI1	0.7951	0.0269	0.7491	0.844
SI2	0.8153	0.0242	0.7613	0.8579
SII	0.8308	0.0182	0.7969	0.8648
FC1	0.7904	0.0279	0.7326	0.85
FC2	0.8475	0.0226	0.8089	0.8949
FC3	0.7909	0.0312	0.7275	0.854
FC4	0.8354	0.0202	0.7998	0.8751
AG1	0.905	0.0148	0.8703	0.9328
AG2	0.7985	0.0343	0.7242	0.8605
AG3	0.3514	0.1276	0.0314	0.5204
OP1	0.6807	0.0376	0.6037	0.7502
OP2	0.8939	0.0139	0.8656	0.9199
OP3	0.8654	0.0188	0.8335	0.9003
ET1	0.815	0.0319	0.74	0.8697
ET2	0.9038	0.012	0.8799	0.9272
ET3	0.8075	0.0305	0.7422	0.8604
CT1	0.8736	0.026	0.8171	0.9234
CT2	0.9062	0.0124	0.8815	0.9273
CT3	0.8615	0.0218	0.8193	0.8961
NT1	0.9056	0.0163	0.8672	0.9349
NT2	0.8762	0.0167	0.8341	0.9025
NT3	0.7548	0.0374	0.6692	0.8158
BI1	0.5941	0.0427	0.5047	0.6859
BI2	0.9308	0.0107	0.9059	0.9485
BI3	0.8394	0.0236	0.7892	0.8814
UB1	0.6324	0.0406	0.5572	0.7197
UB2	0.9077	0.0116	0.8837	0.9277
UB3	0.8556	0.0199	0.8176	0.8902

significant and negatively associated with Effort Expectancy of the social media detox app (H11 = -0.5231^{*}, SE = 0.0526, 95% CI = -0.6085 − -0.401).

However, hypotheses H5 (Facilitating Conditions → Behavioral Intention), H7 (Openness to experience → Performance Expectancy) and H10 (Conscientiousness → Effort Expectancy) were not supported due to the occurrence of zero values in CIs.

Table 6 Model FIT

	Estimate	SE	95%CI_LB	95%CI_UB
FIT	0.5668	0.0125	0.5434	0.595
Adjusted FIT (AFIT)	0.5629	0.0126	0.5393	0.5914
GFI	0.9788	0.0072	0.961	0.9868
SRMR	0.3697	0.0146	0.3488	0.4078

Table 7 Estimates of path coefficients

	Estimates	Std.Error	95%CI_LB	95%CI_UB
BI → UB (H1)	0.9878*	0.0054	0.9768	0.9977
PE → BI (H2)	0.5418*	0.1083	0.333	0.7389
EE → BI (H3)	0.9948*	0.1323	0.7574	1.2211
SI → BI (H4)	0.1597*	0.0796	0.0485	0.3225
FC → UB (H5)	0.0085	0.0151	−0.0216	0.0362
AG → PE (H6)	0.6824*	0.0553	0.5796	0.7982
OP → PE (H7)	−0.0543	0.0476	−0.129	0.076
ET → PE (H8)	0.285*	0.0566	0.1603	0.3915
ET → EE (H9)	0.6057*	0.1206	0.3946	0.8632
CT → EE (H10)	−0.0092	0.1052	−0.2435	0.1606
NT → EE (H11)	−0.5231*	0.0526	−0.6085	−0.401

* statistically significant at 0.05 level

5 Discussion

5.1 Theoretical implication

One of the most noteworthy findings was the amount of variation explained by the combination of the FFM and UTAUT models (56.68 percent). Clearly, the UTAUT is a valid paradigm for investigating this sort of technological behavior. The current study's findings validated the majority of the predicted correlations among the factors in the combined model. The notable exception being that Facilitating Conditions was not found to predict Behavioral Intention, Openness to experience was not found to influence Performance Expectancy and Conscientiousness was not found to affect Effort Expectancy. This is a departure from the finding of Venkatesh et al. (2003) who found FC to significantly predict usage behavior. Similarly, while (Rosen and Kluemper, 2008) found that Conscientiousness was the predictor of perceived ease of use of technology, the current study finding did not support the hypothesis. However, the lack of a significant finding for H7 aligns with Devaraj et al. (2008) who also found that personal trait of Openness to experience did not predict Performance Expectancy. One probable reason for these non-significant findings is that, as described in the first section, the majority of users had smartphones (80.69 percent), implying that

