PROBLEMATIC INTERNET TECHNOLOGY USE: ASSESSMENT, RISK FACTORS, COMORBIDITY, ADVERSE CONSEQUENCES AND INTERVENTION

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PROBLEMATIC INTERNET TECHNOLOGY USE: ASSESSMENT, RISK FACTORS, COMORBIDITY, ADVERSE CONSEQUENCES AND INTERVENTION

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EDITORIAL
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Editorial: Problematic Internet Technology Use: Assessment, Risk Factors, Comorbidity, Adverse Consequences and Intervention

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Editorial on the Research Topic

Problematic Internet Technology Use: Assessment, Risk Factors, Comorbidity, Adverse Consequences and Intervention

There is no doubt that many personal and societal advantages are associated with using Internet technology such as social networking sites (SNS), gaming, and smartphones. For instance, smartphones have enhanced productivity in workplace (1) and educational (2) settings, and can facilitate health and mental health treatment with apps designed to complement traditional interventions (3). Furthermore, using SNS can boost social capital (4, 5), which can in turn promote mental health (6, 7). Such advantages of Internet technology use are relevant when such use is of mild to moderate frequency, conducted in healthy and adaptive ways. However, Internet technology is a double-edged sword, and can alternatively be used in unhealthy, maladaptive ways (8, 9).

In the current Research Topic, we address when Internet technology is used in ways that are problematic or excessive, causing dysfunction in daily life. Problematic use of Internet technology is influenced by risk factors such as mental health symptoms (10–12) which drive such problematic use in an effort to alleviate negative affect (13, 14). Additional risk factors for problematic Internet use involve predispositional characteristics such as personality, genetics and other biological factors, deep seated cognitions (14–16), as well as cognitive and affective responses and dysfunctional coping processes (17, 18). In fact, theoretical models have been developed and supported that discuss how this variety of risk factors may contribute to problematic Internet use (19). Furthermore, consequences of problematic Internet use include physical pain in the hands and neck (20, 21), pedestrian and driving collisions (22), distraction and poor performance in school and work (23–25), and can involve cyberbullying (26), problematic pornography use (27), and internet radicalization (28).

In the present Research Topic, authors present research in several domains related to problematic Internet use. Several papers report the development and/or validation of scales used to measure aspects of problematic Internet use—including problematic use symptoms [(29), Paschke et al.] and distractions from the smartphone (Throuvala et al.). These papers also report how these scales are related to external constructs such as mental health symptoms. For instance, Burkauskas et al. discovered that the nine-item Problematic Internet Use Questionnaire was valid in a sample of Lithuanian residents, and correlated positively with mental health symptom severity.

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Paschke et al. found that their newly developed Social Media Use Disorder Scale for Adolescents correlated positively with severity of depression and stress in German adolescents. And Throuvala et al. discovered that their newly developed Smartphone Distraction Scale correlated positively with emotional dysregulation and problematic SNS use in a sample of British university students. Such studies are important in providing researchers and clinicians with valid assessment instruments for measuring problematic Internet use and its consequences.

Other authors in this Research Topic examined stress and anxiety as potential risk factors for the problematic use of Internet technology (Yang et al.; Li et al.; Zhao and Zhao). These papers also importantly examine potential mediators or moderators (mechanisms) that can explain how stress or anxiety are related to problematic Internet use, including the fear of missing out (FOMO) on rewarding experiences (Yang et al.), self-efficacy (Li et al.), and active SNS use or SNS flow (Zhao and Zhao). Examining such mechanisms is important because psychopathology alone may not adequately explain the development or maintenance of problematic Internet use (14, 15). For example, Yang et al. revealed that FOMO mediated relations between stress and problematic smartphone use severity in a sample of Chinese university students. Li et al. found support for self-efficacy in partially mediating associations between anxiety and problematic smartphone use symptoms in a sample of Chinese college students. And Zhao and Zhao discovered that active SNS use and SNS flow mediated relations between stress about COVID-19 and problematic SNS use in Chinese college students. We believe that future research should continue to prioritize testing of moderators and mediators that explain associations between both stress and anxiety with problematic Internet use.

