Journal of the Association for Information Systems

Volume 24 | Issue 2 Article 5

2023

Unraveling the Effects of Mobile Application Usage on Users' Health Status: Insights from Conservation of Resources Theory

Shaoxiong Fu
Nanjing Agricultural University, fu_shaoxiong@163.com

Zhao Cai
University of Nottingham Ningbo China, zhao.cai@nottingham.edu.cn

Eric Lim
UNSW Sydney, e.t.lim@unsw.edu.au

Yong Liu
Aalto university, Yong.Liu@aalto.fi

Chee-Wee Tan
Copenhagen Business School, ct.digi@cbs.dk

See next page for additional authors

Recommended Citation

Fu, Shaoxiong; Cai, Zhao; Lim, Eric; Liu, Yong; Tan, Chee-Wee; and Lin, Yanqing (2023) "Unraveling the Effects of Mobile Application Usage on Users' Health Status: Insights from Conservation of Resources Theory," *Journal of the Association for Information Systems*, 24(2), 452-489.
DOI: 10.17705/1jais.00808
Available at: https://aisel.aisnet.org/jais/vol24/iss2/5

Unraveling the Effects of Mobile Application Usage on Users' Health Status: Insights from Conservation of Resources Theory

Authors

Shaoxiong Fu, Zhao Cai, Eric Lim, Yong Liu, Chee-Wee Tan, and Yanqing Lin

Journal of the Association for Information Systems (2023) **24**(2), 452-489
doi: 10.17705/1jais. 1jais.00808

RESEARCH ARTICLE

ISSN 1536-9323

Unraveling the Effects of Mobile Application Usage on Users' Health Status: Insights from Conservation of Resources Theory

Shaoxiong Fu,[1] Zhao Cai,[2] Eric Lim,[3] Yong Liu,[4] Chee-Wee Tan,[5] Yanqing Lin,[6] Shengli Deng[7]

[1]College of Information Management, Nanjing Agricultural University, China, fu_shaoxiong@163.com
[2]University of Nottingham Ningbo China, China, zhao.cai@nottingham.edu.cn
[3] UNSW Business School, UNSW Sydney, Australia, e.t.lim@unsw.edu.au
[4]School of Business, Aalto University, Finland, yong.liu@aalto.fi
[5]Department of Digitalization, Copenhagen Business School, Denmark, ct.digi@cbs.dk
[6]School of Business, Aalto University, Finland, yanqing.lin@aalto.fi
[7]School of Information Management, Wuhan University, China, victorydc@sina.com

Abstract

Numerous studies have documented adverse consequences arising from increased technology usage and advocated for a reduction in such usage as a plausible remedy. However, such recommendations are often infeasible and oversimplistic given mounting evidence attesting to users' growing reliance on technology in both their personal and professional lives. Building on conservation of resources (COR) theory, we construct a research model to explain how mobile application usage, as delineated by its breadth and depth, affects users' nomophobia and sleep deprivation, which can have negative impacts on users' health status. We also consider the moderating influence of physical activity in mitigating the effects of mobile application usage on users' health. We validated our hypotheses via data collected by surveying 5,842 respondents. Empirical findings reveal that (1) nomophobia is positively influenced by mobile application usage breadth but negatively influenced by mobile application usage depth, (2) sleep deprivation is negatively influenced by mobile application usage breadth but positively influenced by mobile application usage depth, and (3) sleep deprivation and nomophobia negatively impact users' health status, whereas (4) physical activity attenuates the impact of mobile application usage on sleep deprivation but not nomophobia. The findings from this study not only enrich the extant literature on the health outcomes of mobile application usage by unveiling the impact of mobile application usage patterns and physical activity on users' health but they also inform practitioners on how calibrating usage breadth and depth, along with encouraging physical activity, can promote healthy habits among users.

Keywords: Mobile Application Usage, Conservation of Resources, Health Status, Nomophobia, Sleep Deprivation, Dark Side of Technology

Jason Bennett Thatcher was the accepting senior editor. This research article was submitted on June 5, 2019 and underwent four revisions.

1 Introduction

The proliferation of mobile phones compels many users to spend massive amounts of time on mobile applications for both personal and professional purposes (Fu et al., 2021; Kuem et al., 2021). Despite the convenience afforded by mobile applications, scholars have accumulated abundant empirical evidence connecting mobile application usage to adverse physiological and psychological consequences (Fu et al., 2021; Kim et al., 2015; Lepp et al., 2014). In particular, *nomophobia*, which captures one's anxiety about being detached from their mobile phone, is a prominent *psychological consequence* of mobile application usage (Fu et al., 2021; Yildirim & Correia, 2015). Studies have documented that 23% of undergraduates exhibit symptoms of nomophobia and 64% of undergraduates are at risk of being nomophobic (Bhattacharya et al., 2019). Conversely, a predominant *physiological consequence* of mobile application usage acknowledged within the extant literature is *sleep deprivation,* which denotes a settled tendency to sleep late (Fu et al., 2021; Liu et al., 2017; Salo et al., 2019). A recent study has revealed that teens who use their mobile phones at night are more likely to have insomnia symptoms due to interference with the body's natural sleep-wake cycle (Sleep Foundation, 2021a). It is therefore unsurprising that scholars have found nomophobia and sleep deprivation to be key physiological and psychological impediments to the health of mobile application users, especially young people (Agathão et al., 2020; MacLean et al., 2015; Xue et al., 2018).

To cope with the detrimental effects of mobile application usage, a handful of studies have advocated for measures to reduce time spent on mobile applications (e.g., Barkley et al., 2016; Dhir et al., 2018; Fu et al., 2021). However, such recommendations tend to be blanket solutions that neglect the growing integrative role played by mobile applications in both leisure and work settings (Fu et al., 2021). Indeed, numerous studies have attested to the critical role of mobile applications in bolstering productivity and inducing positive moods (Klenk et al., 2017; Lee et al., 2019; Papagiannidis & Marikyan, 2020). Consequently, to resolve the tension between adverse health consequences and mobile application usage, there have been scholarly calls for a more nuanced understanding of how mobile application usage patterns affect users' health status such that concrete steps can be taken to mitigate the detrimental effects of such usage while preserving its desired benefits (Bhattacharya et al., 2019; Horwood & Anglim, 2019). However, with the exception of Ferdous et al. (2018), who alluded to the significant effects of mobile application usage frequency and duration on users' well-being, research scrutinizing the role of mobile application usage patterns in driving health-related outcomes is limited.

Breadth and *depth* are meaningful dimensions that have been previously employed by scholars to depict patterns in information systems (IS) problem solving and mobile technology usage (Khatri & Vessey, 2016; Chircu & Mahajan, 2009). Extrapolated to this study, the breadth of mobile application usage denotes the range of mobile applications used in a given period, whereas its depth refers to the intensity of a user's interaction with each mobile application (Limayem et al., 2007). Application usage statistics released by SIMFORM (2021) indicate that most millennials have more than 67 mobile applications installed on their smartphones, representing a wide breadth of mobile application usage. Likewise, discrepancies in mobile application usage depth have also been recorded: the average smartphone owner uses 10 mobile applications per day and 30 apps each month with 25% of these apps being used only once after being downloaded (BuildFire, 2021). Yet despite the variations in mobile application usage breadth and depth among individual users, less attention has been paid to comprehending how mobile application usage breadth and depth affect users' physiological and psychological health. To this end, we delineate mobile application usage patterns according to their breadth and depth to serve as antecedents affecting users' nomophobia and sleep deprivation (Beard et al., 2019; Harrison & Klein, 2007; Zheng et al., 2019).

To disentangle how mobile application usage patterns affect users' health status, we build on *conservation of resources* (COR) *theory*, which has been applied in the extant literature to decipher unfavorable personal states and emotional management (Moqbel & Bartelt, 2018; Xu et al., 2015; Zhang & Wang, 2016). COR theory conceives an individual as owning a collection of physiological and psychological resources that will be consumed by performing personal activities and experiencing unpleasant events (Halbesleben et al., 2014). These resources can be replenished through recovery actions such as rest and relaxation (Probst et al., 2018). COR theory holds that excessive consumption of these resources will culminate in health problems for users (Halbesleben et al., 2014). Applying COR theory to this study, patterns of mobile application usage (i.e., breadth and depth) may deplete and/or build users' physiological and psychological resources differently, leading to varying degrees of physiological and psychological consequences (i.e., nomophobia and sleep deprivation). Consequently, we seek an answer to the following research question on the impact of mobile application usage patterns on users' physical and psychological health:

Research Question 1: How do mobile application usage breadth and depth affect users' health with regard to nomophobia and sleep deprivation?

The effect of mobile application usage on users' health is inevitably subjected to other activities performed by users. *Physical activity*, conceived as bodily movement involving energy consumption, has been widely regarded as an effective coping strategy for alleviating the adverse consequences of mobile application usage by helping users consolidate and recover resources (Bloodworth et al., 2012; Lepp et al., 2013; Li, 2009). In line with the tenets of COR theory, engaging in physical activity can aid individuals in coping with resource consumption by enabling them to consolidate resources and recover their resource stockpiles (Toker & Biron, 2012), which in turn mitigates the detrimental effects of mobile application usage on users' health. Furthermore, physical activity can facilitate individuals in expanding their total pool of physiological and psychological resources by boosting their physical energy and perpetuating positive emotions (Bloodworth et al., 2012; Das & Horton, 2012). As such, physical activity likely moderates the impact of mobile application usage on one's health. Given the potential moderating influence of physical activity, it nevertheless remains unclear how physical activity mitigates the effects of mobile application usage on users' physiological and psychological health. Despite the assertion that physical activity is beneficial for consolidating and recovering users' resource stockpiles by enhancing their physical fitness and regulating their moods from the standpoint of COR theory (Bloodworth et al., 2012; Bulley et al., 2009; Li, Lu, & Wang, 2009), another stream of research alleges that engaging in physical activity could aggravate one's fatigue by consuming physical energy (Schmaling et al., 2005). This study hence endeavors to elucidate the moderating influence of physical activity by answering the research question below:

Research Question 2: How does physical activity moderate the impact of mobile application usage breadth and depth?

To answer these two research questions, we administered a survey questionnaire to 5,842 respondents. Analytical results attest to the distinct roles played by the breadth and depth of mobile application usage in driving nomophobia and sleep deprivation, which, in turn, negatively affect users' health. The moderating influence of physical activity was corroborated for most relationships hypothesized in the research model. This study contributes to theory on three fronts. First, it illuminates the consequences of mobile application usage patterns by uncovering the differential impacts of breadth and depth on physiological and psychological symptoms. In so doing, our research extends previous scholarly work scrutinizing the relationship between mobile application usage and user well-being (e.g., Barkley et al., 2016; Karimikia et al., 2021; Salo et al., 2019). Second, this study constitutes a pioneering attempt to apply COR theory to comprehend the health consequences of mobile application usage, delivering a novel theoretical lens worth considering in future inquiries of mobile application usage. Third, by shedding light on the role of physical activity in mitigating the detrimental effects of mobile application usage, we advance contemporary knowledge on how to deal with the dark side of mobile application usage based on a nuanced understanding of the underlying mechanisms (e.g., Cao et al., 2018; Gong et al., 2021; Horwood & Anglim, 2019). Additionally, the findings from this study contribute to practice in two ways. First, given the popularity of mobile phone usage in daily life, we offer recommendations for how users can adjust their usage patterns to alleviate their detrimental impacts on health. Second, we advocate for engagement in physical activity as a means to counteract the detrimental effects of mobile application usage.

2 Theoretical Foundation

2.1 The Dark Side of Mobile Application Usage and Its Impact on Users' Health

The pervasiveness of mobile applications bears witness to their utility in everyday life (Nah et al., 2005). However, the penetration of mobile applications and the associated adverse consequences has fueled an increasingly heated debate on the well-being of mobile application users (cf. Turel, 2021; Turel & Qahri-Saremi, 2016). With renewed focus on the dark side of mobile application usage (Harris et al., 2020; Maier et al., 2020; Vaghefi et al., 2020), it is unsurprising that scholars have discovered a number of adverse physiological and psychological health conditions that stem from mobile application addiction, overdependence, and/or overuse, as summarized in Table 1 below (Barkley et al., 2016; Kim et al., 2017; Maier et al., 2020; Turel, 2015; Vaghefi et al., 2020).

On the one hand, a handful of studies have confirmed excessive mobile application usage as a primary cause of harmful physiological states like insomnia (Fu et al., 2021), poor-quality sleep (Enez Darcin et al., 2016; Liu et al., 2017), and other sleep difficulties (Salo et al., 2019), all of which are manifestations of *sleep deprivation*. On the other hand, prior research has also reported that mobile applications can evoke strong psychological attachment, culminating in excessive usage, which in turn gives rise to *nomophobia* (Fu et al., 2021). Symptoms of nomophobia include anxiety (Lepp et al., 2014; Woods & Scott, 2016), depression (Kim et al., 2017; Woods & Scott, 2016), feelings of guilt (Turel, 2015), loneliness (Enez Darcin et al., 2016), intensified pressure (Sarker et al., 2012), reduced life satisfaction (Lepp et al., 2014), and social isolation (Turel & Serenko, 2012).

Given these adverse health consequences, scholars have expended considerable effort to unravel how mobile application usage affects users' health (e.g., Fu et al., 2021; Kim et al., 2017; Salo et al., 2019). One stream of research has concentrated on deciphering how usage of a given mobile application (e.g., social media) is instrumental in inducing anxiety, depression, displease, feelings of guilt, psychological dependence, and sleep loss (Baccarella et al., 2018; Jeong et al., 2019; Turel, 2015; Wang et al., 2015; Woods & Scott, 2016). Collectively, studies belonging to this research stream have hinted that users' health consequences from mobile application usage are dependent on the range (or *breadth*) of mobile applications being used.

Table 1. Summary of Extant Literature on the Impact of Mobile Phone Usage

Health type	Reference	Sample	Theoretical frame of reference	Antecedents	Negative outcomes
Physiological health	Fu et al. (2021)	College students (Sample *N* = 6,855)	Stimulus-organism-response (SOR) theory	Mobile phone overuse	Insomnia, poor eyesight
	Salo et al. (2019)	Social media users (Sample *N* = 32)	Technostress framework	Social media overdependence	Sleep problems
	Kim et al. (2015)	International students (Sample *N* = 110)	–	Mobile phone addiction	Less working steps, less consumed calories, increased fat mass, and decreased muscle mass
	Barkley et al. (2016)	College students (Sample *N* = 236)	–	Daily mobile phone usage	More sedentary behavior
	Maier et al. (2015b)	College Students (Sample *N* = 82)	–	Social media usage	Exhaustion
	Cao et al. (2018)	Mobile social media users (Sample *N* = 505)	Stress-strain-outcome theory	Social media usage	Techno-exhaustion
	Liu et al. (2017)	Chinese Adolescents (Sample *N* = 1,196)	–	Mobile phone addiction	Poor sleep quality
Psychological health	Gong et al. (2021)	Users of honor of kings (Sample *N* = 627)	Dual-system theory	Obsessive online social gaming	Addiction
	Karimikia et al. (2021)	Related studies (Sample *N* = 52)	Transactional theory of stress	Smartphone overuse	Stress, exhaustion
	Kuem et al. (2021)	Smartphone users (Sample *N* = 441)	Incentive-sensitiation theory	Smartphone overuse	Addiction
	Fu et al. (2021)	College students (Sample *N* = 6,855)	Stimulus-organism-response (SOR) theory	Mobile phone overuse	Nomophobia
	Li & Chan (2021)	Smartphone users (Sample *N* = 992)	–	Smartphone overuse	Information overload, negative emotions
	Kim et al. (2017)	College students (Sample *N* = 608)	–	Mobile phone overuse	Depression, stress, and suicidal inclination
	Enez Darcin et al. (2016)	Students (Sample *N* = 367)	–	Mobile phone addiction	Loneliness, social phobia
	Turel (2015)	Facebook users (Sample *N* = 510)	Social cognitive theory	Social media addiction	Feelings of guilt
	Woods & Scott (2016)	Scottish adolescents (Sample *N* = 467)	–	Social media usage	Anxiety, depression
	Lepp et al. (2014)	College students (Sample *N* = 496)	–	Mobile phone usage	Anxiety, reduced satisfaction with life
	Horwood & Anglim (2019)	Australian adults (Sample *N* = 539)	–	Problematic mobile phone usage	Anxiety, lack of control, and negative emotions
	Jeong et al. (2019)	Social media users (Sample *N* = 425)	Cognitive dissonance theory	Social media usage	Displeasure, uncomfortable psychological states
	Wang et al. (2015)	Social media users (Sample *N* = 470)	Rational addiction theory	Social media usage	Psychological dependence

In contrast, another stream of research has testified to the significant influence of mobile application usage duration and frequency on users' health status (Fu et al., 2021; Horwood & Anglim, 2019; Kim et al., 2017). Acknowledging the pivotal role played by users' intensity of interaction with mobile applications in determining their health status, studies belonging to this research stream have pointed to the inevitability of considering the depth of mobile application usage in impacting users' health (e.g., Enez Darcin et al., 2016; Salo et al., 2019; Woods and Scott, 2016). Yet, despite advances in understanding the detrimental effects of mobile application usage, there is a dearth of research that delves into the effects of mobile application usage patterns on one's health, thereby hampering the enactment of targeted measures to regulate usage behaviors to mitigate their adverse health consequences. This study thus strives to bridge the aforementioned knowledge gap by unraveling the role of mobile application usage patterns (i.e., mobile application usage breadth and depth) in shaping users' health status.