FC in specific settings is no longer a required component of adoption or usage behavior. As such, in the subsequent study, FC factor can be eliminated or substituted with other potential arising candidates. In terms of Conscientiousness, the current study did not support the findings of (Lakhal and Khechine, 2017; Rosen & Kluemper, 2008) where the authors found an effect between Conscientiousness and Effort Expectancy. One plausible explanation for this phenomenon may be attributed to the fact that as work-oriented people spend more time on getting a job done, they already had substantial amount of time exploring technologies at the beginning. And overtime, this effort has decreased to some extents. As reported in Table 3, mean and standard deviation for Effort Expectancy are fluctuated, implying an inconsistent effort for technology acceptance. As such, researchers should pay attention to users' experience as a mediator to investigate the relationship between Conscientiousness and Effort Expectancy in future studies. In terms of Openness, findings of the current study also aligns with (Devaraj et al., 2008) where there was no relationship between Openness and Perceived Usefulness, implying that open-minded people had a different point of views on technology ease of use.

Nevertheless, findings of this study contribute to the body of knowledge in two folds: (1) it empirically verified the effects on relationship embedded in existing theories, thus it can be employed as a reference in a similar setting, and (2) for hypotheses which were not supported, more studies are called to investigate these non-significant behaviors.

5.2 Practical implication

The study's context stems from the fact that more users are exposed to digital devices, particularly teachers/students who are forced to teach and learn in an online environment due to the Covid-19 pandemic (Ahmed & Opoku, 2022). In general, users and students are undoubtedly distracted by their use of social media (Mao, 2014; Dontre, 2021). As a result, there is a strong need to leverage digital devices while mitigating the negative impact of social media usage.

In terms of technology acceptance, the findings from the UTAUT model revealed that Performance Expectancy, Effort Expectancy, and Social Influence all had a relationship with behavioral intention, which in turn influences usage behavior. Policymakers should focus on educating citizens about the drawbacks of social media and enacting regulations to prevent irrelevant content from being shared. Higher performance of a social media detox app would increase its behavioral intention to use, so software developers should focus on its immediate usability with less effort to help users abstain from social media.

In terms of personality traits, the findings revealed that four out of six relationships existed to explain social media detox adoption. Therefore, practitioners, managers, or parents can tailor their policies or methods to fit individuals' needs to help them avoid social media distraction.

5.3 Limitations

Though the conclusions are based on the aforementioned contributions, they will inevitably be restricted by various constraints. These restrictions, when coupled with the unexpected findings, lead to a potential research platform for the future. This study used non-probability sampling to ensure respondents were using social media detox apps on their devices. Although widely acknowledged in the literature, this sampling technique limits the generalizability of findings beyond the sample characteristics reported in this study. Second, since this study examined the use of the social media detox app over a short period of time, especially in light of Covid-19, it is necessary to revisit the study's findings after the outbreak. Additionally, because the current study solely employed variables derived from personal characteristics as its theoretical framework, other mediators and moderators not incorporated into the UTAUT were not evaluated.

6 Conclusion and future work

This study examined the factors that influence people's intentions to utilize social media detox apps by incorporating The Big Five Personality Traits with The extended Unified Theory of Acceptance and Use of Technology model. The study's findings, based on data from 263 individuals, verified the majority of the expected correlations between the factors in the hybrid model. The significant exceptions were that Facilitating Conditions did not predict Behavioral Intention, Openness to Experience did not impact Performance Expectancy, and Conscientiousness did not influence Effort Expectancy. The reasons for these non-significant correlations will be investigated further in a large-scale user experience study.