Other papers examine additional risk factors for problematic Internet use. Guo et al. sampled Chinese residents using a population-based survey, and examined how using different features of the smartphone may relate not only to problematic use but also to its different facets. Schivinski et al., Zhang et al., and Heng et al. examined social-related variables in association with problematic Internet use. Specifically, Schivinski et al. used an English-speaking sample of SNS users, finding that particular social motives (especially intrapersonal) were related to problematic SNS use severity. Heng et al. used a Chinese sample of undergraduates, discovering that social capital mediated relations between within-game social interactions and problematic gaming. And Zhang et al. sampled participants from China and Germany, finding that autistic traits were related to problematic Internet use. Finally, Luo et al. sampled Chinese college students, finding that adaptability regarding emotions, homesickness, and learning were related to perceived distress from losing smartphone access (or nomophobia). Studying such risk factors as social-related variables, autistic traits, and adaptability are important in furthering our understanding of why some people excessively engage in Internet use.

Finally, we mention the important commentary by Montag and Hegelich. The authors present a compelling argument that an important determinant of problematic SNS use is the way in which SNSs were developed and operate financially. That is, it is the intention of SNSs to prolong users' SNS use in order to use their data and profit from it. The authors also discuss significant societal adverse effects from the SNS business model, including problematic use, privacy infringement, and impingement on democracy through the spread of fake news.

To conclude, the present Research Topic provides readers with recent cross-national findings considering the assessment of different forms of problematic Internet technology use, and the complex mechanisms underlying the association between problematic Internet technology use and mental health that involve different inter- and intrapersonal as well as environmental and societal factors. The works published in this Research Topic contribute to the understanding of Internet technology use associations with daily-life adversities and may be useful for professionals working in this line of research.

AUTHOR CONTRIBUTIONS

All authors wrote and edited this paper.

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OPINION
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Understanding Detrimental Aspects of Social Media Use: Will the Real Culprits Please Stand Up?

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Keywords: Facebook, Instagram, personality, data business model, social media use, social media addiction, problematic social media use, social networks use disorder

MUCH RESEARCH INVESTIGATING DETRIMENTAL ASPECTS OF SOCIAL MEDIA USE FOCUSES ON PERSON CHARACTERISTICS AND HAPPENS IN ISOLATION FROM EACH OTHER

Currently, nearly four billion people all over the world use platforms such as Facebook, Instagram, WeChat or TikTok (Clement, 2020; Wearesocial.com, 2020). Given the impact that social media platforms have on humanity, it is not surprising that important lines of research seek to shed light on the *who* and *why* questions in the context of (over-)use of social media [for a comprehensive definition of the term "social media" see (Carr and Hayes, 2015)]. The *who*-question aims to understand *who* uses social media, whereas the *why*-question asks *why* people are using social media.

The *who*-question has been answered, among others, by personality psychologists, providing insights into sociodemographic variables and personality traits more likely being associated with social media use (Correa et al., 2010). A new large-scale study by Marengo et al. (2020) recently observed that social media users differ from non-users, with users (of Facebook-owned platforms) being younger, more often female and slightly more extraverted than non-users. Works such as by Brailovskaia and Margraf (2017) and Sindermann et al. (2020a,b), yielded insights that certain personality traits, such as being more neurotic/narcissistic, are associated with higher tendencies toward *problematic social media use* or *social networks use disorder*, with the terminology itself being a matter of fierce debate among scientists (Hussain et al., 2020; Wegmann et al., 2020; Montag et al., in press).

Of importance, *problematic social media use*—in light of a mental health problem—does not present the only detrimental aspect when (over-)using social media. Further detrimental aspects of social media use comprise misinformation campaigns via social media and loss of privacy for billions of humans. We are aware that valuable research exists in each mentioned area (e.g., Krasnova et al., 2010; Flaxman et al., 2016), but we believe that many researchers in their respective research fields under-estimate or at least under-emphasize that problems such as the addictive nature of social media, loss of privacy or problems arising for society due to misinformation campaigns in filter-bubbles all can indirectly be linked to each other – via the data business model behind social media platforms (see also **Figure 1**). This said, the importance to not investigate the aforementioned problems in isolation have been also put forward by laudable initiatives such as from the Center for Humane Technology (https://www.humanetech.com) stating on their website "As long as social media companies profit from outrage, confusion, addiction, and depression, our well-being and democracy will continue to be at risk."

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Against this background, it is not our objective in the present work to discuss the actual nature of excessive social media use, but rather to highlight the need to seek a new perspective on the prevalent research agenda, namely to keep in mind when studying detrimental aspects of social media use that the mentioned adverse aspects of social media use could be all solved to some extent when the data business model behind social media platforms would be improved or exchanged by a better alternative.