2.2 Conservation of Resources Theory

Conservation of resources (COR) theory holds that individuals are motivated to preserve their current resources while at the same time acquiring new ones (Halbesleben et al., 2014; Moqbel & Bartelt, 2018; Zhang & Wang, 2016). According to COR theory, changes in physiological and psychological health are reactions to circumstances involving a threat of resource loss, an actual net loss of resources, or a lack of resource gain after resource consumption (Hobfoll, 1989). These resources, including physiological (e.g., physical energy, eyesight, and limb flexibility) and psychological (e.g., autonomy, control, and emotion) resources, are considerable supports that can help users stay healthy (Halbesleben et al., 2014). Originating from organization research (e.g., Halbesleben et al., 2014), COR theory has been applied to a handful of information systems studies to explain phenomena such as information security policy compliance, work stress, and family-work conflict (Moqbel & Bartelt, 2018; Zhang & Wang, 2016). Among these studies, COR theory has widely been considered a useful lens for explaining the diversity of unfavorable personal states, such as burnout (Zhang & Wang, 2016; Xu et al., 2015), insomnia, stress (Moqbel & Bartelt, 2018), and the loss of subjective well-being (Wiese et al., 2017). Given that COR theory has been applied to identify the impacts of activities such as conflict resolution, emotional management, and stress relief on personal states (Bamberger et al., 2017), there is a scarcity of research leveraging this lens to evaluate the health consequences induced by technology usage.

COR theory proposes three basic principles. First, external equipment usage leads to users' physiological and psychological resource losses or gains (Halbesleben et al., 2014). In this sense, mobile application usage can potentially induce resource depletion or attainment, which exerts diverging influences on users' health status. Second, COR theory contends that initial physiological and psychological resource losses/gains will bring about further physiological and psychological resource losses/gains (Demerouti et al., 2004). This principle indicates the sequential effects of the initial resource losses/gains caused by external equipment usage. After external equipment usage, resource losses/gains are reflected in the level of instant symptoms. This sequential consequence of resource losses/gains is represented by users' health status, which reflects the available resources owned by users. Third, users with ample resources are more likely to gain resources, whereas those with fewer resources are more likely to lose resources (Hobfoll, 1989). This principle indicates that users with larger resource stockpiles can recover resources faster after depletion than users with smaller ones. The consequences induced by external equipment usage could be mitigated by the size of resource stockpiles that users possess.

Subscribing to the first principle of COR theory, we contend that discrete patterns of using mobile applications could affect the users' resources differently. Specifically, the breadth of mobile application usage encompasses the range of mobile applications used to accomplish a variety of tasks (Fu et al., 2019). Aided by different categories of mobile applications, users can complete tasks with high efficiency (Larsen-Ledet et al., 2020), thereby conserving physiological energy. But at the same time, using a wide range of mobile applications demands intense attention via multitasking (Ren et al., 2012), which in turn consumes psychological resources. Conversely, by encapsulating the intensity of using a specific category of mobile application, the depth of mobile application usage is indicative of users' immersive usage experience (Fu et al., 2019; Peukert et al., 2019). Studies have found that immersion in a mobile application evokes positive emotions (e.g., fun, joy, and happiness) in users (Peukert et al., 2019; Zhan et al., 2018), leading to the replenishment of psychological resources. Concurrently, the intense usage of mobile applications has been shown to induce physical fatigue due to prolonged periods of expended effort (Lin et al., 2020), representing a depletion of physiological resources. When physiological and psychological resources become depleted, adverse health consequences like nomophobia and sleep deprivation are likely to arise.

Subscribing to the second principle of COR theory, users with symptoms of nomophobia and sleep deprivation have fewer psychological and physiological resources available to recover from resource losses, thus leading to further psychological and physiological resource losses (Hobfoll, 2001; Halbesleben et al., 2014). Also, as unfavorable psychological and physiological states, nomophobia and sleep deprivation can further deplete resources and erode users' health (Agathão et al., 2020; Fu et al., 2021; MacLean et al., 2015; Xue et al., 2018). Taken together, the sequential consequences of initial resource losses will likely be damaging to users' health.

According to the third principle of COR theory, engaging in physical activity helps users develop physical power (Kohl et al., 2012; Lovelace et al., 2007) and maintain positive moods (cf. Biddle et al., 2000; Li et al., 2009; Tejpal, 2015), thereby enlarging their resource stockpiles (Toker & Biron, 2012). With larger stockpiles of resources, users are much more resilient to external factors that can deplete their resources. In this sense, the detrimental effects of mobile application usage on nomophobia and sleep deprivation would be expected to be reduced when users engage in physical activity. COR theory offers a compelling theoretical lens for interpreting the impacts of mobile application usage on users' health via resource depletion and acquisition.

3 Hypotheses Formulation

Drawing on COR theory, we construct a research model to expound on the impact of mobile application usage patterns on health status (Figure 1). Specifically, we investigate the impact of mobile application usage breadth and depth on nomophobia and sleep deprivation, which in turn negatively influence users' health. According to the principles of COR theory, users' mobile application usage induces initial losses and gains of physiological and psychological resources, reflected by the levels of nomophobia and sleep deprivation (Halbesleben et al., 2014). COR theory also argues that initial resource losses lead to further resource losses (Demerouti et al., 2004). In this research model, the sequential resource losses are manifested by the impact of nomophobia on sleep deprivation as well as the influence of nomophobia and sleep deprivation on one's health. Moreover, the speed of recovery and depletion of resources has been documented by COR principles (Hobfoll, 1989), which is reflected by the moderating role of physical activity. Users engaging in physical activity possess large resource stockpiles that can help them recover from resource losses and protect themselves from losing resources through mobile application usage (Halbesleben et al., 2009; Vinokur & Schul, 2002; Halbesleben & Wheeler, 2008; Ng & Feldman, 2012). Table 2 provides definitions for all constructs in this research model.

3.1 Effects of Mobile Application Usage on Nomophobia and Sleep Deprivation

Mobile application usage can be measured by the breadth and depth of the usage of different applications (Harrison & Klein, 2007). Mobile application usage breadth reflects the range of mobile applications accessed by a user. Users typically employ different types of mobile applications to satisfy different needs in daily life, such as communication, travel, and entertainment (Chung et al., 2020; Fang et al., 2019; Shulman & Geng, 2019; Gong et al., 2019). For this reason, the wider users' demand is for different categories of mobile applications, the greater the variety of mobile applications they use to meet their needs. Processing different tasks with various mobile applications requires a high attention level that consumes users' psychological resources. As psychological resources are depleted, users experience stress. In the context of mobile application usage, users become psychologically dependent on mobile phones, which can cause stress (Gao et al., 2018; Gligor & Mozoș, 2019; Gutiérrez et al., 2016). In other words, users may experience discomfort, panic, worry, and nervousness when they are away from mobile phones (Gao et al., 2020; Yildirim & Correia, 2015). Given that using more mobile applications consumes more psychological resources, we anticipate that users will be more likely to develop nomophobia if they use a variety of mobile applications to fulfill their needs. Considering that the usage of a wide range of mobile applications consumes users' psychological resources, we therefore hypothesize that:

H1a: Mobile application usage breadth positively influences nomophobia.

Using a wide range of mobile applications is conducive to fulfilling users' professional and personal needs (Chung et al., 2020; Fang et al., 2019; Gong et al., 2020; Shulman & Geng, 2019). Mobile applications are designed to assist users in efficiently completing work-related tasks (Chung et al., 2020; Hu et al., 2019). A wide range of mobile applications enables users to finish tasks without time and space constraints (Larsen-Ledet et al., 2020; Tarute et al., 2017). This allows them to, for example, use fragmented time, such as that spent commuting, to complete tasks, which then frees up the time that would have otherwise been spent completing these tasks (Larsen-Ledet et al., 2020). Users can also leverage different categories of mobile applications to satisfy their personal needs online (Tarute et al., 2017). For example, users can fulfill social needs using social media applications without leaving home to meet people physically (Krancher et al., 2018). Efficient need fulfillment can create additional free time, which leads to the preservation of physiological resources and improves sleep quality (Lee et al., 2019). We therefore hypothesize that:

H1b: Mobile application usage breadth negatively influences sleep deprivation.

Mobile application usage depth reflects the intensity of the usage of a specific category of mobile applications (Harrison & Klein, 2007). Through intensive usage of a specific category of mobile applications, such as shopping and travel applications, users are immersed in a category of mobile applications that can induce positive emotions such as happiness, joy, and excitement (Hammedi et al., 2017). This immersive experience thus replenishes users' psychological resources, relieving their stress (Chen, 2020). Low stress levels prevent users' overdependence on mobile phones (Chiu, 2014). In addition, the intensive usage of a specific category of mobile applications can fulfill users' psychological needs, which in turn lessens their likelihood of psychological dependence on mobile phones (King et al., 2013; Kwon et al., 2016). As such, users' application usage depth may actually alleviate symptoms of nomophobia, which is a manifestation of psychological resource consumption. Taken together, we hypothesize that:

H2a: Mobile application usage depth negatively influences nomophobia.

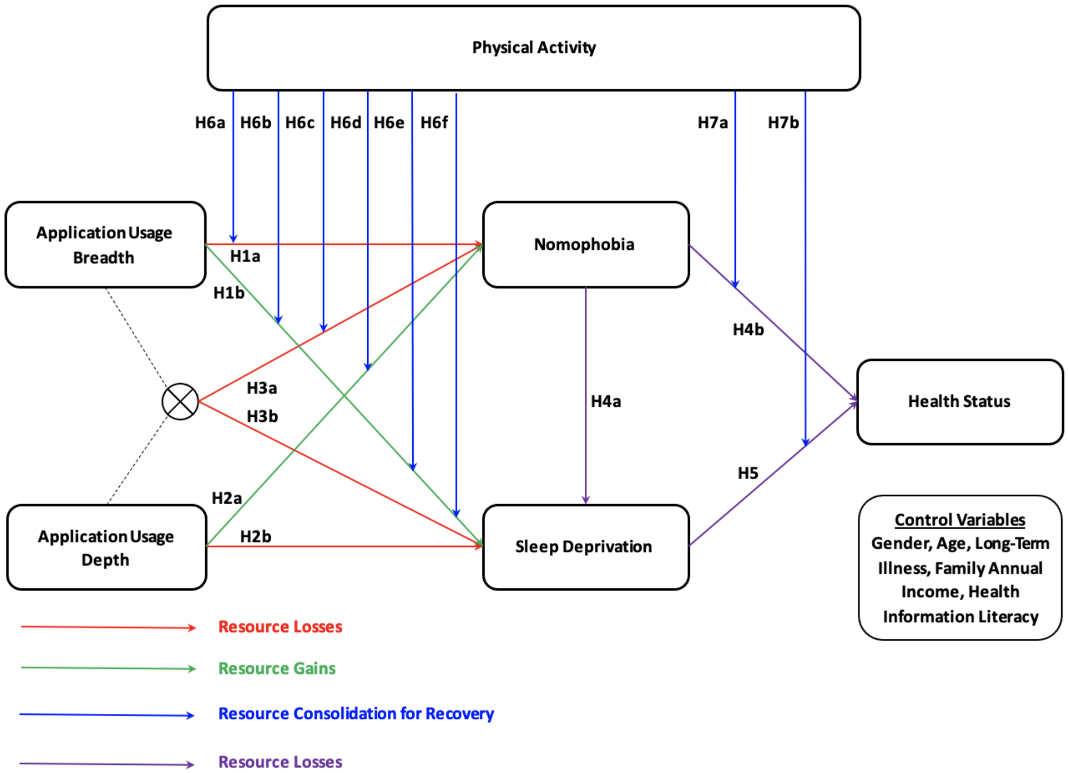


Figure 1. Research Model of the Effects of Mobile Application Usage on Users' Health Status

Table 2. Definitions of Key Concepts in This Study

Construct	Definition	References
Application usage breadth	Range of different categories of mobile applications used by a user in a given period	Adapted from Fu et al. (2019)
Application usage depth	Intensity of interaction with each category of mobile application	Adapted from Fu et al. (2019)
Nomophobia	Symptoms of psychological unease reflecting the worry of losing mobile phone contact	Adapted from Yildirim & Correia (2015) and Gao et al. (2020)
Sleep deprivation	Unfavorable physiological symptoms reflecting going to bed later than usual and/or sleep disorders in which users have trouble falling and/or staying asleep	Adapted from Amschler & McKenzie (2005), Arakawa et al. (2001), and Liu & Liu (2005)
Health status	Overall evaluation of the status of physiological and psychological well-being	Adapted from Martikainen et al. (1999)

However, the intensive usage of a specific category of mobile applications leads to long periods of time spent on a specific activity. This can cause users' physiological resources to be consumed, leading to symptoms such as staying up late (Salo et al., 2019) and insomnia (Fu et al., 2021), both of which lead to sleep deprivation (Amschler & McKenzie, 2005; Arakawa et al., 2001; Liu & Liu, 2005). Further, intensively using a specific type of mobile application may also lead to prolonged screen time at night, which increases sleep onset latency (Woods & Scott, 2016), decreases overall sleep duration (Peracchia & Curcio, 2018), reduces the time spent in deep sleep (Advanced Sleep Medicine Service, 2015), and diminishes sleep quality (Liu et al., 2017; Peracchia & Curcio, 2018). Moreover, recent reports on mobile applications like social media (BBC, 2019a), games (Advanced Sleep Medicine Service, 2015), and shopping (BBC, 2019a; 2019b) have shown that in-depth usage of these categories of mobile applications is a main reason that users stay up late. Based on the above, users' mobile application usage depth leads to sleep deprivation, which is a manifestation of physiological resource consumption. We therefore hypothesize that mobile application usage depth has detrimental effects on users' sleep deprivation:

H2b: Mobile application usage depth positively influences sleep deprivation.

Mobile application usage breadth reflects the range of mobile applications used by an individual, whereas mobile application usage depth reflects the intensity of usage of a specific category of mobile application (Harrison & Klein, 2007). A high level of mobile application usage breadth and depth means that a significant amount of intense individual attention is spent on a wide range of mobile applications. This state of mobile application overuse is widely regarded as a trigger of psychological resource consumption that leads to symptoms of nomophobia (Fu et al., 2021). Specifically, nomophobia represents the worry that being apart from one's mobile phone will result in the potential loss of contact with friends and family or other negative outcomes (Yildirim & Correia, 2015). Excessive usage of mobile applications can thus promote compulsive checking habits (Oulasvirta et al., 2012), the compulsive usage of mobile applications (Wang & Lee, 2020), and symptoms of the fear of missing out (aka FOMO) (Dhir et al., 2018), all of which are closely related to characteristics of nomophobia (Fu et al., 2021; Gao et al., 2020; Yildirim & Correia, 2015). Given that the interaction between mobile application usage breadth and depth can cause the excessive loss of psychological resources with symptoms of nomophobia, we hypothesize that:

H3a: The interaction between mobile application usage breadth and depth positively influences nomophobia.

Likewise, a high level of breadth and depth in mobile application usage can be excessively costly to users' physical energy stores, which often results in the extra consumption of physiological resources. Specifically, the intensive usage of a wide range of mobile applications occupies users' nights, leading users to sleep late (Woods & Scott, 2016). The light from mobile phone screens has repeatedly been linked to the postponement of the onset of wakefulness by inhibiting the secretion of melatonin, a chemical necessary for ensuring high sleep quality (Higuchi et al., 2003). Both staying up late and the delayed onset of wakefulness can induce the depletion of more physiological resources. Moreover, scholars have found that spending too much time on mobile applications can result in insomnia and other sleep disorders (Fu et al., 2021; Woods & Scott, 2016), which hinder users' physiological resource recovery. Given that the interaction between mobile application usage breadth and depth leads to the additional loss of physiological resources, we hypothesize that:

H3b: The interaction between mobile application usage breadth and depth positively influences sleep deprivation.

3.2 The Effects of Nomophobia and Sleep Deprivation on Health Status

In the context of mobile application usage, the consumption of psychological resources inevitably leads to the consumption of physiological resources (Demerouti et al., 2004; Enez Darcin et al., 2016; Fu et al., 2021; Salo et al., 2019). To this end, nomophobia induced by mobile application usage has been shown to trigger discomfort in users' daily lives (Tarafdar et al., 2020; Osatuyi & Turel, 2020). Scholars have suggested that the most obvious impact of nomophobia on users is interference with sleep (Fu et al., 2021). Worrying about being separated from one's phone can contribute to the loss of physiological resources that are closely associated with sleep disorders (Darcin et al., 2016; Fu et al., 2021; Salo et al., 2019). Through producing excessive digital screen exposure before bedtime, mobile phone overdependence can interfere with melatonin production and delay circadian rhythms, which impedes the development of healthy sleep habits (Woods & Scott, 2016). Research has also shown that mobile phone dependence makes it difficult for users to relax at bedtime because they fear they will miss out on new content, which makes it difficult for them to recover physiological resources (Salo et al., 2019). The detriments of nomophobia for causing physiological resource losses and hindering physiological resource recovery have been extensively demonstrated in extant literature in terms of physiological disorders such as longer sleep latencies (Exelmans & Van den Bulck, 2016), insomnia symptoms (Fu et al., 2021; Liu et al., 2017), shorter sleep duration (Exelmans & Van den Bulck, 2016; Fu et al., 2021), and later bedtimes and wake-up times (Exelmans & Van den Bulck, 2016). As such, nomophobia induces physiological resource consumption, leading to symptoms related to poor sleep habits. Drawing on the principle within COR theory that initial psychological resource losses will lead to further physiological resource losses, we hypothesize that:

H4a: Nomophobia positively influences sleep deprivation.