Declarations

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- The authors have no competing interests to declare that are relevant to the content of this article

References

Abbad, M.M. (2021). Using the utaut model to understand studentn usage of e-learning systems in developing countries. *Education and Information Technologies*, 1–20.

Abdel-Hameed, F.S.M., Tomczyk Ł., & Hu, C. (2021). The editorial of special issue on education, it, and the covid-19 pandemic. *Education and information technologies*, *26*(6), 6563–6566.

Abdelguiom, G.A., & Iahad, N.A. (2020). Potential benefits of social media to healthcare: A systematic literature review. In *International Conference of Reliable Information and Communication Technology, Springer, pp 230–241*.

Ahmed, V., & Opoku, A. (2022). Technology supported learning and pedagogy in times of crisis: the case of covid-19 pandemic. *Education and Information Technologies*, *27*(1), 365–405.

Ahmed, Y.A., Ahmad, M.N., Ahmad, N., & et al. (2019). Social media for knowledge-sharing: A systematic literature review. *Telematics and informatics*, *37*, 72–112.

Ajzen, I (1985). From intentions to actions: A theory of planned behavior. In *Action control. Springer, p 11–39*.

Alshurafat, H., Al Shbail, M.O., Masadeh, W.M., & et al. (2021). Factors affecting online accounting education during the covid-19 pandemic: an integrated perspective of social capital theory, the theory of reasoned action and the technology acceptance model. *Education and Information Technologies*, 1–19.

Anderson, J.C., & Gerbing, D.W. (1984). The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. *Psychometrika*, *49*(2), 155–173.

Barnett, T., Pearson, A.W., Pearson, R., & et al. (2015). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, *24*(4), 374–390.

Barrick, M.R., & Mount, M.K. (1991). The big five personality dimensions and job performance: a meta-analysis. *Personnel psychology*, *44*(1), 1–26.

Beaunoyer, E., Arsenault, M., Lomanowska, A.M., & et al. (2017). Understanding online health information: Evaluation, tools, and strategies. *Patient education and counseling*, *100*(2), 183–189.

Beaunoyer, E., Dupéré, S, & Guitton, M.J. (2020). Covid-19 and digital inequalities: Reciprocal impacts and mitigation strategies. *Computers in Human Behavior*, *111*, 106,424.

Black, W. (1983). Discontinuance and diffusion: Examination of the post adoption decision process. ACR North American Advances.

Booker, C.L., Kelly, Y.J., & Sacker, A. (2018). Gender differences in the associations between age trends of social media interaction and well-being among 10-15 year olds in the uk. *BMC Public Health*, *18*(1), 1–12.

Calaguas, N.P., & Consunji, P.M.P. (2022). A structural equation model predicting adults' online learning self-efficacy. *Education and Information Technologies*, 1–17.

Cao, X., & Sun, J. (2018). Exploring the effect of overload on the discontinuous intention of social media users: An sor perspective. *Computers in Human Behavior*, *81*, 10–18.

Chuang, H.M., & Liao, Y.D. (2021). Sustainability of the benefits of social media on socializing and learning: An empirical case of facebook. *Sustainability*, *13*(12), 6731.

Chugh, R., Grose, R., & Macht, S.A. (2021). Social media usage by higher education academics: A scoping review of the literature. *Education and Information Technologies*, *26*(1), 983–999.

Costa P.T. Jr, McCrae, R.R., & Dye, D.A. (1991). Facet scales for agreeableness and conscientiousness: A revision of the neo personality inventory. *Personality and Individual Differences*, *12*(9), 887–898.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.

Davis, F.D., Bagozzi, R.P., & Warshaw, P.R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology*, *22*(14), 1111–1132.

Devaraj, S., Easley, R.F., & Crant, J.M. (2008). Research note—how does personality matter? relating the five-factor model to technology acceptance and use. *Information Systems Research*, *19*(1), 93–105.