The fact that the distinct views taken by many scientists in their respective disciplines provide a too narrow view on the topic, for instance can be supported by empirical evidence: Coming back to the initially posed question "*who* uses social media?," abundant evidence exists linking certain personality traits to excessive or problematic social media use, but effect sizes are usually only small to moderate. To illustrate this: Sindermann et al. (2020a) observed a small correlation of $rho = 0.17$ between the personality trait of neuroticism and Facebook use disorder leaving much room for other explanations on *who* spends (too much) time on social media. Of interest, similar observations regarding effect sizes can be made, when it has been investigated which personality traits are associated with daily news consumption via-social media only (Sindermann et al., 2020c) or understanding privacy concerns from a personality psychologist's perspective (Bansal et al., 2016).

Aside from the *who*-question, which pointed toward the personality structure being the culprit behind (over-)use of social media, *uses and gratification theory* carved out hedonic, utilitarian and social motives as highly relevant to understand *why* people (over-)use social media (Hsiao et al., 2016; Kircaburun et al., 2020). Ergo, *uses and gratification theory* tries to understand the *why*-question by investigating which basic human needs are satisfied by social media use. Again, correlations in this area usually also do not reach high effect sizes, leaving again much room for another important factor or factors driving detrimental aspects of social media use.

In sum, investigating personality traits or usage-motives in the context of detrimental aspects of social media use is helpful, but by far not enough to get the full picture of how to understand and tackle the manifold adverse aspects of social media (over-)use. We believe that the "real" culprit to be focused upon in research represents *the data business model* behind social media platforms and we will outline that a stronger focus on the data business model and social media platform design is needed in independent research.

A STRONGER FOCUS ON THE DATA BUSINESS MODEL AND SOCIAL MEDIA PLATFORM DESIGN IS NEEDED IN INDEPENDENT RESEARCH

As nothing comes free in life, we should not be surprised that we pay for the usage of a social media service with our personal data on a daily basis. Such a focus on harvesting digital footprints from each user to get better insights into their psychological profiles and to sell these insights to marketing companies (Matz et al., 2017; Azucar et al., 2018; Marengo and Montag, 2020) led engineers behind social media platforms to design applications which naturally aim at the prolongation of usage time. Longer social media usage equals more data on a user, and worsens the already excessive intrusion on individual privacy. In recent years, platforms like Facebook and YouTube have went from "more time spent" to "time well spent": instead of optimizing the pure amount of time, platform-algorithms now try to show users content that triggers reactions in the form of "comments," "shares" or "likes" (Papakyriakopoulos et al., 2020b). This might lead to even more time spent as well as to a more detailed digital footprint of the users (less privacy). Elements such as "Likes," personalized news-feeds, endless scrolling, read receipts, to name a few, likely lead to more immersion on the user side (Montag et al., 2019). This keeps users longer on the social media platforms and/or lures them to check in more often than they like (see also push-notifications). Although the effects of the Like-button have been well-studied from a psychological point of view (Steinfield et al., 2008; Scissors et al., 2016; Burrow and Rainone, 2017; Zell and Moeller, 2018), the remaining in-built elements of social-media-platforms are understudied (e.g., the read-receipt, see a work by Blabst and Diefenbach, 2017). Furthermore, it is vastly understudied how each of these elements by themselves or in their interaction with each other actually drive human behavior on social media platforms and prolong the usage time. It is of utmost importance to get insights into effect sizes in this context. In addition, while the diversity of social-media-platforms is high, the cross-platform validity of an observed effect is questionable: the effects of a "Like" on Instagram cannot be simply transferred to TikTok (Serrano et al., 2020). On a methodological level, studying social media is challenging as well: Given an uneven distribution of activities—most users are quite passive in their usage while a handful of others produce the main share of reactions (Papakyriakopoulos et al., 2020b) —mean-related statistical measures are often misleading and analyzing these "non-normal" distributions requires huge datasets.