Following the tenets of COR theory, users' health status is determined by their physiological and psychological resources (Penley et al., 2002; Halbesleben et al., 2014). It is alleged that nomophobia consumes users' psychological resources (Penley et al., 2002; Wolfers et al., 2020). Nomophobia also can induce negative psychological states such as stress (King et al., 2013), further depleting the resources necessary to cope with them and ultimately damaging users' overall health. In addition, nomophobia has been shown to precipitate the loss of physiological resources through its association with sleep problems such as insomnia (Fu et al., 2021; King et al., 2013). The consumption of physiological resources has been linked to poor health outcomes, including the emergence of ophthalmic issues induced by nomophobia (Ratnayake et al., 2018). Considering the consumption of physiological and psychological resources caused by nomophobia, we hypothesize that:

H4b: Nomophobia negatively influences health status.

Similarly, the consumption of physiological resources represented by sleep deprivation can impair health. It has been asserted that adequate sleep can boost the recovery of physiological resources and improve health (Chen et al., 2006; Tahmasian et al., 2020). Sleep deprivation, however, leads to daytime sleepiness and cognitive disorders, which in turn cause the loss of physiological resources, potentially leading to consequences such as diabetes, hypertension, and obesity (Chen et al., 2006; Tahmasian et al., 2020). In addition, sleep deprivation consumes psychological resources through psychological disorder symptoms such as depression, panic, and anxiety (Angehrn et al., 2020; Lemola et al., 2015; MacLean et al., 2015). The depletion of psychological resources inevitably leads to negative health impacts. Considering the consumption of physiological and psychological resources induced by sleep deprivation, we hypothesize that:

H5: Sleep deprivation negatively influences health status.

3.3 Moderating Influence of Physical Activity

Physical activity is widely acknowledged as an effective practice for consolidating and recovering physiological and psychological resources (Bulley et al., 2009; Bloodworth et al., 2012; Li et al., 2009). Following the third principle of COR theory, engaging in physical activity enlarges users' stockpiles of available resources, which can alleviate the severity of the health consequences induced by resource depletion and acquisition (Halbesleben et al., 2014; Hobfoll, 1989). Moreover, when engaging in physical activity, users typically focus on the offline world and pay less attention to mobile applications, which is conducive to the recovery of depleted resources.

Based on this view of COR theory, engaging in physical activity helps users enlarge their psychological resource stockpiles by supporting positive emotional states (cf. Biddle et al., 2000; Li et al., 2009; Tejpal, 2015). Thus, users who maintain a high degree of physical activity are likely more resilient to the impact generated by psychological resource changes because of their large psychological resource stockpiles (Halbesleben et al., 2014; Hobfoll, 1989). In this sense, the influences exerted by mobile application usage breadth and depth on nomophobia will be less salient to users who engage in regular physical activity. Specifically, users who engage in regular physical activity are more likely to maintain positive and optimistic psychological states and will therefore have sufficient mental energy to cope with external inferences (Biddle et al., 2000). The detrimental impacts (e.g., panic, worry, and nervousness) generated by a wide range of mobile application usage are thus far less likely to induce mobile phone addiction symptoms in users who are resilient to the psychological fatigue caused by mobile applications. Furthermore, although in-depth mobile application usage is conducive to recovering mental energy through immersive experiences, we anticipate that its benefit is less salient for users who are already mentally energetic. Likewise, we predict that the interaction between mobile application usage breadth and depth has a smaller influence on users who engage in sufficient physical activity. By contrast, users who rarely participate in physical activity may have limited available psychological resources, making them more vulnerable to psychological resource fluctuation caused by other behaviors (Halbesleben et al., 2009; Halbesleben et al., 2014). In such cases, the effects of mobile application usage on nomophobia may be intensified (Whitman et al., 2014). We therefore hypothesize that:

H6a-c: Physical activity weakens the impact of mobile application usage **(a)** breadth, **(b)** depth, and **(c)** their interaction on nomophobia.

Similarly, adhering to COR theory, engaging in physical activity helps users enlarge their physiological resource stockpiles through developing physical power (Kohl et al., 2012; Lovelace et al., 2007). Thus, high degrees of physical activity enhance the size of users' physiological resource stockpiles by improving their fitness levels (Bloodworth et al., 2012; Halbesleben et al., 2014; Hobfoll, 1989). As with nomophobia, the sleep deprivation of users who engage in regular physical activity will be less influenced by mobile application usage breadth and depth. Specifically, using a wide range of mobile applications may enable users to satisfy different kinds of personal needs and can help users restore physiological resources by freeing up extra time to relax (Lee et al., 2019). Although the recovery of physical power is beneficial, it is a less obvious benefit for users who are robust to external changes because of their excellent physical condition. Moreover, the intense usage of mobile applications consumes users' physiological resources by inducing symptoms such as staying up late (Salo et al., 2019) and insomnia (Fu et al., 2021). Engaging in physical activity can mitigate those detrimental impacts by strengthening users' physiological base, allowing them to resist external harm. The same applies to the interaction between mobile application usage breadth and depth, which is less influential for such users (Woods & Scott, 2016). By contrast, when users engage in little physical exercise, their total amount of physiological resources may be diminished due to poor physical fitness, which makes them more likely to be affected by mobile applications (Halbesleben et al., 2009; Halbesleben et al., 2014). We hypothesize that physical activity can alleviate the impact of mobile application usage on sleep deprivation:

H6d-f: Physical activity weakens the impact of mobile application usage **(d)** breadth, **(e)** depth, and **(f)** their interaction on sleep deprivation.

According to COR theory, users with larger psychological resource stockpiles can recover psychological resources faster after depletion than users with smaller ones (Hobfoll, 1989). It has been well documented that physical activity is critical for alleviating the negative effect of psychological discomfort on human well-being (Bulley et al., 2009; Wiese et al., 2017). Regular physical activity is one of the best ways to consolidate and expand one's psychological resource stockpiles (Bloodworth et al., 2012). When users possess sufficient resources, they can overcome the detrimental effects generated by nomophobia, thereby preventing their overall health status from deteriorating (Hobfoll, 1989). Also, we anticipate the active mood and high self-esteem supported by physical activity can mitigate the damages of psychological unease on users' health (Biddle et al., 2000; Li et al., 2009; Tejpal, 2015). By contrast, users who rarely engage in physical activity may have insufficient psychological resource stockpiles and may also be vulnerable to the psychological resource depletion caused by nomophobia, which may lead to negative health outcomes. Accordingly, since physical activity can potentially mitigate the negative impacts of nomophobia, we propose the following hypothesis:

H7a: Physical activity weakens the impact of nomophobia on health status.

In line with COR theory, users with larger physiological resource stockpiles can also recover physiological resources more quickly following depletion than those with smaller ones (Hobfoll, 1989). Physical activity is widely considered critical to improving the speed of physiological resource recovery because it enlarges users' physiological resource stockpiles (Kohl et al., 2012; Lovelace et al., 2007). Specifically, physical activity is strongly associated with users' physical fitness (Bloodworth et al., 2012). A generally healthy body is key to a quick recovery from the depletion of physiological resources (Melin et al., 2019). Users who exercise regularly can recover physiological resources by enhancing their general physical health (Bloodworth et al., 2012). Physical activity can therefore expedite users' recovery from the loss of physiological resources caused by sleep deprivation (Halbesleben et al., 2009, 2014). This is also evidenced by anecdotal reports suggesting the positive role of physical activity in alleviating sleep problems (Sleep Foundation, 2021b). In contrast, users who infrequently engage in physical activity may recover from the depletion of physiological resources more slowly due to suboptimal physical health and thus may be more impacted by sleep deprivation (Halbesleben et al., 2009; Halbesleben et al., 2014). Accordingly, we hypothesize that physical activity can mitigate the negative role of sleep deprivation:

H7b: Physical activity weakens the impacts of sleep deprivation on health status.

4 Methodology

4.1 Sampling and Data Collection

We collected our data through a large-scale questionnaire survey aimed at understanding the effect of mobile application usage on students' well-being at a renowned Chinese university with over 30,000 undergraduate students. Our research was supported by the university's Physical Education (PE) department. The questionnaire was designed by the researchers of this study and was distributed by the university's PE department. The department conducts annual physical tests that are compulsory for all undergraduates. The questionnaire was sent to students randomly, based on when they logged into the department's official website to view their test results. This survey was designed to obtain information on students' health, health-related habits (e.g., sleep habits), engagement in physical activity (e.g., sports), and mobile application usage patterns. At the beginning of the questionnaire, we stated, "*This survey aims to investigate the relationship between mobile application usage and health status. This questionnaire is completely anonymous and only for academic research. Research conclusions will be published in academic journals.*" Respondents were asked to answer questions related to their health status first. A separate part of the questionnaire was designed to collect their responses to questions on mobile application usage. Given that this survey was conducted in Chinese, back-translation was performed to ensure consistency between the Chinese and English versions. Before conducting the questionnaire survey, we conducted a pilot test to ensure readability and face validity. The questionnaire was revised in accordance with feedback from respondents in the pilot study.

Questionnaires were distributed via the university's questionnaire platform. A total of 6,948 questionnaires were returned, of which 5,842 were retained for preliminary analysis after those that did not qualify because of incompleteness, extremely short completion time, or inconsistent answers to identical questions were removed (Goode et al., 2017). Table 3 depicts the demographic breakdown of the sample. Of the 5,842 participants, 4,659 (79.75%) participants reported having more than three years of internet experience.

Table 3. Breakdown of Sample Demographic Attributes (Sample N = 5,842)

Demographic attributes		Number	Percentage (%)
Gender	Male	3,112	53.26
	Female	2,730	46.73
Age	≤18	122	2.09
	19	606	10.37
	20	930	15.92
	21	1,095	18.74
	22	1,189	20.35
	23	1,230	21.06
	24	511	8.75
	≥25	159	2.72
Internet experience (IE)	< 0.5 year	231	3.96
	0.5 year ≤ IE < 1 year	304	5.20
	1 year ≤ IE < 2 years	259	4.43
	2 years ≤ IE < 3 years	389	6.66
	≥ 3 years	4,659	79.75
Long-term illness	Yes	299	5.12
	No	5,543	94.88
Family annual income (FAI, in RMB)	< 20,000	1,433	24.53
	20,000 ≤ FAI < 50,000	1,394	23.86
	50,000 ≤ FAI < 100,000	1,351	23.13
	100,000 ≤ FAI < 200,000	1,123	19.22
	≥ 200,000	541	9.26

4.2 Measurement Development

Nomophobia was measured via the scale developed and validated by Yildirim and Correia (2015). Physical activity was assessed by the length of time and the frequency with which participants engaged in sports (Booth et al., 2001). We adopted a single-item measurement of health status from earlier studies in the healthcare domain (DeSalvo et al., 2006a; Martikainen et al., 1999). Earlier studies have also revealed that a single-item measurement of health status is valuable for large population studies and useful for monitoring self-reported health, which helps to capture the basic information needed to improve healthcare quality (DeSalvo et al., 2006b, 2009; Zhang et al., 2007). Sleep deprivation is a formative construct measured by the frequency with which users stay up late (Amschler & McKenzie, 2005; Arakawa et al., 2001) and the frequency of insomnia (Liu & Liu, 2005). In addition, a pretest was conducted to collect information on the categorization of mobile applications and time spent on each type of mobile application. Following the results of the pretest, we measured mobile application usage based on nine categories of mobile applications, including social media, news, travel, video (or music), shopping, selfies, searches, gaming, books, and others. Respondents were asked to report the amount of time they spend on these categories. This survey also collected respondents' demographic information, such as gender, age, family annual income, health information literacy, and long-term illnesses. Details of the measurement can be found in Appendix A.

In this study, mobile application usage patterns contained two dimensions: breadth and depth. Following the formula proposed by Fu et al. (2019), the depth of mobile application usage of user i on mobile application j was formulated as follows:

$$\text{Usage Depth}_{i,j} = (PV_{i,j} - \alpha_j) / \delta_j \qquad (1)$$

where $PV_{i,j}$ is user i's average time of using mobile application j per day, α_j is the average time spent using mobile application j across the entire sample, and δ_j is the standard deviation of the average time spent using mobile application j.

The depth of mobile application usage for user i was formulated as follows:

$$\text{Usage Depth}_i = \sum_1^{10} \left((PV_{i,j} - \alpha_j) * \alpha_j / (\delta_j * \Sigma_1^{10} \alpha_j) \right), \quad j = 1, 2, \ldots\ldots 10 \qquad (2)$$

where $PV_{i,j}$ is user i's average time spent using mobile application j per day, α_j is the average time spent using mobile application j across the entire sample, and δ_j is the standard deviation of the average time spent using mobile application j.

The breadth of mobile application usage of user i was formulated as:

$$\text{Usage Breadth}_i = (n_i - N) / \mu \qquad (3)$$

where n_i is the number of distinct mobile application categories used by user i, N is the average number of mobile application categories used across all users, and μ is the standard deviation of the number of mobile application categories accessed by all users. The descriptive statistics for the focal variables are summarized in Table 4.

Table 4. Descriptive Statistics for Focal Variables

Variable	Mean	*SD*	Min.	Max.
Application usage breadth	0.018	0.986	-2.808	1.004
Application usage depth	-0.003	0.609	-1.426	2.501
Nomophobia	3.805	1.538	1.000	7.000
Sleep deprivation, 1	3.039	1.117	1.000	5.000
Sleep deprivation, 2	2.150	0.835	1.000	4.000
Physical activity, 1	2.317	0.731	1.000	4.000
Physical activity, 2	1.735	0.745	1.000	4.000
Health status	2.353	0.586	1.000	3.000

4.3 Reliability and Validity

Structural equation modeling (SEM) was employed to test the research framework via AMOS 27.0, which is suitable for model analysis based on a large dataset. Adhering to Hulland's (2015) recommended procedure, we verified the measurement model by assessing both the reliability and validity of each latent-variable measurement. After this, we tested the structural model by estimating the path coefficients as well as the corresponding significance level.

Given the reflective items capturing the effects of the construct under scrutiny (Hu & Bentler, 1999), we assessed reliability by checking the standard estimates of Cronbach's alpha, composite reliability, and average variance extracted (AVE) (Fornell & Larcker, 1981). As shown in Table 5, all latent variables of nomophobia, physical activity, and health information literacy exceed the thresholds recommended by Chin (1998), indicating adequate reliability. Additionally, verification of the validity involved the estimation of both convergent validity and discriminant validity. Specifically, for the criterion of convergent validity to hold, the factor loadings of one construct need to correlate highly with others. Conversely, sufficient discriminant validity is determined based on whether measurement items loaded more highly onto their intended constructs than onto other constructs (Cook & Campbell, 1979). The other criterion for adequate discriminant validity is that the square root of the AVE for each construct must be greater than its correlations with any other construct. As presented in Table 5, the minimal factor loadings on nomophobia, physical activity, and health information literacy are not only higher than those for other constructs but also exceed 0.8, indicating both convergent and discriminant validity.

Table 6 illustrates that the square root of the AVE for each construct is greater than its correlations with any other constructs, suggesting sufficient discriminant validity of all the constructs (Fornell & Larcker, 1981). Taken together, we confirmed both convergent validity and discriminant validity. Before the path coefficients in the structural model were assessed, we assessed model fit to ascertain whether the structural model accurately represented the underlying pattern in our data (Hooper et al., 2008). After fulfilling the model fit requirement of the SEM method (Hu & Bentler, 1999), the goodness-of-fit index (GFI), comparative-fit index (CFI), Tucker-Lewis coefficient (TLI), and normed-fit index (NFI) should be greater than 0.900. Likewise, the adjusted goodness-of-fit index (AGFI) should have a value greater than 0.850. The standardized root mean square residual (SRMR) index and the root mean square error of approximation (RMSEA) values must be lower than 0.080. As shown in Table 7, the GFI is 0.990, the AGFI was 0.976, the CFI is 0.988, the TLI is 0.975, the NFI is 0.986, the RMSEA is 0.029, and the SRMR is 0.014. Thus, we were able to continue the work. Moreover, the variance inflation factors (VIF) for all constructs in this study fell below 3.000, eliminating the potential multicollinearity issue (Neter et al., 1996).

Our research sample conformed to the normal distribution. We performed a Harman's single-factor test, a widely applied method for evaluating common method bias (CMB) (Podsakoff et al., 2003). The largest variance explained by the individual factor is 33.31%, indicating that CMB is not a significant problem in this study. Further, the scales for the independent variables and dependent variables differed in our research model, thereby inducing methodological separation, which also reduces the threat of common method bias (Carter et al., 2020). Finally, we employed a marker variable approach to examine the presence of CMB. The marker variable is academic performance, which is less theoretically related to the other variables. Appendix B shows the test results of the baseline model and the marker variable model. All parameter estimates remained stable after the marker variable was included, which further supports the absence of CMB.

5 Analytical Results

5.1 Structural Model

Figure 2 and Table 9 show the results of our hypotheses testing. Table 8 provides the weights and associated *p*-values for the measurement items contributing to the formative variable. All weights for formative variables are significant at the $p < 0.001$ level, indicating that the measurement is acceptable.