Dontre, A.J. (2021). The influence of technology on academic distraction: A review. *Human Behavior and Emerging Technologies*, *3*(3), 379–390.

Eksail, F.A.A., & Afari, E. (2020). Factors affecting trainee teachers' intention to use technology: A structural equation modeling approach. *Education and Information Technologies*, *25*(4), 2681–2697.

El-Khoury, J., Haidar, R., Kanj, R.R., & et al. (2021). Characteristics of social media 'detoxification'in university students. *Libyan Journal of Medicine*, *16*(1), 1846,861.

Ellis, K., & Goggin, G. (2013). Disability and social media. In *The social media handbook. Routledge, p 134–151*.

Fishbein, M. (1979). A theory of reasoned action: some applications and implications.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric, 10*(2).

Fishbein, M., & Ajzen, I. (2011). Predicting and changing behavior: The reasoned action approach. Psychology press.

González Bravo, L., Fernández Sagredo, M., Torres Martínez, P., & et al. (2020). Psychometric analysis of a measure of acceptance of new technologies (utaut), applied to the use of haptic virtual simulators in dental students. *European Journal of Dental Education*, *24*(4), 706–714.

Guitton, M.J. (2021). Something good out of something bad: ehealth and telemedicine in the post-covid era. *Computers in Human Behavior*, *123*, 106,882.

Hammond, M. (2010). What is an affordance and can it help us understand the use of ict in education?. *Education and Information Technologies*, *15* (3), 205–217.

Hanney, R., & Skirkeviciutey, G. (2020). Reflection, identity, community: Affordances of blogging for social interaction and reflective dialogue. *Education and Information Technologies*, *25*(3), 1553–1569.

Henseler, J. (2012). Why generalized structured component analysis is not universally preferable to structural equation modeling. *Journal of the Academy of Marketing Science*, *40*(3), 402–413.

Humble, N. (2021). Teacher observations of programming affordances for k-12 mathematics and technology. *Education and Information Technologies*, 1–18.

Hwang, H., & Takane, Y. (2014). Generalized structured component analysis: A component-based approach to structural equation modeling. CRC Press.

Jarman, H.K., Marques, M.D., McLean, S.A., & et al. (2021). Motivations for social media use: Associations with social media engagement and body satisfaction and well-being among adolescents. *Journal of Youth and Adolescence*, 1–15.

John, O.P., Srivastava, S., & et al. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives, vol 2. University of California Berkeley.

Jung, K., Nguyen, V.T., Piscarac, D., & et al. (2020). Meet the virtual jeju dol harubang—the mixed vr/ar application for cultural immersion in korea's main heritage. *ISPRS International Journal of Geo-Information*, *9*(6), 367.

Jung, K., Nguyen, V.T., & Lee, J. (2021). Blocklyxr: An interactive extended reality toolkit for digital storytelling. *Applied Sciences*, *11*(3), 1073.

Karahanna, E., & Straub, D.W. (1999). The psychological origins of perceived usefulness and ease-of-use. *Information & Management*, *35*(4), 237–250.

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, *25*(1), 79–93.

Khechine, H., Raymond, B., & Augier, M. (2020). The adoption of a social learning system: Intrinsic value in the utaut model. *British Journal of Educational Technology*, *51*(6), 2306–2325.

Kietzmann, J.H., Hermkens, K., McCarthy, I.P., & et al. (2011). Social media? get serious! understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251.

Klar, S., Krupnikov, Y., Ryan, J.B., & et al. (2020). Using social media to promote academic research: Identifying the benefits of twitter for sharing academic work. *PloS One*, *15*(4), e0229,446.

Kline, R.B. (2015). Principles and practice of structural equation modeling. Guilford publications.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in pls-sem: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261.

Krouska, A., Troussas, C., & Sgouropoulou, C. (2021). Mobile game-based learning as a solution in covid-19 era: Modeling the pedagogical affordance and student interactions. *Education and Information Technologies*, 1–13.