Social media platforms are, in many ways, black-boxes, where independent researchers looking from outside-in are handicapped by a variety of problems. The social media companies themselves possess richer data and insights into user behavior gained via AB-testing over many years. They know what combination of design-elements on social media platforms (also in Freemium-games on smartphones) function best in attracting and keeping the attention of their users. They also possess better insights into human behavior guided by design elements such as a personalized news-feed, which is widely believed to be responsible for filter-bubbles (Pariser, 2011) and echo-chambers (Shahrezaye et al., 2019), but likely only in the case when users inform themselves about the daily political news exclusively via social media (Sindermann et al., 2020c). Of note, personalized news-feeds are a good example to demonstrate how the addictive nature of social media and detrimental effects for society can be all linked to each other via a design-element and the data business model on social media. The personalized news-feed has been designed to create a highly interesting personalized website, where users like to spend much time and as a consequence produce more digital footprints (imagine the contrary: a boring

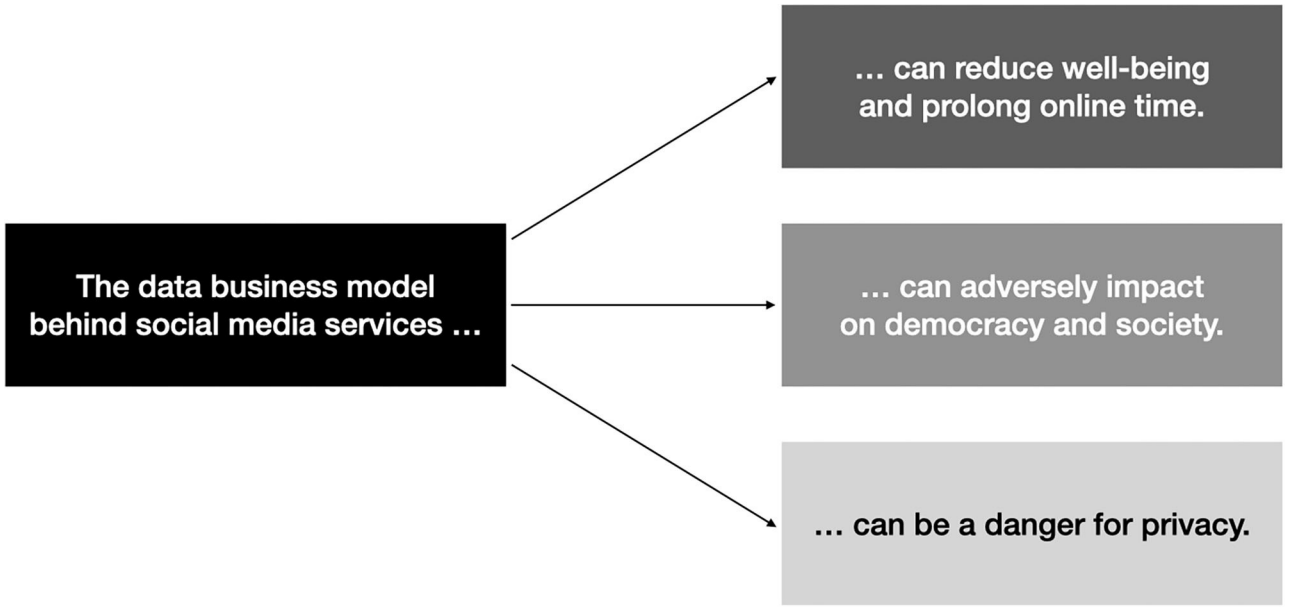

FIGURE 1 | Detrimental aspects of the data business model behind social media services.

news-feed would result in lower online time). On the one side this design element leads to higher online-time with higher risk for users to develop addictive tendencies toward the platform. On the other side this design element (fulfilling its purpose of the data collection) can result in filter-bubbles, because the social media companies typically show users what they are likely interested in (e.g., by having "liked" something earlier on social media).

With these few examples, it becomes apparent, that research on social media usage not only touches upon issues related to individual well-being and health, but also has broad political and privacy dimensions (see also **Figure 1**).