Table 5. Construct Validity of Reflective Variables

Variable	Minimal factor loading	Cronbach's alpha (α)	Composite reliability	Average variance extracted (AVE)
Nomophobia	0.847	0.849	0.907	0.765
Physical activity	0.815	0.601	0.833	0.714
Health information literacy	0.849	0.919	0.939	0.755

Table 6. Interconstruct Correlation Coefficients

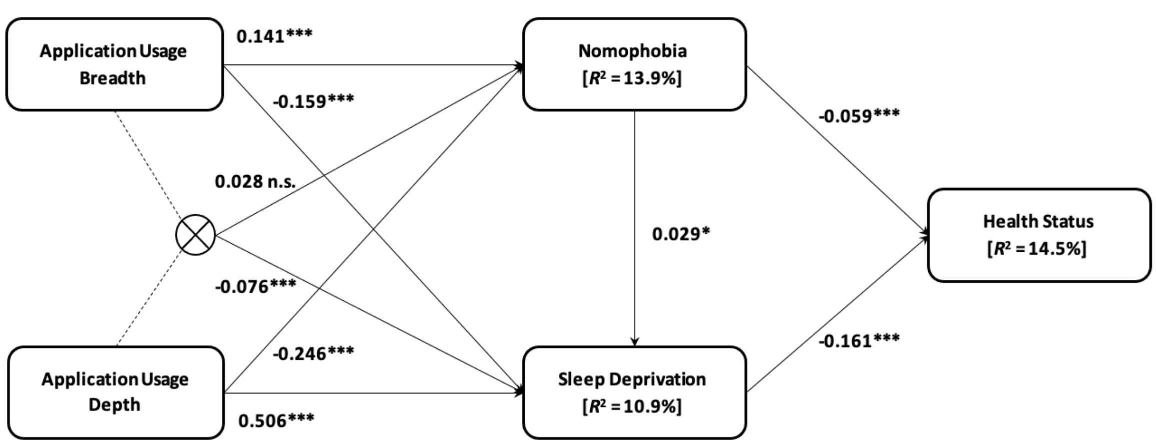
Construct	AUB	AUD	IBD	NOM	SD	PA	HS	Gen	Age	LTI	FAI	HIL
Application usage breadth (AUB)	1.000											
Application usage depth (AUD)	0.653***	1.000										
Interaction between app usage breadth and depth (IBD)	-0.659***	-0.374***	1.000									
Nomophobia (Nom)	0.009	-0.071***	0.004	0.875								
Sleep deprivation (SD)	0.172***	0.265***	-0.173***	0.022	1.000							
Physical activity (PA)	0.129***	0.112***	-0.095***	-0.006	-0.003	0.845						
Health status (HS)	-0.125***	-0.140***	0.138***	-0.122***	-0.298***	0.173***	1.000					
Gender (Gen)	0.160***	0.179***	-0.058***	0.005	0.098***	-0.100***	-0.077***	1.000				
Age (Age)	0.026*	-0.033*	0.031*	-0.028*	0.008	-0.064***	0.005	0.013	1.000			
Long-term illness (LTI)	0.155***	0.132***	-0.206***	0.012	0.117***	0.136***	-0.094***	0.017	-0.018	1.000		
Family annual income (FAI)	0.069***	0.099***	-0.041**	-0.006	0.053***	0.088***	0.029*	0.087***	0.036**	0.112***	1.000	
Health information literacy (HIL)	-0.010	-0.072***	0.012	0.319***	-0.009	-0.005	-0.036**	0.007	-0.027*	-0.004	-0.001	0.869
Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$												

Table 7. Model Fit

Indicator	GFI (> 0.90)	AGFI (> 0.85)	CFI (> 0.90)	TLI (> 0.90)	NFI (> 0.90)	RMSEA (< 0.08)	SRMR (< 0.08)
Coefficient	0.990	0.976	0.988	0.975	0.986	0.029	0.014

Table 8. Weights and *t*-Statistics for Formative Variables

Variable	Measurement	Weight	*p*-value
Sleep deprivation	(1) Frequency of staying up	0.810	< 0.001
	(2) Frequency of insomnia	0.420	< 0.001



Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Figure 2. Structural Model Analysis

Table 9. Results of Hypotheses Testing

Hypothesis		Coefficient	*t*-test value	Support?
H1a	Application usage breadth → Nomophobia [+]	0.141***	4.688	Supported
H1b	Application usage breadth → Sleep deprivation [-]	-0.159***	7.305	Supported
H2a	Application usage depth → Nomophobia [-]	-0.246***	6.174	Supported
H2b	Application usage depth → Sleep deprivation [+]	0.506***	17.533	Supported
H3a	Interaction between application usage breadth and depth → Nomophobia [+]	0.028n.s.	1.786	Not supported
H3b	Interaction between application usage breadth and depth → Sleep deprivation [+]	-0.076***	6.776	Not supported
H4a	Nomophobia → Sleep deprivation [+]	0.029*	2.558	Supported
H4b	Nomophobia → Health status [-]	-0.059***	8.815	Supported
H5	Sleep Deprivation → Health status [-]	-0.161***	21.748	Supported
H6a	Application usage breadth × Physical activity → Nomophobia [-]	0.070*	2.432	Not supported
H6b	Application usage depth × Physical activity → Nomophobia [+]	0.001n.s.	0.034	Not supported
H6c	Interaction between application usage breadth and depth × Physical activity → Nomophobia [-]	0.052***	3.821	Not supported
H6d	Application usage breadth × Physical activity → Sleep deprivation [+]	0.129***	6.180	Supported
H6e	Application usage depth × Physical activity → Sleep deprivation [-]	-0.065***	4.076	Supported
H6f	Interaction between application usage breadth and depth × Physical activity → Sleep deprivation [-]	0.078***	7.966	Partly supported
H7a	Nomophobia × Physical activity → Health status [+]	-0.012n.s.	1.549	Not supported
H7b	Sleep deprivation × Physical activity → Health status [+]	0.049***	7.223	Supported

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

First, we examined the detrimental health impacts induced by mobile application usage patterns. Consistent with our expectations in H1a and H1b, we found that mobile application usage breadth exerts a positive impact on nomophobia ($\beta = 0.141$; $p < 0.001$) and a negative impact on sleep deprivation ($\beta = -0.159$; $p < 0.001$). Our findings also indicate that mobile application usage depth negatively influences nomophobia ($\beta = -0.246$; $p < 0.001$) and positively influences sleep deprivation ($\beta = 0.506$; $p < 0.001$), supporting H2a and H2b. Furthermore, the interaction between mobile application usage breadth and depth was found to have an insignificant impact on nomophobia ($\beta = 0.028$; $p < 0.1$), rejecting H3a, and a negative impact on sleep deprivation ($\beta = -0.076$; $p < 0.001$), rejecting H3b.

Then we examined the detrimental impact of nomophobia and sleep deprivation on health status. Consistent with our hypotheses, we found that nomophobia exerts a positive impact on sleep deprivation ($\beta = 0.029$; $p < 0.05$), confirming H4a. Furthermore, our findings indicate that both nomophobia ($\beta = -0.059$; $p < 0.001$) and sleep deprivation ($\beta = -0.161$; $p < 0.001$) exert significant negative impacts on health status, validating H4b and H5.

Next, we examined the moderating role of physical activity in effects generated by mobile application usage patterns. We found that physical activity strengthens the relationship between mobile application usage breadth and nomophobia ($\beta = 0.070$; $p < 0.05$), rejecting H6a. Similarly, our findings indicate that physical activity does not weaken the impact of mobile application usage depth on nomophobia ($\beta = 0.001$; $p = 0.973$), rejecting H6b. The impact generated by the interaction between mobile application usage breadth and depth on nomophobia was also found to be strengthened by physical activity ($\beta = 0.052$; $p < 0.001$), rejecting H6c. Further, the effect exerted by mobile application usage breadth on sleep deprivation was found to be weakened ($\beta = 0.129$; $p < 0.001$), as proposed in H6d. H6e is supported by the finding that physical activity weakens the impact of mobile application usage depth on sleep deprivation ($\beta = -0.065$; $p < 0.001$). Moreover, the impact of the interaction between mobile application usage breadth and depth on sleep deprivation was also found to be weakened, as proposed in H6f (β = 0.078; p < 0.001). H6f proposes that physical activity weakens the positive interaction effect on sleep deprivation, but the results show that the negative interaction effect is weakened, thereby partly supporting H6f.

Finally, we examined how physical activity moderated the impacts of nomophobia and sleep deprivation on health status. Inconsistent with our expectation in H7a, we found that physical activity insignificantly moderates the impact of nomophobia on health status (β = -0.012; p = 0.121) but positively moderates the impact of sleep deprivation on health status (β = 0.049; p < 0.001), as hypothesized in H7b. The R^2 values of nomophobia, sleep deprivation, and health status are 13.9%, 10.9%, and 14.5% respectively. We checked the potential reverse causality between mobile application usage patterns and user health status, and constructed two comparison models, as shown in Appendix C. Our research model examined the impact of mobile application usage patterns on user health status, while the comparison model looked at the impact of users' health status on mobile application usage patterns. Our research model (NFI = 0.986, SRMR = 0.014) exhibited a better model fit than the comparison model (NFI = 0.698, SRMR = 0.081; Hu & Bentler, 1999; Lohmöller, 1989). As can be inferred from this fit, the hypothesized relationships among the six constructs in our research model constitute a more accurate reflection of the empirical observations.

We performed a robustness check by using a formative measurement for mobile application usage depth. We marked each item of mobile application usage depth by category (i.e., from 1 to 6). For instance, if a user never accessed book-reading applications, the item value of using book-reading applications was "0." If a user accessed book-reading applications for a period equal to or greater than 15 minutes but less than 30 minutes, the item value of using book-reading applications was "2." The same applied to the items of other categories of mobile application usage depth. Given that the item for measuring mobile application usage breadth was binary, we kept the original formula. The results show highly similar findings, thus further validating the effectiveness of the formulas for measuring mobile application usage patterns and the proposed hypotheses (see Appendix D for more details).

We adopted the graphical procedure suggested by Aiken and Stephen (1991) to display the interaction and moderating effects, as shown in Figure 3. We assigned values one standard deviation above and below the mean to mobile application usage depth to plot its interaction effects with mobile application usage breadth. Likewise, we assigned physical activity values one standard deviation above and below the mean to plot its moderating effects on the proposed relationships. The three-way interactions appear in Figure 4.

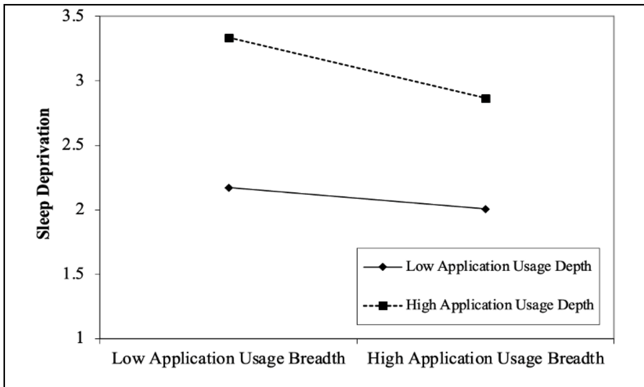
5.2 Post Hoc Analysis

We further conducted subsample analyses based on the age and gender of respondents to generate deeper insights into our hypothesized relationships. First, we divided groups according to gender. As shown in Table 10, the Model 1 male sample displays consistent results with the full sample, while the female sample contains observations that deviate from the full sample for four paths, namely nomophobia → sleep deprivation, application usage breadth × physical activity → sleep deprivation, application usage depth × physical activity → sleep deprivation, and application usage breadth × application usage depth × physical activity → nomophobia.

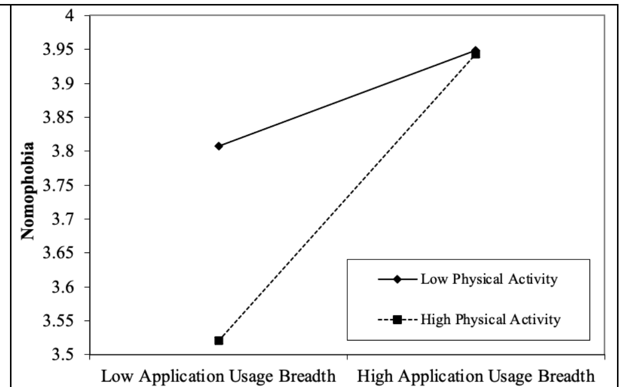
Second, we conducted an analysis based on two age groups (≤ 21 years old and > 21 years old). Our analytical results show that results are identical to the full sample for respondents in the older age group (Model 2). However, analytical results for the younger age group (Model 1) differ from the full sample for two paths: nomophobia → sleep deprivation and application usage breadth × physical activity → nomophobia.

We further performed a mediation analysis to ascertain whether mobile application usage breadth, mobile application usage depth, and the interaction between mobile application usage breadth and depth were fully or partially mediated by nomophobia and sleep deprivation. The results of the mediation analysis appear in Table 12. Nomophobia was found to have no statistically significant mediating role in the impact of mobile application usage breadth on health status, the impact of mobile application usage depth on health status, and the impact of the interaction between mobile application usage breadth and depth on health status. Sleep deprivation was found to fully mediate the impact of mobile application usage breadth on health status, partially mediate the impact of mobile application usage depth on health status, and partially mediate the impact of the interaction between mobile application usage breadth and depth on health status. We found no statistically significant mediating role for the impact of nomophobia on health status.

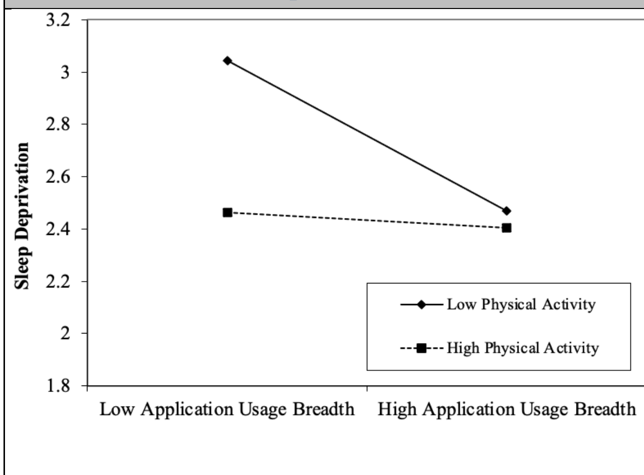
Considering the potential direct effects of physical activity on nomophobia, sleep deprivation, and health status, we further examined the direct effects of physical activity on nomophobia, sleep deprivation, and health status. As shown in Appendix E, the direct impact of physical activity on nomophobia is insignificant (β = -0.006; p = 0.639). We also found that the R^2 of nomophobia, sleep deprivation, and health status decreased if physical activity changed from the moderator to the independent variable. Analytical results confirm the validity of considering the moderating effect of physical activity.



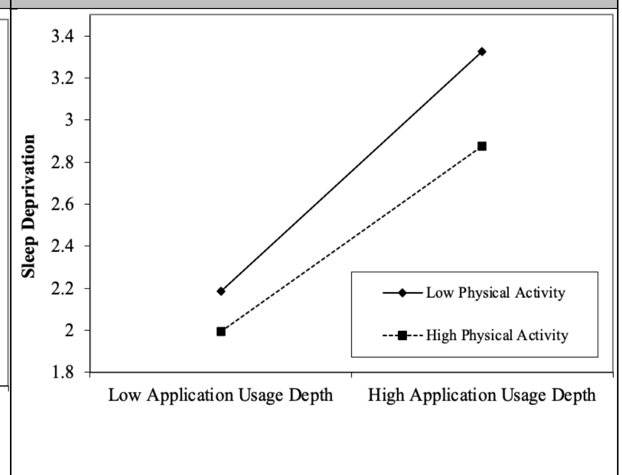
H3b: Application Usage Breadth × Depth → Sleep Deprivation



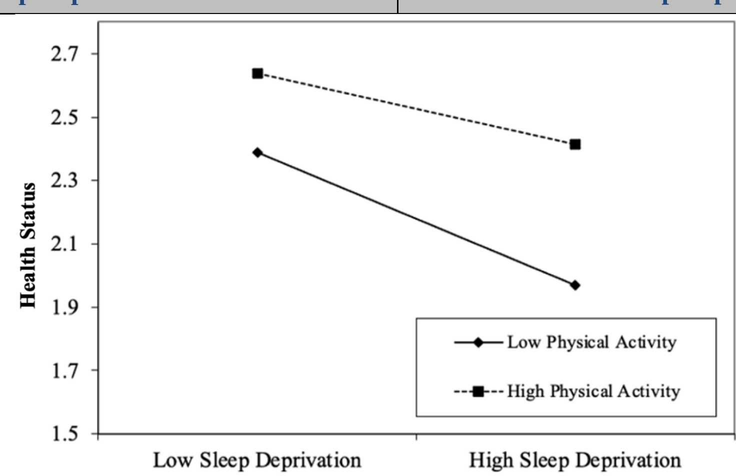
H6a: Application Usage Breadth × Physical Activity → Nomophobia