Kuo, B.C., Roldan-Bau, A., & Lowinger, R. (2015). Psychological help-seeking among latin american immigrants in canada: Testing a culturally-expanded model of the theory of reasoned action using path analysis. *International Journal for the Advancement of Counselling*, *37*(2), 179–197.

Lakhal, S., & Khechine, H. (2017). Relating personality (big five) to the core constructs of the unified theory of acceptance and use of technology. *Journal of Computers in Education*, *4*(3), 251–282.

Lavidas, K., Achriani, A., Athanassopoulos, S., & et al. (2020). University students' intention to use search engines for research purposes: A structural equation modeling approach. *Education and Information Technologies*, *25*(4), 2463–2479.

Lederman, R., Wadley, G., Gleeson, J., & et al. (2014). Moderated online social therapy: Designing and evaluating technology for mental health. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *21*(1), 1–26.

Lemay, D, Doleck, T, & Bazelais, P (2018). The influence of the social, cognitive, and instructional dimensions on technology acceptance decisions among college-level students. *EURASIA Journal of Mathematics, Science and Technology Education*, *14*(12), em1635.

Lesch, L. (2014). Creative learning for the information age: how classrooms can better prepare students. Rowman & Littlefield.

Maheshwari, G. (2021). Factors affecting students' intentions to undertake online learning: An empirical study in vietnam. *Education and Information Technologies*, 1–21.

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the covid-19 pandemic: An extended tam model. *Education and Information Technologies*, 1–21.

Manosuthi, N., Lee, J.S., & Han, H. (2020). Impact of distance on the arrivals, behaviours and attitudes of international tourists in hong kong: A longitudinal approach. *Tourism Management*, *78*, 103,963.
Mao, J. (2014). Social media for learning: A mixed methods study on high school students' technology affordances and perspectives. *Computers in Human Behavior*, *33*, 213–223.
Meier, A., & Reinecke, L. (2020). Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research*, 0093650220958224.
Naslund, J.A., Bondre, A., Torous, J., & et al. (2020). Social media and mental health: benefits, risks, and opportunities for research and practice. *Journal of Technology in Behavioral Science*, *5*(3), 245–257.
Nazir, S., Ahram, T., & Karwowski, W. (2020). Advances in human factors in training, education, and learning sciences. Springer.
Nguyen, V.T., Jung, K., & Dang, T. (2020). Blocklyar: A visual programming interface for creating augmented reality experiences. *Electronics*, *9*(8), 1205.
Obar, J.A., & Wildman, S.S. (2015). Social media definition and the governance challenge: An introduction to the special issue. *Telecommunications Policy*, *39*(9), 745–750.
Osterberg, L. (2021). 7 unexpected benefits of a digital detox. https://www.huffpost.com/entry/digital-detox_b_8361700/, Last accessed date on November 9, 2021.
Przybylski, A.K., Thuy-vy, T.N., Law, W., & et al. (2021). Does taking a short break from social media have a positive effect on well-being? evidence from three preregistered field experiments. *Journal of Technology in Behavioral Science*, 1–8.
Radtke, T., Apel, T., Schenkel, K., & et al. (2021). Digital detox: An effective solution in the smartphone era? a systematic literature review. *Mobile Media & Communication*, 20501579211028647.
Rogers, E.M. (2010). Diffusion of innovations. Simon and Schuster.
Rosen, P.A., & Kluemper, D.H. (2008). The impact of the big five personality traits on the acceptance of social networking website. AMCIS 2008 proceedings, 274.
Schmitt, J.B., Breuer, J., & Wulf, T. (2021). From cognitive overload to digital detox: Psychological implications of telework during the covid-19 pandemic. *Computers in Human Behavior*, 106899.
Schmuck, D. (2020). Does digital detox work? exploring the role of digital detox applications for problematic smartphone use and well-being of young adults using multigroup analysis. *Cyberpsychology, Behavior, and Social Networking*, *23*(8), 526–532.
Schønning, V., Hjetland, G.J., Aarø, L.E., & et al. (2020). Social media use and mental health and well-being among adolescents–a scoping review. *Frontiers in psychology*, *11*, 1949.
Shachak, A., Kuziemsky, C., & Petersen, C. (2019). Beyond tam and utaut: Future directions for hit implementation research. *Journal of Biomedical Informatics*, *100*, 103,315.
Skogen, J.C., Hjetland, G.J., et al., & Bøe, T (2021). Through the looking glass of social media. focus on self-presentation and association with mental health and quality of life. a cross-sectional survey-based study. *International Journal of Environmental Research and Public Health*, *18*(6), 3319.
Smailhodzic, E., Hooijsma, W., Boonstra, A., & et al. (2016). Social media use in healthcare: A systematic review of effects on patients and on their relationship with healthcare professionals. *BMC health services research*, *16*(1), 1–14.
Soper, D. (2016). Calculator: a-priori sample size for structural equation models. Retrieved October.
Statista Research Department. (2021). Number of social network users worldwide from 2017 to 2025. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/. Last accessed date on November 7, 2021.
Svendsen, G.B., Johnsen, J.A.K., Almås-Sørensen, L., & et al. (2013). Personality and technology acceptance: the influence of personality factors on the core constructs of the technology acceptance model. *Behaviour & Information Technology*, *32*(4), 323–334.
Syvertsen, T., & Enli, G. (2020). Digital detox: Media resistance and the promise of authenticity. *Convergence*, *26*(5-6), 1269–1283.
Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, *22*, 960–967.
Teasdale, J.D. (1978). Self-efficacy: Toward a unifying theory of behavioural change?. *Advances in Behaviour Research and Therapy*, *1*(4), 211–215.
Terzis, V., Moridis, C.N., & Economides, A.A. (2012). How student's personality traits affect computer based assessment acceptance: Integrating bfi with cbaam. *Computers in Human Behavior*, *28*(5), 1985–1996.
Thompson, R.L., Higgins, C.A., & Howell, J.M. (1994). Influence of experience on personal computer utilization: Testing a conceptual model. *Journal of Management Information Systems*, *11*(1), 167–187.