OUTLOOK

In order to be able to establish sustainable guidelines and policies toward social media platforms that do not aim to prolong online time (addictive potential of social media), and to protect the individual from (potentially) detrimental aspects of social media use, such as being caught in the filter-bubble (Sindermann et al., 2020c) and loss of privacy (Zuboff, 2015), it is of importance to (a) rethink the data business model (Sindermann et al., 2020d) and (b) to understand exactly what a "good" or "healthy" social media platform might look like. It is of particular relevance that academic research and public policy work toward building of a social media architecture that does not endanger democratic processes (Shahrezaye et al., 2019; Papakyriakopoulos et al., 2020b) or fosters sexism (Papakyriakopoulos et al., 2020a), radicalization or "fake news" and conspiracy theories (Papakyriakopoulos et al., 2020b). For example, the aforementioned problems around filter-bubbles and echo-chambers might be mitigated by excluding domains such as daily political news from news-feed personalization. Also, for instance, hiding "Likes" from users might diminish problems linked to social comparison and undue reinforcement of social media usage habits. An easy to understand orientation concerning healthy and fair social media platform design represents the *ethical design manifesto* (https://2017.ind.ie/ethical-design/; see also **Figure 2**). Using a Maslow like pyramid three stages are proposed – all to be considered to create fair online platforms. The bottom of the pyramid asks engineers to build among others decentralized, secure, sustainable and open platforms respecting human rights. One step higher in the pyramid it is argued to design platforms which are functional, convenient and reliable. Respecting these design principles ensures that humans do not waste life energy while visiting and interacting with an online platform (human effort should be taken into account). Finally, the persons behind the initiative value human experience, in short - the interaction with the online platform should be a fun experience.

We believe this *ethical design manifesto* to be of interest, but both the manifesto itself together with our earlier ideas need extensive testing for the validity of their premise and the relative merits of the various forms in which they could be implemented. Therefore, it is of utmost importance to get access to real-world data from tech-companies such as Facebook to answer such questions [but see problems with the recently launched "Social Science One"-initiative; (Ledford, 2019; Hegelich, 2020)]. Alternatively, when it is not possible to web-scrape data without intruding into user privacy, one could invest more research energy and funding into simulations of social media platforms, where different constellations of in-built features are tested for a variety of research questions targeting usage time, well-being (Brooks, 2015; Duradoni et al., 2020) and effects of filter-bubbles

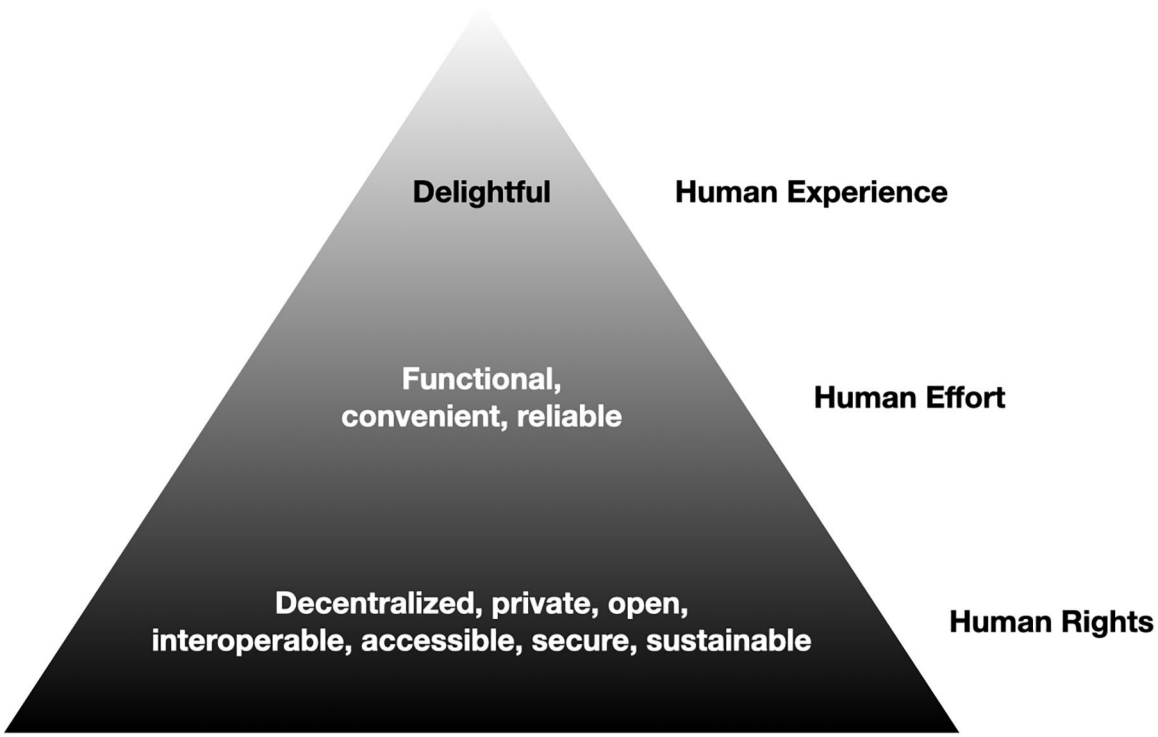

FIGURE 2 | The *ethical design manifesto* according to the initiative of Ind.ie (https://2017.ind.ie/ethical-design/). The pyramid is presented in original wording as presented on the Ind.ie website. The graphical presentation slightly differs. Please note that the figure is under Creative Commons Attribution 4.0 International.