H6d: Application Usage Breadth × Physical Activity → Sleep Deprivation

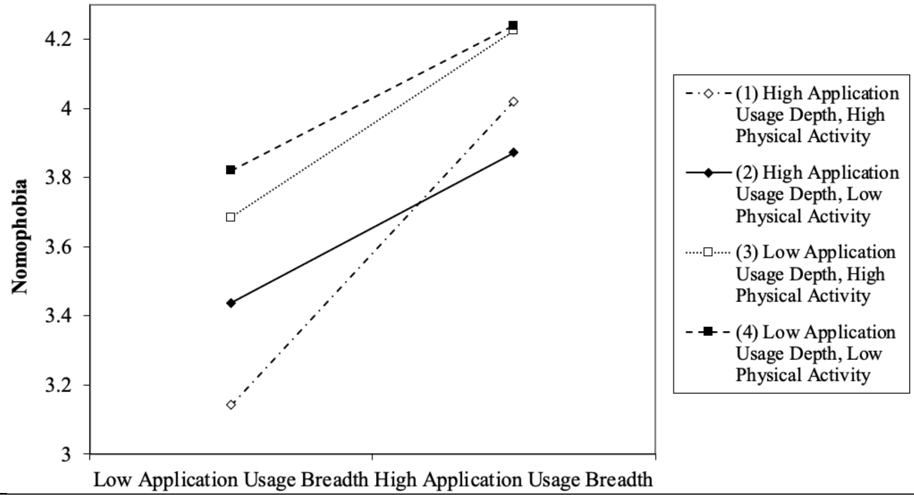


H6e: Application Usage Depth × Physical Activity → Sleep Deprivation

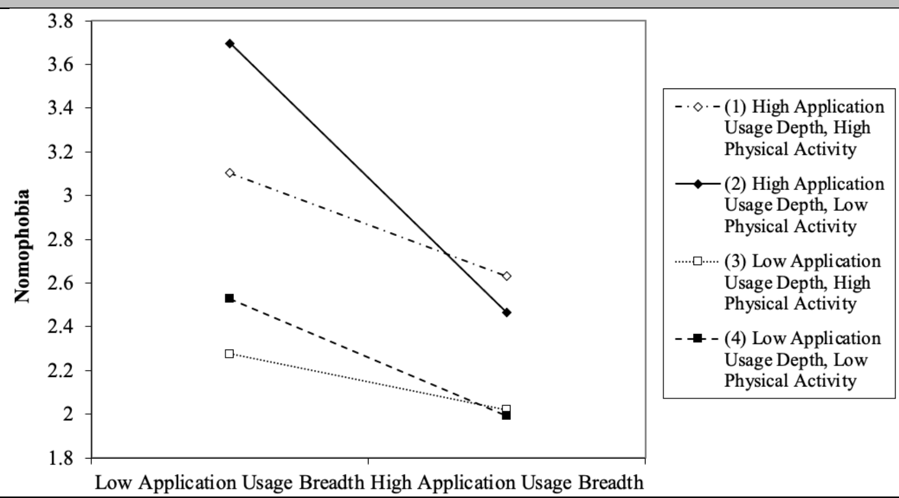


H7b: Sleep Deprivation × Physical Activity → Health Status

Figure 3. Interaction and Moderating Effects



H6c: Interaction between Application Usage Breadth and Depth × Physical Activity → Nomophobia



H6f: Interaction between Application Usage Breadth and Depth × Physical Activity → Sleep Deprivation

Figure 4. Three-Way Interaction Effects

Table 10. Analytical Results based on Gender of Participants

Path	**Baseline model (full sample)**		**Model 1 (male sample)**		**Model 2 (female sample)**	
	Coefficient	***t*-test value**	**Coefficient**	***t*-test value**	**Coefficient**	***t*-test value**
AUB → NOM	0.141***	4.688	0.144***	4.445	0.067*	2.356
AUD → NOM	-0.246***	6.174	-0.155***	5.878	-0.091***	3.796
IBD → NOM	0.028n.s.	1.786	0.046n.s.	1.762	0.022n.s.	0.890
AUB → SD	-0.159***	7.305	-0.122**	3.369	-0.142***	4.770
AUD → SD	0.506***	17.533	0.265***	9.991	0.307***	12.275
IBD → SD	-0.076***	6.776	-0.126***	4.554	-0.119***	4.586
NOM → SD	0.029*	2.558	0.046**	2.725	0.013n.s.	0.638
NOM → HS	-0.059***	8.815	-0.095***	5.917	-0.136***	7.602
SD → HS	-0.161***	21.748	-0.289***	16.078	-0.252***	13.652
AUB × PA → NOM	0.070*	2.432	0.072*	2.341	0.016n.s.	0.536
AUB × PA → SD	0.129***	6.180	0.187***	5.919	0.056n.s.	1.710
AUD × PA → NOM	0.001n.s.	0.034	-0.011n.s.	0.497	0.013n.s.	0.556
AUD × PA → SD	-0.065***	4.076	-0.079**	3.176	-0.031n.s.	1.150
IBD × PA → NOM	0.052***	3.821	0.069**	2.879	0.033n.s.	1.433
IBD × PA → SD	0.078***	7.966	0.175***	6.711	0.070**	2.836
Nom × PA → HS	-0.012n.s.	1.549	-0.022n.s.	1.327	-0.019n.s.	1.149
SD × PA → HS	0.049***	7.223	0.089***	5.461	0.066***	3.896

R²			
NOM	13.9%	11.0%	11.6%
SD	10.9%	11.4%	9.7%
HS	14.5%	15.9%	12.8%
Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status. *** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = "not significant."			

Table 11. Analytical Results Based on the Age of Participants

Path	**Baseline Model (Full Sample)**		**Model 1 (≤ 21 years old)**		**Model 2 (> 21 years old)**	
	Coefficient	***t*-test Value**	**Coefficient**	***t*-test Value**	**Coefficient**	***t*-test Value**
AUB → NOM	0.141***	4.688	0.090**	3.005	0.104***	3.571
AUD → NOM	-0.246***	6.174	-0.090***	3.431	-0.126***	5.495
IBD → NOM	0.028n.s.	1.786	0.042n.s.	1.709	0.027n.s.	1.120
AUB → SD	-0.159***	7.305	-0.101**	3.005	-0.168***	5.050
AUD → SD	0.506***	17.533	0.265***	9.533	0.309***	12.462
IBD → SD	-0.076***	6.776	-0.114***	4.171	-0.117***	4.344
NOM → SD	0.029*	2.558	0.031n.s.	1.696	0.039*	2.159
NOM → HS	-0.059***	8.815	-0.116***	6.468	-0.113***	7.149
SD → HS	-0.161***	21.748	-0.266***	14.502	-0.273***	15.030
AUB × PA → NOM	0.070*	2.432	0.023n.s.	0.780	0.070*	2.434
AUB × PA → SD	0.129***	6.180	0.100**	3.010	0.144***	4.608
AUD × PA → NOM	0.001n.s.	0.034	0.006n.s.	0.246	-0.006n.s.	0.308
AUD × PA → SD	-0.065***	4.076	-0.070**	2.677	-0.057*	2.317
IBD × PA → NOM	0.052***	3.821	0.053*	2.416	0.060**	2.700
IBD × PA → SD	0.078***	7.966	0.108***	4.238	0.130***	5.217
Nom × PA → HS	-0.012n.s.	1.549	-0.026n.s.	1.604	-0.012n.s.	0.684
SD × PA → HS	0.049***	7.223	0.083***	4.998	0.076***	4.559
R²						
NOM	13.9%		11.5%		11.1%	
SD	10.9%		10.9%		11.3%	
HS	14.5%		14.5%		15.2%	
Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status. *** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = "not significant."						

Table 12. Results of the Mediation Analysis

Independent variable	**Relationship**	**Direct effect**	**Specific indirect effect**	**Mediation effect**
AUB	AUB → NOM → HS	-0.013 n.s.	-0.002 n.s.	No mediation
AUB	AUB → SD → HS	-0.013 n.s.	0.039***	Full mediation
AUD	AUD → NOM → HS	-0.074***	0.003 n.s.	No mediation
AUD	AUD → SD → HS	-0.074***	-0.084***	Partial mediation
IBD	IBD → NOM → HS	0.059***	-0.001 n.s.	No mediation
IBD	IBD → SD → HS	0.059***	0.033***	Partial mediation
NOM	NOM → SD → HS	-0.059***	-0.003 n.s.	No mediation
Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status. *** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = "not significant."				

6 Discussion

Grounded in COR, this study scrutinizes the impact of mobile application usage patterns on nomophobia and sleep deprivation, which in turn affects users' health status. We also consider the moderating role of physical activity in this research model. Our findings reveal different impacts of mobile application usage breadth and depth on users' nomophobia and sleep deprivation. We also demonstrate the influence of nomophobia and sleep deprivation on health status. The results indicate that some hypothesized moderating effects remain unsupported.

Our analytical results reveal distinct roles of mobile application usage breadth and depth in inducing physiological and psychological symptoms. Consistent with our hypotheses (i.e., H1a, H1b, H2a, and H2b), the results indicate a trade-off between breadth and depth in the usage of mobile applications. Specifically, mobile application usage breadth depletes psychological resources in terms of nomophobia but replenishes physiological resources regarding the improvement of sleep. For mobile application usage depth, although it reduces sleep by consuming physiological resources, it contributes to the elimination of nomophobia bolstering providing psychological resources. We also found that the interaction between breadth and depth has no significant effect on nomophobia (i.e., H3a) but has a negative effect on sleep deprivation (i.e., H3b). In other words, using a large range of mobile applications for a long time has no additional impact on nomophobia but can alleviate the detrimental impact of mobile application usage depth on sleep. This unexpected finding may be due to the exhaustion users perceive when they use many mobile applications (Dhir et al., 2018). Their perceived fatigue may make them fall asleep faster rather than fostering insomnia. Finally, the mobile application usage patterns uncovered in our analytical results determined over 10% of variance of nomophobia and sleep deprivation, indicating the pivotal role that mobile application usage plays in impacting health. Our findings resonate with past studies on the impact of mobile application usage on physiological and psychological health, with R^2 varying from 10.0% to 20.0% (e.g., Dallinga et al., 2015; Woods & Scott, 2016; Cao et al., 2018). Although physiological and psychological health is determined by many aspects such as diet (McCarthy & Birney, 2021), genetics (McCarthy & Birney, 2021), and interpersonal relationships (Meyer et al., 2021), the significance of mobile application usage on health outcomes cannot be understated in the digital era.

Our findings show that the influences of nomophobia and sleep deprivation are similar. Specifically, the negative impact of nomophobia on sleep deprivation is significant (i.e., H4a), consistent with Salo et al. (2019), who showed that the increasing use of social media contributes to the development of delayed bedtimes and sleep disorders. Nevertheless, the negative impact of nomophobia on sleep deprivation was shown to be insignificant for female and younger users. A possible reason for this is that female and younger users may be resistant to the interference of psychological resource consumption on sleep. Aligning with our hypothesis (i.e., H4b), nomophobia exerts a harmful impact on health status. This finding coincides with prior empirical evidence advocating the unfavorable health consequences of nomophobia, including depression, anxiety, social overload, internet addiction, and exhaustion (e.g., Maier et al, 2015a, b; Primack et al., 2017; Turel & Serenko, 2012; Salo et al., 2019). Similarly, we found that sleep deprivation exerts a detrimental impact on health status (i.e., H5), which extends extant findings on this impact to the mobile application usage context (Agathão et al., 2020; Chen et al., 2006; Lemola et al., 2015; Tahmasian et al., 2020).

In addition, our research model explains a 14.5% variance in health status, which is comparable with prior research focusing on health status, ranging from 9.0% to 13.8% (e.g., Hale et al., 2005; Dallinga et al., 2015; Suso-Ribera et al., 2019). Although health status is impacted by other factors like hearing impairment (Marmamula et al., 2021), negative emotions (Lepp, Barkley, & Karpinski, 2014), and poor eyesight (Marmamula et al., 2021), our findings reveal that mobile application usage is an important factor that impacts health status by drawing on users' physiological and psychological resources.

Some of the moderating effects of physical activity we hypothesized are not supported by the results. The hypothesized moderating effects of physical activity are not supported in relationships involving nomophobia (i.e., H6a, H6b, H6c, and H7a), which is induced by the consumption of psychological resources. This result could be attributed to the ineffective role of physical activity in consolidating and restoring users' psychological resources (Tanaka et al., 2009).

In particular, our findings show that physical activity increases the harmful impact of mobile application usage breadth on nomophobia. One explanation is that the time spent on physical activity reduces the time users have to perform other tasks, causing them to rely on mobile applications to efficiently fulfill obligations. In this sense, such users would be more vulnerable to nomophobia induced by using a wide range of mobile applications to solve problems. However, physical activity was not shown to strengthen the harmful impact of mobile application usage breadth on nomophobia among younger users. A possible reason is that younger students have more idle time, allowing them to devote time to physical activity without reducing time allocated to other activities. Regarding the impact of mobile application usage depth on nomophobia, our findings show that physical activity is ineffective for alleviating the psychological resource consumption caused by long-term usage of a specific category of mobile applications. While we hypothesized that physical activity would weaken the interactional effects of mobile application usage breadth and depth on nomophobia, we found the opposite to be true. As explained before, users engaging in intense physical activity may have less time available for other tasks, which may cause them to rely more on mobile applications to complete tasks efficiently. This would strengthen the effect of the interaction between mobile application usage breadth and depth on nomophobia. In addition, we found that physical activity is insignificant for alleviating the negative effects of nomophobia on health status (i.e., H7a). This could also be attributed to the argument that physical activity does not bolster one's psychological resources and thus does not counter the negative health effects caused by nomophobia (Tanaka et al., 2009).

Hypotheses pertaining to the moderating role of physical activity in relationships involving sleep deprivation (i.e., H6d, H6e, and H6f) are mostly supported. Specifically, we found that physical activity generally weakens the influence of mobile application usage breadth and depth on sleep deprivation. However, for female users, we found that physical activity does not weaken the influence of mobile application usage breadth and depth on sleep deprivation, which could be attributed to gender differences in terms of physiological resource stockpile recovery through physical activity. Although the interactional effects generated by mobile application usage breadth and depth on sleep deprivation are reversed per our expectations, physical activity further weakens this interaction effect. Moreover, we found that physical activity alleviates the negative effect of sleep deprivation on health status (i.e., H7b). These findings resonate with the advice to engage in physical activity to reduce the negative impact of mobile application usage on sleep quality (Haripriya et al., 2019; Kim et al., 2015; Sleep Foundation, 2021b).

Interestingly, our findings suggest that physical activity is not always the ideal way to cope with the detrimental effects of mobile application usage, which depend on mobile application usage patterns. These findings provide a nuanced interpretation of the role of physical activity in countering the negative health effects of mobile application usage, which differs from previous findings maintaining that physical activity is always the best way to improve health (e.g., Bulley et al., 2009; Bloodworth, 2012; Kohl et al., 2012; Li et al., 2009; Lovelace, 2007).

6.1 Implications for Theory

This study contributes to the extant literature on three fronts. First, it scrutinizes mobile application usage patterns by investigating the distinct impacts of breadth and depth on physiological and psychological symptoms (i.e., nomophobia and sleep deprivation). The existing literature on the impact of mobile phone usage on physiological and psychological health has mostly focused on the intensity of usage, such as mobile phone overuse (Fu et al., 2021; Kim et al., 2017; Li & Chan, 2021; Kuem et al., 2021), problematic mobile phone usage (Horwood & Anglim, 2019; Gong et al., 2021), social media overdependence (Salo et, 2019), and mobile phone addiction (Enez Darcin et al., 2016; Kim et al., 2015; Turel, 2015; Liu et al., 2017). Little attention has been paid to usage patterns and how they might help users determine how to strategically use different categories of mobile applications to reduce detrimental impacts on health and increase positive impacts. By using breadth and depth to measure mobile application usage patterns (Harrison & Klein, 2007; Limayem et al., 2007; Chircu & Mahajan, 2009; Khatri & Vessey, 2016), this study reveals the different impacts exerted by these two dimensions. Specifically, using a wide range of mobile applications (breadth) causes nomophobia but reduces sleep deprivation. In contrast, frequent usage of certain mobile applications (depth) increases sleep deprivation but may relieve nomophobia. Further, while symptoms of nomophobia are aggravated when users frequently access a wide range of mobile applications, this usage pattern can actually reduce sleep deprivation. These interesting findings on the different roles of the breadth and depth of mobile application usage illuminate the importance of adopting a multidimensional view to understand the influence of mobile application usage patterns on health status.

Second, this study is among the pioneering attempts to systematically introduce COR theory to the study of mobile application usage. Although past studies have examined the detrimental impact of mobile phone usage through a variety of theoretical lenses, they have omitted the fundamental role of resources in inducing physiological and psychological symptoms that undermine health status. By addressing the role of resources, COR theory presents a useful lens with which to unravel the underlying mechanism by adopting the perspective of user resource depletion and acquisition to comprehend the effects of mobile application usage patterns (Hobfoll, 2001; Halbesleben et al., 2014). This study's results further support the applicability of COR theory in addressing mobile application usage, enriching previous research by explicating different mechanisms of mobile application usage breadth and depth in affecting users' physiological and psychological resources (Liu et al., 2017; Elhai et al., 2018; Park et al., 2019; Salo et al., 2019; Fu et al., 2021). We found that mobile application usage breadth consumes physiological resources but replenishes psychological resources. In contrast, mobile application usage depth consumes psychological resources but replenishes physiological resources.

Third, this study enriches the literature on the moderating role of physical activity in alleviating the detrimental impact of mobile application usage. Previous studies recommended that users engage in physical activity to recover from the resource consumption caused by mobile application usage (Kohl et al., 2012; Xu, Turel, & Yuan, 2012; Wiese et al., 2017; Mahapatra, 2019; Cemiloglu et al., 2022). Our findings, however, indicate that the role of physical activity in expanding resource stockpiles depends on different scenarios. Contrary to our expectations, we found that physical activity aggravates the detrimental impact on nomophobia caused by mobile application usage breadth, likely due to its consumption of users' mental energy. This study therefore extends previous studies by identifying the scenarios where physical activity reduces the detrimental effects of mobile application usage. Given the effective role of physical activity in enlarging the stockpiles of physiological resources rather than psychological resources (Tanaka et al., 2009), the moderating role of physical activity is reflected more in alleviating the negative impact of mobile application usage on sleep deprivation rather than on nomophobia.