Turel, O., & Vaghefi, I. (2019). Social media detox: Relapse predictors. *Psychiatry Research*, 112488.
Ugur, N.G., & Koc, T. (2015). Time for digital detox: Misuse of mobile technology and phubbing. *Procedia-Social and Behavioral Sciences*, *195*, 1022–1031.
Valentine, L., McEnery, C., D'Alfonso, S., & et al. (2019). Harnessing the potential of social media to develop the next generation of digital health treatments in youth mental health. *Current Treatment Options in Psychiatry*, *6*(4), 325–336.
Valkenburg, P.M., Meier, A., & Beyens, I. (2021). Social media use and its impact on adolescent mental health: An umbrella review of the evidence. Current Opinion in Psychology.
Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.
Venkatesh, V., Morris, M.G., Davis, G.B., & et al. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.
Venkatesh, V., Thong, J.Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the association for Information Systems*, *17*(5), 328–376.
White, T.R. (2013). Digital social media detox (dsmd): Responding to a culture of interconnectivity. In *Social media and the new academic environment: Pedagogical challenges. IGI Global, 414–430*.
Wilcockson, T.D., Osborne, A.M., & Ellis, D.A. (2019). Digital detox: The effect of smartphone abstinence on mood, anxiety, and craving. *Addictive Behaviors*, *99*, 106,013.
Williams, M.L., Saunderson, I.P., & Dhoest, A. (2021). Students' perceptions of the adoption and use of social media in academic libraries: A utaut study. *Communicatio*, *47*(1), 76–94.
Yee, M.L.S., & Abdullah, M.S. (2021). A review of utaut and extended model as a conceptual framework in education research. *Jurnal Pendidikan Sains Dan Matematik Malaysia*, *11*, 1–20.
Yu, L., Cao, X., Liu, Z., & et al. (2018). Excessive social media use at work: Exploring the effects of social media overload on job performance. Information Technology & People.