on radicalization (Zuiderveen Borgesius et al., 2016), among others. Additionally, it is crucial to combine information on digital footprints with self-report data in order to get deeper insights into *how* different groups of people are using social media (Montag and Elhai, 2019; Peterka-Bonetta et al., in press). Ultimately, the *who*-, *why*- and *how*- questions need to be brought together.

In sum, to tackle problems related to social media usage, it is high time to point to the real culprit: the data business model behind social media platforms and their design in itself. As also depicted in **Figure 1**, detrimental aspects of social media use can be seen in very different research areas, therefore scientists need also to reflect on this bird's eye view if they really want to change social media for the better, and this regardless on which area of social media research they are in. It needs to be mentioned that the different problem areas related to social media use likely impact differently on society in terms of persons afflicted. Whereas overuse of social media or being caught in the filter-bubble might only be a problem for a "few percent" of an investigated population at the moment (Bányai et al., 2017; Sindermann et al., 2020c; Wartberg et al., 2020), we are convinced that loss of privacy is a problem for every single user of a social media platform.

As the actual data business model has proven negative effects on society, it should be clear that more and more rigor and regulation is needed, just as it is for other forms of general infrastructure in society. Regulation could happen from the governmental side prohibiting the extent to which data is collected. Results from independent research could help to provide design-guidelines to answer what design-elements can be implemented (in what combination) on social media platforms. Such regulation and research is overdue and is expected to have a wide impact. One could, in fact, put a number to how many people stand to profit from a rigorous scientific agenda investigating social media – nearly 4 billion and rising.

AUTHOR CONTRIBUTIONS

CM drafted the first version of this opinion, which was critically revised by SH. Both authors contributed to the article and approved the submitted version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Nevertheless, for reasons of transparency CM mentions that he has received (to Ulm University and earlier University of Bonn) grants from agencies such as the German Research Foundation (DFG). CM has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from the gaming or social media industry. CM mentions that he is part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-digitalitaet-und-verantwortung/) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he receives no salary for his activities. Finally, he mentions that he currently functions as independent scientist on the scientific advisory board of the Nymphenburg group. This activity is financially compensated.

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BRIEF RESEARCH REPORT
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Exploring the Role of Social Media Use Motives, Psychological Well-Being, Self-Esteem, and Affect in Problematic Social Media Use

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Given recent advances in technology, connectivity, and the popularity of social media platforms, recent literature has devoted great attention to problematic Facebook use. However, exploring the potential predictors of problematic social media use beyond Facebook use has become paramount given the increasing popularity of multiple alternative platforms. In this study, a sample of 584 social media users (M_{age} = 32.28 years; 67.81% female) was recruited to complete an online survey assessing sociodemographic characteristics, patterns, and preferences of social media use, problematic social media use (PSMU), social media use motives, psychological well-being, self-esteem, and positive and negative affect. Results indicated that 6.68% (n = 39) of all respondents could be potentially classed as problematic users. Moreover, further analysis indicated that intrapersonal motive (β = 0.38), negative affect (β = 0.22), daily social media use (β = 0.18), surveillance motive (β = 0.12), and positive affect (β = −0.09) each predicted PSMU. These variables accounted for about 37% of the total variance in PSMU, with intrapersonal motive driving the greatest predictive contribution, over and above the effects of patterns of social media use and sociodemographic variables. These findings contribute to the increasing literature on PSMU. The results of this study are discussed in light of the existing literature on PSMU.

Keywords: problematic social media use, social media motives, problematic behavior, well-being, self-esteem, affect, problematic consumer behavior

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INTRODUCTION

The use of social media has been growing exponentially, with social media being a globally recognized tool used not only by individuals, but by organizations, brands, and celebrities globally. In this study, social media is defined as "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system" (Boyd and Ellison, 2007). Examples of popular social media platforms include Facebook, Instagram, YouTube, Twitter, and LinkedIn, among others.