6.2 Implications for Practice

The findings from this research offer guidelines on how to manage the detrimental impact of mobile application usage on two fronts: adjusting mobile app usage patterns and participating in physical activity, depending on the scenarios involved. First, given the difficulty of reducing mobile application usage, this study endeavors to provide suggestions on how users can arrange their usage breadth and depth to ameliorate detrimental impacts on health status. Currently, most studies demonstrate the detrimental effects of mobile application usage on health and suggest restricting access to mobile applications as a solution (e.g., Turel, 2015; Zhang et al., 2016; Salo et al., 2019). However, merely cutting down mobile application usage is not feasible for many users, given the increasing role of mobile applications in users' daily lives. This difficulty is evidenced by a recent report in Finland that found that a quarter of Finnish middle school students have tried but failed to spend less time on their mobile phones (Yle, 2019). Our study provides an alternative approach to dealing with this problem by focusing on the breadth and depth of usage across mobile application categories. Our findings reveal that the breadth of mobile application usage may induce nomophobia but, at the same time, reduce sleep deprivation, whereas the depth of mobile application usage can induce sleep deprivation but reduce nomophobia. In this way, the different roles of breadth and depth indicate a possibility for reshaping users' usage patterns based on their health conditions. For example, users who exhibit symptoms of nomophobia should attempt to reduce the categories of mobile applications with which they engage. Meanwhile, sleep-deprived users should attempt to reduce their mobile application usage frequency. Maintaining good sleep habits is important to counter the detrimental impact of mobile application usage on one's health.

Second, users should carefully determine their level of physical activity based on their health conditions to alleviate the harmful impact of mobile application usage. As this study has shown, physical activity is not a universal solution. Those who use a wide range of mobile applications should be aware that intense physical activity may increase their vulnerability to nomophobia. Individuals who use mobile applications extensively should consider getting more physical exercise to mitigate sleep deprivation. Moreover, for mobile application users who suffer from nomophobia, physical activity is not a viable way to prevent detrimental effects on their health. However, for users with sleep problems, physical activity is useful for improving their health.

As shown in Table 13, we develop a set of remedies based on our findings to help users with different mobile phone usage patterns deal with symptoms of nomophobia and/or sleep deprivation. We suggest that users carefully consider their mobile application usage patterns and symptoms to decide on the appropriate remedy to improve their health. For users who use mobile applications widely and intensively, if they have symptoms of nomophobia, we recommend that they reduce the number of mobile applications categories they engage with in order to reduce their psychological resource consumption and allocate exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications. If users have symptoms of sleep deprivation, we recommend that they reduce their in-depth usage of mobile applications to decrease physiological resource consumption and engage in more physical activity to enlarge their physiological resource stockpiles. For users who use mobile applications widely and nonintensively, if they have symptoms of nomophobia, we recommend that they reduce the number of mobile applications categories they engage with in order to reduce psychological resource consumption, increase the in-depth usage of mobile applications to replenish psychological resources, and allocate exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications. If users suffer from sleep deprivation, we recommend that they engage in more physical activity to enlarge their physiological resource stockpiles. For users who use mobile applications narrowly and intensively, if they have symptoms of nomophobia, we recommend that they allocate exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications. If such users suffer from sleep deprivation, we recommend that they expand the number of categories of mobile applications they engage with to ensure efficient need fulfillment, reduce in-depth usage of mobile applications to decrease physiological resource consumption, and engage in more physical activity to enlarge their physiological resource stockpiles. For users who use mobile applications narrowly and nonintensively, if they have symptoms of nomophobia, we recommend that they increase their in-depth usage of mobile applications appropriately to replenish psychological resources and allocate exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications. If such users suffer from sleep deprivation, we recommend that they expand the numbers of categories of mobile applications they engage with to ensure efficient need fulfillment and engage in more physical activity to enlarge their physiological resource stockpiles.

Table 13. Remedies for Managing the Detrimental Impact of Mobile Application Usage

<table>
<tr><th>Users' mobile application usage pattern</th><th>Symptom</th><th>Remedy</th></tr>
<tr><td rowspan="2">High application usage breadth
High application usage depth</td><td>Nomophobia</td><td>• Narrowing down the categories of mobile applications to reduce psychological resource consumption
• Allocating exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications</td></tr>
<tr><td>Sleep deprivation</td><td>• Reducing in-depth usage of mobile applications to decrease physiological resource consumption
• Engaging in more physical activity to enlarge physiological resource stockpile</td></tr>
<tr><td rowspan="2">High application usage breadth
Low application usage depth</td><td>Nomophobia</td><td>• Narrowing down the categories of mobile applications to reduce psychological resource consumption
• Increasing the in-depth usage of mobile applications appropriately to replenish psychological resources
• Allocating exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications</td></tr>
<tr><td>Sleep deprivation</td><td>• Engaging in more physical activity to enlarge physiological resource stockpiles</td></tr>
<tr><td rowspan="2">Low application usage breadth
High application usage depth</td><td>Nomophobia</td><td>• Allocating exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications</td></tr>
<tr><td>Sleep deprivation</td><td>• Expanding the categories of mobile applications to ensure efficient need fulfillment
• Reducing in-depth usage of mobile applications to decrease physiological resource consumption
• Engaging in more more physical activity to enlarge physiological resource stockpile</td></tr>
<tr><td rowspan="2">Low application usage breadth
Low application usage depth</td><td>Nomophobia</td><td>• Increasing in-depth usage of mobile applications appropriately to replenish psychological resources
• Allocating exercise time appropriately vis-à-vis other daily tasks to reduce reliance on mobile applications</td></tr>
<tr><td>Sleep deprivation</td><td>• Expanding the categories of mobile applications to ensure efficient needs fulfillment
• Engaging in more physical activity to enlarge physiological resource stockpiles</td></tr>
</table>

6.3 Limitations and Avenues for Future Research

This study has several limitations that provide avenues for future research. First, this research focuses on the detrimental health impacts of mobile application usage and neglects its benefits to users in other areas. We therefore recommend that future research jointly consider the costs and benefits associated with mobile application usage to determine how these two aspects interact when contributing to users' well-being.

Second, we analyze nine categories of mobile applications, which offers a foundation for future scrutiny of more detailed and sophisticated types of mobile applications. Scholars might investigate specific categories to figure out their impact on users' health. For example, fitness applications can potentially contribute to users' health by reminding them to exercise.

Third, we introduced COR theory as a novel perspective for studying the effects of mobile application usage on users' health status. Future research could probe the countermeasures for the negative impacts of mobile application usage on users' health status from different theoretical perspectives such as coping theory. Coping theory delineates approaches through which users can leverage different physiological and psychological resources to deal with health issues induced by mobile application usage (Lazarus, & Folkman, 1984). Although this study considers the physiological and psychological consequences of nomophobia and sleep deprivation on general health status, future studies might explore specific psychological outcomes (e.g., stress, anxiety, or depression) and physiological outcomes (e.g., poor eyesight, headaches, or tenosynovitis). Moreover, detrimental impacts can be measured in diverse ways; thus, future work might introduce testing for other dimensions of detrimental impacts, such as those related to work and academic performance.

Finally, our study is based on a questionnaire survey conducted among university students in China. Although using such a large sample size is important to ensure the validity of the results, future studies should extend this work to other contexts. By incorporating respondents from multiple cultures and age groups, scholars can work toward improving generalizability. Future research could also collect longitudinal data to address potential issues regarding causality and endogeneity existing in cross-sectional data sets. Additionally, future research could collect secondary mobile usage data to objectively measure mobile application usage breadth and depth (Lim et al., 2016; Wu et al., 2022), thus further verifying the relevant conclusions of this study.

Acknowledgments

We warmly acknowledge the support received from the National Social Science Fund of China (22CTQ018).

References

Aiken, L. S., & Stephen, G. (1991). *Multiple regression: Testing and interpreting interactions*. SAGE.

Agogo, D., & Hess, T. J. (2018). "How does tech make you feel?" A review and examination of negative affective responses to technology use. *European Journal of Information Systems*, *27*(5), 570-599.

Amschler, D. H., & McKenzie, J. F. (2005). Elementary students' sleep habits and teacher observations of sleep-related problems. *Journal of School Health*, *75*(2), 50-56.

Arakawa, M., Taira, K., Tanaka, H., Yamakawa, K., Toguchi, H., Kadekaru, H., Yamamoto., Y., Uezu, E., & Shirakawa, S. (2001). A survey of junior high school students' sleep habit and lifestyle in Okinawa. *Psychiatry and Clinical Neurosciences*, *55*(3), 211-212.

Agathão, B. T., Lopes, C. S., Cunha, D. B., & Sichieri, R. (2020). Gender differences in the impact of sleep duration on common mental disorders in school students. *BMC Public Health*, 20(1), e148.

Angehrn, A., Teale Sapach, M. J., Ricciardelli, R., MacPhee, R. S., Anderson, G. S., & Carleton, R. N. (2020). Sleep quality and mental disorder symptoms among Canadian public safety personnel. *International Journal of Environmental Research and Public Health*, *17*(8), e2708.

Advanced Sleep Medicine Service. (2015). *Does pre-bed video gaming ruin your sleep?* https://www.sleepdr.com/the-sleep-blog/does-pre-bed-video-gaming-ruin-your-sleep/

Baccarella, C. V, Wagner, T. F., Kietzmann, J. H., & Mccarthy, I. P. (2018). Social media? It's serious! Understanding the dark side of social media. *European Management Journal*, *36*(4), 431-438.

Bamberger, P. A., Geller, D., & Doveh, E. (2017). Assisting upon entry: Helping type and approach as moderators of how role conflict affects newcomer resource drain. *Journal of Applied Psychology*, *102*(12), 1719-1732.

Barkley, J. E., Lepp, A., & Salehi-Esfahani, S. (2016). College students' mobile telephone use is positively associated with sedentary behavior. *American Journal of Lifestyle Medicine*, *10*(6), 437-441.

Beard, C., Silverman, A. L., Forgeard, M., Wilmer, M. T., Torous, J., & Björgvinsson, T. (2019). Smartphone, social media, and mental health app use in an acute transdiagnostic psychiatric sample. *JMIR mHealth and uHealth, 7*(6), Article e13364.

Bhattacharya, S., Bashar, M. A., Srivastava, A., & Singh, A. (2019). NOMOPHOBIA: No mobile phone phobia. *Journal of Family Medicine and Primary Care, 8*(4), 1297-1300.

Booth, M. L., Okely, A. D., Chey, T., & Bauman, A. (2001). The reliability and validity of the physical activity questions in the WHO health behaviour in schoolchildren (HSBC) survey: A population study. *British Journal of Sports Medicine, 35*(4), 263-267.

Bulley, C., Donaghy, M., Payne, A., & Mutrie, N. (2009). Personal meanings, values and feelings relating to physical activity and exercise participation in female undergraduates: A qualitative exploration. *Journal of Health Psychology, 14*(6), 751-760.

BuildFire. (2021). *Mobile app download and usage statistics 2021*. https://buildfire.com/app-statistics/

Bloodworth, A., McNamee, M., & Bailey, R. (2012). Sport, physical activity and well-being: An objectivist account. *Sport, Education and Society*, *17*(4), 497-514.

Biddle, S., Fox, K., Boutcher, S., & Faulkner, G. (2000). The way forward for physical activity and the promotion of psychological well-being. In S. H. B. Stuart Biddle, Kenneth R. Fox (Ed.), *Physical activity and pscyhological well-being* (pp. 154-168). Routledge.

BBC. (2019a). *Heavy social media use linked to poor sleep*. https://www.bbc.com/news/health-5014011

BBC. (2019b). *Why are people shopping online late at night?* https://www.bbc.com/news/business-49 633006

Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in Human Behavior, 85*, 163-174.

Carter, M., Petter, S., Grover, V., & Thatcher, J. B. (2020). Information technology identity: A key determinant of IT feature and exploratory usage. *MIS Quarterly, 44*(3): 983-1021.

Cemiloglu, D., Almourad, M. B., McAlaney, J., & Ali, R. (2022). Combatting digital addiction: Current approaches and future directions. *Technology in Society, 68*, 101832.

Cook, T. D., Campbell, D. T., & Day, A. (1979). *Quasi-experimentation: Design & analysis issues for field settings*. Houghton Mifflin.

Chen, M., Wang, E. K., & Jeng, Y. (2006). Adequate sleep among adolescents is positively associated with health status and health-related behaviors. *BMC Public Health, 6*, Article e59.

Chen, C. (2020). Playing mobile games for stress recovery purposes: A survey of Chinese adolescents. *Telematics and Informatics*, Article e101481.

Chiu, S. I. (2014). The relationship between life stress and smartphone addiction on Taiwanese university student: A mediation model of learning self-efficacy and social self-efficacy. *Computers in human behavior*, *34*, 49-57.

Chircu, A. M., & Mahajan, V. (2009). Perspective: Revisiting the digital divide: An analysis of mobile technology depth and service breadth in the BRIC countries. *Journal of Product Innovation Management*, *26*(4), 455-466.

Chung, S., Animesh, A., Han, K., & Pinsonneault, A. (2020). Financial returns to firms' communication actions on firm-initiated social media: Evidence from Facebook business pages. *Information Systems Research, 31*(1), 258-285.

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

Dallinga, J. M., Mennes, M., Alpay, L., Bijwaard, H., & De La Faille-Deutekom, M. B. (2015). App use, physical activity and healthy lifestyle: A cross sectional study. *BMC Public Health*, *15*(1), Article e833.

Das, P., Horton, R. (2012). Rethinking our approach to physical activity. *Lancet*, *380*(9838): 189-190.

Demerouti, E., Bakker, A. B., & Bulters, A. (2004). The loss spiral of work pressure, work-home interface and exhaustion: Reciprocal relations in a three-wave study. *Journal of Vocational Behavior, 64*, 131-149.

DeSalvo, K. B., Bloser, N., Reynolds, K., He, J., & Muntner, P. (2006a). Mortality prediction with a single general self-rated health question. *Journal of General Internal Medicine, 21*(3), 267-275.

DeSalvo, K. B., Fisher, W. P., Tran, K., Bloser, N., Merrill, W., & Peabody, J. (2006b). Assessing measurement properties of two single-item general health measures. *Quality of Life Research, 15*(2), 191-201.

DeSalvo, K. B., Jones, T. M., Peabody, J., McDonald, J., Fihn, S., Fan, V., He, J., & Muntner, P. (2009). Health care expenditure prediction with a single item, self-rated health measure. *Medical Care, 47*(4), 440-447.

Dhir, A., Yossatorn, Y., Kaur, P., & Chen, S. (2018). Online social media fatigue and psychological wellbeing—A study of compulsive use, fear of missing out, fatigue, anxiety and depression. *International Journal of Information Management, 40*, 141-152.

Elhai, J. D., Tiamiyu, M., & Weeks, J. (2018). Depression and social anxiety in relation to problematic smartphone use. *Internet Research, 38*(2): 315-332.

Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep in adults. *Social Science & Medicine, 148*, 93-101.

Enez Darcin, A., Kose, S., Noyan, C. O., Nurmedov, S., Yılmaz, O., & Dilbaz, N. (2016). Smartphone addiction and its relationship with social anxiety and loneliness. *Behaviour & Information Technology*, *35*(7), 520-525.

Fang, B., Zheng, Z., Ye, Q., & Goes, P. B. (2019). Social influence and monetization of freemium social games. *Journal of Management Information Systems*, *36*(3), 730-754.

Ferdous, R., Osmani, V., & Mayora, O. (2018). Smartphone apps usage patterns as a predictor of perceived stress levels at workplace. Available at https://arxiv.org/pdf/1803.03863.pdf

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Fu, S., Chen, X., & Zheng, H. (2021). Exploring an adverse impact of smartphone overuse on academic performance via health issues: A stimulus-organism-response perspective. *Behaviour and Information Technology, 40*(7), 663-675.

Fu, M. Y., Jiang, N., Xiong, B. Q., Tan, C. C, Lim, E., Wang, W. Q (2019). *Seeking connectedness from social media? Deciphering social media usage patterns for working adults.* Presented at the Changing Nature of Work (CNOW) with ICT Workshop at the 23rd Pacific Asia Conference on Information Systems, Xi'an, China.

Gao, T., Li, J., Zhang, H., Gao, J., Kong, Y., Hu, Y., & Mei, S. (2018). The influence of alexithymia on mobile phone addiction: The role of depression, anxiety and stress. *Journal of Affective Disorders, 225*, 761-766.

Gao, Y., Dai, H., Jia, G., Liang, C., Tong, T., Zhang, Z., ... & Zhu, Y. (2020). Translation of the Chinese version of the nomophobia questionnaire and its validation among college students: Factor analysis. *JMIR mHealth and uHealth*, *8*(3), e13561.

Goode, S., Hoehle, H., Venkatesh, V., & Brown, S. (2017). User compensation as a data breach recovery action: An investigation of the Sony PlayStation Network Breach. *MIS Quarterly, 41*(3), 703-727.

Gong, X., Cheung, C. M., Zhang, K. Z., Chen, C., & Lee, M. K. (2021). A dual-identity perspective of obsessive online social gaming. *Journal of the Association for Information Systems*, *22*(5), 1245-1284.

Gong, X., Chen, C., & Lee, M. K. (2020). What drives problematic online gaming? The role of IT identity, maladaptive cognitions, and maladaptive emotions. *Computers in Human Behavior*, *110*, Article e106386.

Gong, X., Zhang, K. Z., Cheung, C. M., Chen, C., & Lee, M. K. (2019). Alone or together? Exploring the role of desire for online group gaming in players' social game addiction. *Information & Management, 56*(6), Article e103139.

Gutiérrez, J. D., Fonseca, F. R. D., & Rubio, G. (2016). Cell-phone addiction: A review. *Frontiers in Psychiatry*, *7*, Article e175.

Gligor, Ș., & Mozoș, I. (2019). Indicators of smartphone addiction and stress score in university students. *Wiener Klinische Wochenschrift, 131*(5-6), 120-125.

Hale, C. J., Hannum, J. W., & Espelage, D. L. (2005). Social support and physical health: The importance of belonging. *Journal of American College Health, 53*(6), 276-284.

Harris, B., Regan, T., Schueler, J., & Fields, S. A. (2020). Problematic mobile phone and smartphone use scales: A systematic review. *Frontiers in Psychology*, *11*, 672.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, *32*(4), 1199-1228.

Hu, Y., Xu, A., Hong, Y., Gal, D., Sinha, V., & Akkiraju, R. (2019). Generating business intelligence through social media analytics: Measuring brand personality with consumer-, employee-, and firm-generated content. *Journal of Management Information Systems, 36*(3), 893-930.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.

Hulland, J. (2015). Use of partial least squares (pls) in strategic management research: A review of four recent studies. *Strategic Management Journal, 20*(2), 195-204.

Halbesleben, J. R., Harvey, J., & Bolino, M. C. (2009). Too engaged? A conservation of resources view of the relationship between work engagement and work interference with family. *Journal of Applied Psychology*, *94*(6), 1452-1465.

Halbesleben, J. R. B., & Wheeler, A. R. (2008). The relative roles of engagement and embeddedness in predicting job performance and intention to leave. *Work & Stress*, *22*, 242-256.

Halbesleben, J. R. B., Neveu, J. P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR": Understanding the role of resources in conservation of resources theory. *Journal of Management*, *40*(5), 1334-1364.

Halbesleben, J. R. B., & Bowler, W. M. (2007). Emotional exhaustion and job performance: The mediating role of motivation. *Journal of Applied Psychology*, *92*, 93-106.

Hammedi, W., Leclerq, T., & Van Riel, A. C. (2017). The use of gamification mechanics to increase employee and user engagement in participative healthcare services. *Journal of Service Management*, *28*(4): 640-661.

Haripriya, S., Samuel, S. E., & Megha, M. (2019). Correlation between smartphone addiction, sleep quality and physical activity among young adults. *Journal of Clinical & Diagnostic Research*, 13(10): 5-9.

Higuchi, S., Motohashi, Y., Liu, Y., Ahara, M., & Kaneko, Y. (2003). Effects of VDT tasks with a bright display at night on melatonin, core temperature, heart rate, and sleepiness. *Journal of Applied Physiology, 94*(5), 1773-1776.

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist, 44*(3), 513-524.

Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. *Applied Psychology*, *50*(3), 337-421.

Horwood, S., & Anglim, J. (2019). Problematic smartphone usage and subjective and psychological well-being. *Computers in Human Behavior, 97*, 44-50.

Jeong, M., Zo, H., Lee, C. H., & Ceran, Y. (2019). Feeling displeasure from online social media postings: A study using cognitive dissonance theory. *Computers in Human Behavior, 97*, 231-240.

Karimikia, H., Singh, H., & Joseph, D. (2021). Negative outcomes of ICT use at work: Meta-analytic evidence and the role of job autonomy. *Internet Research, 31*(1): 159-190.

Khatri, V., & Vessey, I. (2016). Understanding the role of IS and application domain knowledge on conceptual schema problem solving: A verbal protocol study. *Journal of the Association for Information Systems*, *17*(12), 759-803.

Kim, H. J., Min, J. Y., Kim, H. J., & Min, K. B. (2017). Association between psychological and self-assessed health status and smartphone overuse among Korean college students. *Journal of Mental Health, 4*(3), 1-6.

Kim, S. E., Kim, J. W., Jee, Y. S. (2015). Relationship between smartphone addiction and physical activity in Chinese international students in Korea. *Journal of Behavioral Addictions. 4*(3): 200-205.

King, A. L. S., Valença, A. M., Silva, A. C. O., Baczynski, T., Carvalho, M. R., & Nardi, A. E. (2013). Nomophobia: Dependency on virtual environments or social phobia? *Computers in Human Behavior, 29*(1): 140-144.

Kohl, H. W., Craig, C. L., Lambert, E. V., Inoue, S., Alkandari, J. R., Leetongin, G., Kahlmeier, S., & Wells, J. C. (2012). The pandemic of physical inactivity: Global action for public health. *The Lancet, 380*(9838), 294-305.

Kuem, J., Ray, S., Hsu, P. F., & Khansa, L. (2021). Smartphone addiction and conflict: An incentive-sensitisation perspective of addiction for information systems. *European Journal of Information Systems, 30*(4): 403-424.

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). Excessive dependence on mobile social apps: A rational addiction perspective. *Information Systems Research*, *27*(4), 919-939.

Krancher, O., Dibbern, J., & Meyer, P. (2018). How social media-enabled communication awareness enhances project team performance. *Journal of the Association for Information Systems, 19*(9), 813-856.

Larsen-Ledet, I., Korsgaard, H., & Bødker, S. (2020). Collaborative writing across multiple artifact ecologies. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*.

Lazarus, R.S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.

Lee, S., Jackson, C. L., Robbins, R., & Buxton, O. M. (2019). Sleep health and the workplace. In M. A. Grandner, *Sleep and Health* (pp. 457-471). Academic Press.

Lepp, A., Barkley, J. E., & Karpinski, A. C. (2014). The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in Human Behavior, 31*(1), 343-350.

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of US college students. *International Journal of Behavioral Nutrition and Physical Activity, 10*(1), Article e79.

Lemola, S., Perkinson-Gloor, N., Brand, S., Dewald-Kaufmann, J. F., & Grob, A. (2015). Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. *Journal of Youth and Adolescence*, *44*(2), 405-418.

Lim, K. W., Secci, S., Tabourier, L., & Tebbani, B. (2016). Characterizing and predicting mobile application usage. *Computer Communications, 95*, 82-94.

Limayem, M., Hirt, S.G., & Cheung, C.M.K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705-737.

Lin, J., Lin, S., Turel, O., & Xu, F. (2020). The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. *Telematics and Informatics*, *49*, e101374.

Liu, X., & Liu, L. (2005). Sleep habits and insomnia in a sample of elderly persons in China. *Sleep, 28*(12), 1579-1587.

Liu, Q., Zhou, Z., Yang, X., & Kong, F. (2017). Mobile phone addiction and sleep quality among Chinese adolescents: A moderated mediation model. *Computers in Human Behavior, 72*, 108-114.

Li, G. S., Lu, F. J., & Wang, A. H. (2009). Exploring the relationships of physical activity, emotional intelligence and health in Taiwan college students. *Journal of Exercise Science and Fitness, 7*(1), 55-63.

Lovelace, K. J., Manz, C. C., & Alves, J. C. (2007). Work stress and leadership development: The role of self-leadership, shared leadership, physical fitness and flow in managing demands and increasing job control. *Human Resource Management Review*, *17*(4), 374-387.

Mahapatra, S. (2019). Smartphone addiction and associated consequences: Role of loneliness and self-regulation. *Behaviour & Information Technology, 38*(8), 833-844.

Maier, C., Mattke, J., Pflügner, K., & Weitzel, T. (2020). Smartphone use while driving: A fuzzy-set qualitative comparative analysis of personality profiles influencing frequent high-risk smartphone use while driving in Germany. *International Journal of Information Management*, *55*, Article 102207.

Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2015a). Giving too much social support: Social overload on social networking sites. *European Journal of Information Systems, 24*(5), 447-464.

Maier, C., Laumer, S., Weinert, C., & Weitzel, T. (2015b). The effects of technostress and switching stress on discontinued use of social networking services: A study of Facebook use. *Information Systems Journal*, *25*(3), 275-308.

Marmamula, S., Kumbham, T. R., Modepalli, S. B., Barrenkala, N. R., Yellapragada, R., & Shidhaye, R. (2021). Depression, combined visual and hearing impairment (dual sensory impairment): a hidden multi-morbidity among the elderly in Residential Care in India. *Scientific Reports, 11*(1), 1-9.

Martikainen, P., Aromaa, A., Heliövaara, M., Klaukka, T., Knekt, P., Maatela, J., & Lahelma, E. (1999). Reliability of perceived health by sex and age. *Social Science and Medicine, 48*(8), 1117-1122.

McCarthy, M., & Birney, E. (2021). Personalized profiles for disease risk must capture all facets of health. *Nature*, *597*(7875), 175-177.

Meeker, M. (2018). *Internet Trends Report 2018*. TechCrunch https://techcrunch.com/2018/05/30/internet-trends-2018/

Melin, A. K., Heikura, I. A., Tenforde, A., & Mountjoy, M. (2019). Energy availability in athletics: Health, performance, and physique. *International Journal of Sport Nutrition and Exercise Metabolism, 29*(2), 152-164.

Meyer, B., Zill, A., Dilba, D., Gerlach, R., & Schumann, S. (2021). Employee psychological well-being during the COVID-19 pandemic in Germany: A longitudinal study of demands, resources, and exhaustion. *International Journal of Psychology*, *56*(4), 532-550.

Moqbel, M., & Bartelt, V. (2018). Social Network Sites in Businesses: Combating Technostress. *Proceedings of the 51st Hawaii International Conference on System Sciences* (pp. 1846-1853).

MacLean, J. V., Faisal-Cury, A., Chan, Y. F., Menezes, P. R., Winters, A., Joseph, R., & Huang, H. (2015). The relationship between sleep disturbance in pregnancy and persistent common mental disorder in the perinatal period (sleep disturbance and persistent CMD). *Journal of Mental Health, 24*(6), 375-378.

Nah, F. F. H., Siau, K., & Sheng, H. (2005). The value of mobile applications: A utility company study. *Communications of the ACM, 48*(2), 85-90.

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models*. Irwin.

Niemel ̈a, R., Ek, S., Eriksson-Backa, K., & Huotari, M. L. (2012). A screening tool for assessing everyday health information literacy. *Libri, 62*(2), 125-134.

Ng, T. W. H., & Feldman, D. C. (2012). Employee voice behavior: A meta-analytic test of the conservation of resources framework. *Journal of Organizational Behavior, 33*, 216-234.

Osatuyi, B., & Turel, O. (2020). Conceptualisation and validation of system use reduction as a self-regulatory IS use behaviour. *European Journal of Information Systems*, *29*(1), 44-64.

Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2012). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing, 16*(1), 105-114.

Papagiannidis, S., & Marikyan, D. (2020). Smart offices: A productivity and well-being perspective. *International Journal of Information Management*, *51*, Article e102027.

Park, C. S. (2019). Examination of smartphone dependence: Functionally and existentially dependent behavior on the smartphone. *Computers in Human Behavior, 93*, 123-128.

Peukert, C., Pfeiffer, J., Meißner, M., Pfeiffer, T., & Weinhardt, C. (2019). Shopping in virtual reality stores: The influence of immersion on system adoption. *Journal of Management Information Systems, 36*(3), 755-788.

Peracchia, S., & Curcio, G. (2018). Exposure to video games: Effects on sleep and on post-sleep cognitive abilities. *Sleep Science, 11*(4), 302-314.

Penley, J. A., Tomaka, J., & Wiebe, J. S. (2002). The association of coping to physical and psychological health outcomes: A meta-analytic review. *Journal of Behavioral Medicine*, *25*(6), 551-603.

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or instinctive? Proactive and reactive coping for technostress. *Journal of Management Information Systems, 36*(4), 1179-1212.

Primack, B. A., Shensa, A., Escobar-Viera, C. G., Barrett, E. L., Sidani, J. E., Colditz, J. B., & James, A. E. (2017). Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among US young adults. *Computers in Human Behavior, 69*, 1-9.

Probst, T. M., Sinclair, R. R., Sears, L. E., Gailey, N. J., & Cheung, J. H. .(2018). Economic stress and well-being: Does population health context matter?. *Journal of Applied Psychology,103*(9): 959-979.

Podsakoff, P. M., MacKenzie, S. B., Lee. J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903.

Ratnayake, K., Payton, J. L., Lakmal, O. H., & Karunarathne, A. (2018). Blue light excited retinal intercepts cellular signaling. *Scientific Reports, 8*(1), Article e10207.

Ren, Y., Harper, F. M., Drenner, S., Terveen, L., Kiesler, S., Riedl, J., & R. E. Kraut (2012). Building member attachment in online communities: Applying theories of group identity and interpersonal bonds. *MIS Quarterly*, *36*(3): 841-864.

Salo, M., Pirkkalainen, H., & Koskelainen, T. (2019). Technostress and social networking services: Explaining users' concentration, sleep, identity, and social relation problems. *Information Systems Journal, 29*(2), 408-435.

Sarker, S., Xiao, X., Sarker, S., & Ahuja, M. (2012). Managing employees' use of mobile technologies to minimize work-life balance impacts. *MIS Quarterly Executive, 11*(4), 143-157.

Schmaling, K. B., Fiedelak, J. I., Bader, J., & Buchwald, D. (2005). A longitudinal study of physical activity and body mass index among persons with unexplained chronic fatigue. *Journal of Psychosomatic Research, 58*(4), 375-381.

Sleep Foundation. (2021a). *Screen time and insomnia: What it means for teens.* https://www.sleepfoundation.org/teens-and-sleep/screen-time-and-insomnia-for-teens

Sleep Foundation. (2021b). *Exercise and sleep*. https://www.sleepfoundation.org/physical-activity/exercise-and-sleep

SIMFORM. (2021). *App usage statistics 2021 that'll surprise you (updated).* https://www.simform.com/the-state-of-mobile-app-usage/

Shulman, J. D., & Geng, X. (2019). Does it pay to shroud in-app purchase prices?. *Information Systems Research, 30*(3), 856-871.

Suso-Ribera, C., Martínez-Borba, V., Martín-Brufau, R. A. M. O. N., Suso-Vergara, S., & García-Palacios, A. (2019). Individual differences and health in chronic pain: are sex-differences relevant?. *Health and Quality of Life Outcomes, 17*(1), 1-11.

Tarafdar, M., Maier, C., Laumer, S., & Weitzel, T. (2020). Explaining the link between technostress and technology addiction for social networking sites: A study of distraction as a coping behavior. *Information Systems Journal, 30*(1), 96-124.

Tarafdar, M., DArcy, J., Turel, O., & Gupta, A. (2015). The dark side of information technology. *Sloan Management Review, 56*(2), 59-70.

Tarute, A., Nikou, S., & Gatautis, R. (2017). Mobile application driven consumer engagement. *Telematics and Informatics, 34*(4), 145-156.

Tanaka, K., de Quadros Jr, A. C., Santos, R. F., Stella, F., Gobbi, L. T. B., & Gobbi, S. (2009). Benefits of physical exercise on executive functions in older people with Parkinson's disease. *Brain and Cognition*, *69*(2), 435-441.

Tao, S., Wu, X., Zhang, Y., Zhang, S., Tong, S., & Tao, F. (2017). Effects of sleep quality on the association between problematic mobile phone use and mental health symptoms in Chinese college students. *Internatioanl Journal of Environmental Research and Public Health, 14*(135), 1-10.

Tahmasian, M., Samea, F., Khazaie, H., Zarei, M., Masouleh, S. K., Hoffstaedter, F., Camilleri, J., Kochunov, P., Yeo, B., Eickhoff, S., & Valk, S. L. (2020). The interrelation of sleep and mental and physical health is anchored in grey-matter neuroanatomy and under genetic control. *Communications Biology, 3*(1), 1-13.

Turel, O. (2021). Agency over social media use can be enhanced through brief abstinence, but only in users with high cognitive reflection tendencies. *Computers in Human Behavior, 115*, 106590.

Tejpal, P. (2015). Enhancing the job satisfaction level through dimensions of employee engagement: An empirical study on private sector bank managers. *Drishtikon: A Management Journal, 7*(1), 22-40.

Turel, O., & Qahri-Saremi, H. (2016). Problematic use of social networking sites: Antecedents and consequence from a dual-system theory perspective. *Journal of Management Information Systems, 33*(4), 1087-1116.

Turel, O. (2015). Quitting the use of a habituated hedonic information system: A theoretical model and empirical examination of Facebook users. *European Journal of Information Systems, 24*(4), 431-446.

Turel, O., & Serenko, A. (2012). The benefits and dangers of enjoyment with social networking websites. *European Journal of Information Systems, 21*(5), 512-528.

Toker, S., & Biron, M. (2012). Job burnout and depression: Unraveling their temporal relationship and considering the role of physical activity. *Journal of Applied Psychology, 97*(3), 699-710.

Vaghefi, I., Qahri-Saremi, H., & Turel, O. (2020). Dealing with social networking site addiction: A cognitive-affective model of discontinuance decisions. *Internet Research, 30*(5): 1427-1453.

Vinokur, A. D., & Schul, Y. (2002). The web of coping resources and pathways to reemployment following a job loss. *Journal of Occupational Health Psychology, 7*, 68-83.

Wang, C., Lee, M. K., & Hua, Z. (2015). A theory of social media dependence: Evidence from microblog users. *Decision Support Systems, 69*, 40-49.

Wang, C., & Lee, M. K. (2020). Why we cannot resist our smartphones: Investigating compulsive use of mobile SNS from a stimulus-response-reinforcement perspective. *Journal of the Association for Information Systems, 21*(1), 175-200.

Whitman, M. V., Halbesleben, J. R., & Holmes IV, O. (2014). Abusive supervision and feedback avoidance: The mediating role of emotional exhaustion. *Journal of Organizational Behavior, 35*(1), 38-53.

Wiese, C. W., Kuykendall, L., & Tay, L. (2017). Get active? A meta-analysis of leisure-time physical activity and subjective well-being. *Journal of Positive Psychology, 13*(1), 57-66.

Woods, H.C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *Journal of Adolescence, 51*, 41-49.

Wolfers, L. N., Festl, R., & Utz, S. (2020). Do smartphones and social network sites become more important when experiencing stress? Results from longitudinal data. *Computers in Human Behavior*, e106339.

Wu, S., Tan, Y., Chen, Y., & Liang, Y. (2022). How is mobile user behavior different? — A hidden Markov model of cross-mobile application usage dynamics. *Information Systems Research*, *33*(3), 1002-1022.

Xue, Y., Dong, Y., Luo, M., Mo, D., Dong, W., Zhang, Z., & Liang, H. (2018). Investigating the impact of mobile SNS addiction on individual's self-rated health. *Internet Research, 28*(2), 278-292.

Xu, A. J., Loi, R., & Lam, L. W. (2015). The bad boss takes it all: How abusive supervision and leader-member exchange interact to influence employee silence. *The Leadership Quarterly, 26*(5), 763-774.

Xu, Z., Turel, O., & Yuan, Y. (2012). Online game addiction among adolescents: Motivation and prevention factors. *European Journal of Information Systems, 21*(3), 321-340.

Yildirim, C., & Correia, A. P. (2015). Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire. *Computers in Human Behavior*, *49*, 130-137.

Yle. (2019). *Teens trying to cut back on smartphone use*. https://yle.fi/uutiset/osasto/news/teens_trying_to_cut_back_on_smartphone_use/10791779

Zheng, J., Qi, Z., Dou, Y., & Tan, Y. (2019). How mega is the mega? Exploring the spillover effects of WeChat using graphical model. *Information Systems Research, 30*(4), 1343-1362.

Zhang, P., & Wang, J. (2016). Family work conflict and information security policy compliance-an empirical study. *Proceedings of 22nd Americas Conference on Information Systems*.

Zhang, S., Zhao, L., Lu, Y., & Yang, J. (2016). Do you get tired of socializing? An empirical explanation of discontinuous usage behaviour in social network services. *Information & Management*, *53*(7), 904-914.

Zhan, G., Zhou, Z., & Cheung, C. (2018). Mobile internet and consumer happiness: The role of risk. *Internet Research*, *28*(3): 785-803.

Zhang, Y., Rohrer, J., Borders, T., & Farrell, T. (2007). Patient satisfaction, self-rated health status, and health confidence: An assessment of the utility of single-item questions. *American Journal of Medical Quality*, *22*(1), 42-49.

Appendix A

Table A1. List of Measurement Items

Construct	Measurement item	Scale
Nomophobia	Running out of battery on my smartphone would scare me.	*Strongly disagree* 1 2 3 4 5 6 7 *Strongly agree*
	If I did not have my smartphone with me, I would be anxious because I could not keep in touch with my family and/or friends.	*Strongly disagree* 1 2 3 4 5 6 7 *Strongly agree*
	If I did not have my smartphone with me, I would feel uncomfortable because I could not stay up to date with my social media networks.	*Strongly disagree* 1 2 3 4 5 6 7 *Strongly agree*
Health status	Do you think you are healthier than six months ago?	A. Less healthy B. No change C. Healthier
Sleep deprivation	Frequency of staying up late	A. Never B. Once or twice a week C. Three or four times a week D. Five or six times a week E. All the time
	Do you have an insomnia problem?	A. Never B. Rarely C. Occasionally D. Often E. Everyday
Physical activity	Frequency of engaging in sport activity	A. Never B. Once or twice a week C. Three or four times a week D. Five or six times a week E. Everyday
	Average time devoted to exercising per day	A. Less than 0.5 hour B. Equal or greater than 0.5 hour but less than 1.0 hour C. Equal or greater than 1.0 hour but less than 2.0 hours D. More than 2.0 hours
Social-media applications	Average time of utilizing social media applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Book-reading applications	Average time of utilizing book-reading applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
News applications	Average time of utilizing news applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Travel applications	Average time of utilizing travel applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours

Music/video applications	Average time of utilizing music/video applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Shopping applications	Average time of utilizing shopping applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Selfie applications	Average time of utilizing selfie applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Search applications	Average time of utilizing search applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Gaming applications	Average time of utilizing gaming applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Other applications	Average time of utilizing other applications via smartphone per day	A. Never B. Less than 15 minutes C. Equal or greater than 15 minutes but less than 30 minutes D. Equal or greater than 30 minutes but less than 1.0 hour E. Equal or greater than 1.0 hour but less than 2.0 hours F. More than 2.0 hours
Health information literacy	I like to get health information from a variety of sources.	Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree
	I know where to seek health information.	Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree
	It is easy to assess the reliability of health information in printed sources (magazines and books).	Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree
	It is easy to assess the reliability of health information on the Internet.	Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree
	I apply health-related information to my own life and/or that of people close to me.	Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

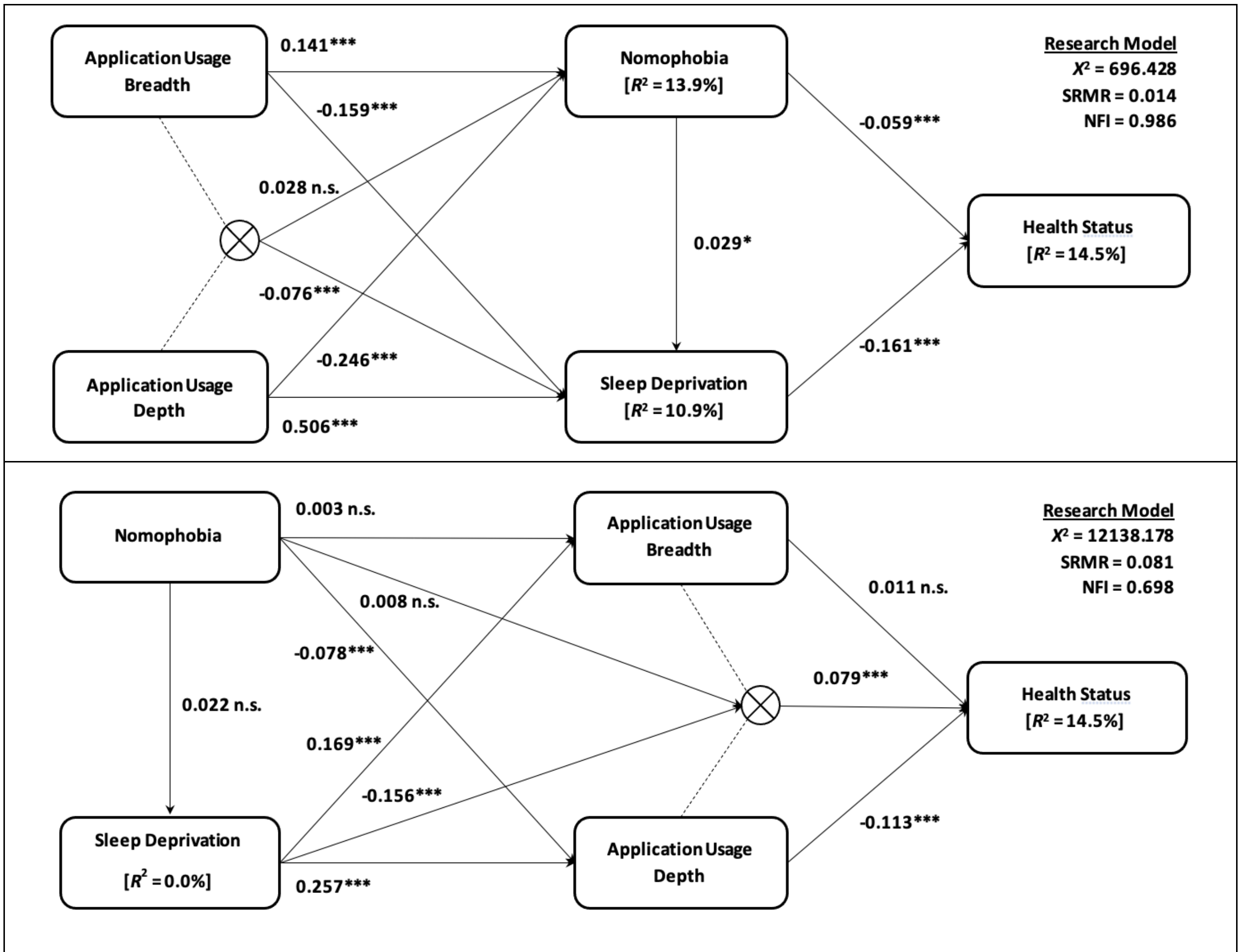
Appendix B

Table B1. AMOS Results for the Baseline Model and the Marker Variable Model

Path	Baseline model		Marker variable model	
	Coeff.	*t*-test	Coeff.	*t*-test
AUB → NOM	0.141***	4.688	0.099***	4.651
AUD → NOM	-0.246***	6.174	-0.112***	6.540
IBD → NOM	0.028n.s.	1.786	0.031n.s.	1.945
Marker → NOM			0.024n.s.	1.824
AUB → SD	-0.159***	7.305	-0.124***	5.311
AUD → SD	0.506***	17.533	0.266***	14.246
IBD → SD	-0.076***	6.776	-0.096***	5.002
NOM → SD	0.029*	2.558	0.033*	2.517
Marker → SD			0.131***	9.305
NOM → HS	-0.059***	8.815	-0.113***	9.479
SD → HS	-0.161***	21.748	-0.253***	20.172
Marker → HS			-0.109***	8.357
AUB × PA → Nom	0.070*	2.432	0.046*	2.328
AUB × PA → SD	0.129***	6.180	0.118***	5.198
AUD × PA → Nom	0.001n.s.	0.034	0.002n.s.	0.106
AUD × PA → SD	-0.065***	4.076	-0.060***	3.394
IBD × PA → Nom	0.052***	3.821	0.054***	3.562
IBD × PA → SD	0.078***	7.966	0.110***	6.314
Nom × PA → HS	-0.012n.s.	1.549	-0.019 n.s.	1.624
SD × PA → HS	0.049***	7.223	0.072***	6.269
R^2				
NOM	13.9%		11.3%	
PSH	10.9%		15.9%	
HS	14.5%		12.4%	

Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status.
*** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = "not significant."

Appendix C



Note: Moderating effect is not shown in Appendix C due to the space limits of the figure.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = “not significant.”

Figure C1. Comparison of Results of Structural Model Analysis

Appendix D

Table D1. Results for the Baseline Model and the Comparison Model

Path	Baseline model		Comparison model	
	Coeff.	***t*-test**	**Coeff.**	***t*-test**
AUB → NOM	0.141***	4.688	0.086***	4.409
AUD → NOM	-0.246***	6.174	-0.111***	6.496
IBD → NOM	0.028n.s.	1.786	0.023n.s.	1.352
AUB → SD	-0.159***	7.305	-0.105***	5.811
AUD → SD	0.506***	17.533	0.285***	16.780
IBD → SD	-0.076***	6.776	-0.089***	4.915
NOM → SD	0.029*	2.558	0.039**	2.947
NOM → HS	-0.059***	8.815	-0.114***	9.688
SD → HS	-0.161***	21.748	-0.270***	20.927
AUB × PA → NOM	0.070*	2.432	0.045*	2.341
AUB × PA → SD	0.129***	6.180	0.115***	5.492
AUD × PA → NOM	0.001n.s.	0.034	0.004n.s.	0.787
AUD × PA → SD	-0.065***	4.076	-0.061***	3.585
IBD × PA → NOM	0.052***	3.821	0.056***	3.648
IBD × PA → SD	0.078***	7.966	0.113***	6.416
Nom × PA → HS	-0.012n.s.	1.549	-0.019n.s.	1.623
SD × PA → HS	0.049***	7.223	0.079***	6.792
R^2				
NOM	13.9%		11.3%	
SD	10.9%		11.2%	
HS	14.5%		14.7%	

Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status. *** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = "not significant."

Appendix E

Table E1. Direct Impact of Physical Activity

Path	Coeff.	*t*-test
AUB → NOM	0.098***	4.724
AUD → NOM	-0.105***	6.076
IBD → NOM	0.031n.s.	1.755
AUB → SD	-0.136***	5.813
AUD → SD	0.295***	16.270
IBD → SD	-0.129***	6.809
NOM → SD	0.041**	3.127
NOM → HS	-0.113***	9.472
SD → HS	-0.281***	22.164
PA → NOM	0.006n.s.	0.469
PA → SD	-0.045**	3.029
PA → HS	0.174***	13.447
	R^2	
NOM	11.0%	
SD	9.6%	
HS	13.9%	

Note: AUB = application usage breadth; AUD = application usage depth; IBD = interaction between app usage breadth and depth; NOM = nomophobia; SD = sleep deprivation; PA = physical activity; HS = health status. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = "not significant."

About the Authors

Shaoxiong Fu is an associate professor in the College of Information Management of Nanjing Agricultural University. He holds a doctor of management degree in information science degree from Wuhan University. His research interests include health information behaviors in IS and the dark side of ICT use. His prior works have been published in prestigious journals in information science and information systems, such as *Internet Research, Information Processing and Management, Behavior & Information Technology, Journal of Information Science* and *Library and Information Science Research,* and in the proceedings of the Pacific Asia Conference on Information Systems, Hawaii International Conference on System Sciences, and the ASIS&T annual meeting.

Zhao Cai is an associate professor in information systems at Nottingham University Business School China, University of Nottingham Ningbo China. His research interests focus on the intersection among digital supply chain management, platform competition, and sharing economy. Findings from his research have appeared in leading journals such as *MIS Quarterly, Journal of Operations Management, International Journal of Operations and Production Management,* and *Information & Management*, among others. Dr. Cai is currently serving as the managing editor of *Industrial Management & Data Systems* and an associate editor for *Internet Research*. Dr. Zhao Cai is the corresponding author of this paper.

Eric T. K. Lim is a tenured senior lecturer in the School of Information Systems and Technology Management (SISTM) at UNSW Business School, UNSW Sydney. He holds a Ph.D. in Business Administration from Simon Fraser University (Canada). Eric's research interests focus on exploring the impact of digitalization on individuals, organizations, and the broader society, paying particular attention to the design and innovation of digital services across a variety of contexts such as crowd platforms, fintech, and healthcare. Eric is a regular presenter at leading international conferences and findings from his research have been published in leading academic journals such as *Information Systems Research, Journal of Management Information Systems, Journal of the Association for Information Systems*, and *Decision Support Systems*, among others. Apart from serving regularly on the conference committees of prestigious information systems conferences (e.g., AMCIS, ECIS, ICIS, and PACIS), Eric is currently serving on the editorial boards of *Australasian Journal of Information Systems*, *Industrial Management & Data Systems, Internet Research*, *Journal of Computer Information Systems,* and *Journal of Management Analytics*.

Yong Liu is an associate professor of information systems at Aalto University School of Business, Finland. He holds a PhD in business administration and economics from Åbo Akademi University. His research interests cover the areas of AI robots, big data, electronic commerce, mobile commerce, social media, and eWOM. He has over 90 publications in international conferences and journals, such as *ACM Transactions on Computer-Human Interaction, Decision Support Systems, Information Systems Journal, Information & Management, Journal of Advertising Research, Government Information Quarterly and European Journal of Information Systems*. He currently serves as an associate editor for *Internet Research*.

Chee-Wee Tan is a professor in the Department of Digitalization at Copenhagen Business School (CBS), an honorary professor of business analytics and digitalization at the University of Nottingham Ningbo China (China), a distinguished research scholar at Lingnan University (Hong Kong), a guest professor at the University of Science and Technology of China (China), and a visiting professorial fellow at the University of New South Wales (Australia). He received his PhD in business administration from the University of British Columbia (Canada). His research interests focus on digital service design and innovation. His work has been published in leading peer-reviewed journals like *MIS Quarterly, Information Systems Research, Journal of Management Information Systems, Journal of the Association for Information Systems, European Journal of Information Systems, and Decision Support Systems*, among others. Chee-Wee is currently serving on the editorial boards for *AIS Transactions on Human-Computer Interaction, Industrial Management & Data Systems (IMDS), IEEE Transactions on Engineering Management, Information & Management, Internet Research, Journal of the Association for Information Systems, Journal of Management Analytics*, and *MIS Quarterly*.

Yanqing Lin is currently a doctoral candidate in Information Systems Science at the Department of Information and Service Management, Aalto University School of Business. Her research interests include the dark side of ICT use and service robots for business values. Her research articles have appeared in journals, such as *Internet Research, Computers in Human Behavior, Information Processing & Management, International Journal of Consumer Studies*, and *Information Research*, as well as in the conference proceedings of the Pacific Asia Conference on Information Systems, European Conference on Information Systems, and Hawaii International Conference on System Sciences.

Shengli Deng is a professor in the School of Information Management at Wuhan University. His research interests include big data, user behaviour, information interaction, and social media. He has more than 150 publications at international conferences and journals, such as *Tourism Management, Computer in Human Behavior, Information Processing & Management, Journal of Information Science, Scientometrics, Cyberpsychology, Behavior, and Social Networking,* and *Online Information Review*.