Social media reaches a large number of users worldwide, with as many as 71% of adolescents accessing more than one platform, with about 24% of all adolescents admitting to being constantly online due to increased mobile accessibility via smartphones (Lenhart et al., 2015). Social media use is not specifically limited to adolescents as adults also use social media platforms as an important socializing and information tool (Heo et al., 2015; Schivinski et al., 2019), with social media use influencing different types of behavior across the entire lifespan (Kuss et al., 2013; Schivinski, 2019). Judicious use of social media leads to many advantageous and beneficial psychosocial outcomes, such as greater social support (Tifferet, 2020), increased friendship quality (Wang et al., 2019b), higher levels of happiness (Ward et al., 2018), and decreased depression levels (Wang et al., 2019a).

However, although moderate use of social media does not interfere with overall functioning and psychological well-being (Twigg et al., 2020), negative effects stemming from social media use have been examined in the context of excessive and problematic usage. Research investigating the negative outcomes of social media use has indicated that problematic social media use (PSMU) may lead to deteriorated psychological well-being (Huang, 2012; Lin et al., 2016) and overall health (Pontes, 2017; Brailovskaia et al., 2020). One of the most prominent negative effects of social media use relates to problematic use stemming from dysregulated usage (Kuss and Griffiths, 2017; Radovic et al., 2017), often triggered by the design of the social media platforms and the prevailing data business model (Montag et al., 2019). However, the literature remains inconclusive, fragmented, and heavily skewed toward the investigation of a single, specific social media platform (e.g., Facebook) (e.g., see Pontes et al., 2016; da Veiga et al., 2019; Rozgonjuk et al., 2020a,b; Sindermann et al., 2020; for exceptions Marengo et al., 2020).

Despite not being an officially recognized mental health disorder, previous research has demonstrated that PSMU can longitudinally influence a wide range of psychiatric outcomes and behaviors, including, but not limited to, increased severity of insomnia, stress, depression, and anxiety (Brailovskaia and Margraf, 2017; Brailovskaia et al., 2019a), in addition to suicide-related outcomes (Brailovskaia et al., 2020). At the cross-sectional level, PSMU has been linked to decreased sleep quality and life satisfaction (Sha et al., 2019; Buda et al., 2020; Duradoni et al., 2020), emotional maladjustment (Hawes et al., 2020), lower productivity (Rozgonjuk et al., 2020d), narcissistic traits (Brailovskaia et al., 2020), poorer psychological functioning (Sampasa-Kanyinga and Lewis, 2015), phubbing (Karadag et al., 2015), binge drinking (Spilkov et al., 2017), and addictive usage (Andreassen and Pallesen, 2014; Ryan et al., 2014; Andreassen, 2015; Pontes et al., 2018).

Early epidemiological research including representative samples reported PSMU prevalence rates of about 4.0% among adolescents in Germany (Müller et al., 2016), 4.5% in Hungarian adolescents (Bányai et al., 2017), 2.9% in the general Belgian population (De Cock et al., 2014), and 4.9% in the British population (Pontes et al., 2018). More recent epidemiological research has reported a 1-year PSMU prevalence of 2.6% among adolescents and younger adults (Wartberg et al., 2020) from the German population (Reer et al., 2020).

Based on these recent developments, the present study aims to contribute to the growing body of knowledge on social media use by exploring the role of key factors accounting for PSMU more broadly (i.e., without being attached to a specific social media platform). Given the relatively high number of studies that have investigated problematic Facebook use specifically, rather than using a broader definition of PSMU, understanding potential contributing factors to broad PSMU is paramount because of the continuous and steady growth of social media users and platforms worldwide. Furthermore, this approach is in agreement with previous literature suggesting that PSMU should be investigated more broadly, without association to specific social media platforms (Griffiths, 2012).

Understanding PSMU risk factors is key to advancing research on social media behavior. In this context, motives for social media use have been suggested as a key correlate of PSMU (Wang et al., 2016). Previous research has shown that individuals high on affiliative tendency and communication competence often use social media to expand their social networks, demonstrating lower levels of self-focus and intrapersonal social media use motives (Lee and Kim, 2014). Similarly, previous research has established that the desire to maintain social relationships among social media users is associated with life satisfaction (Rae and Lonborg, 2015). Psychological well-being, self-esteem, and affect have also been established as key correlates of PSMU, based on the previously established cognitive-behavioral model of pathological internet use (PIU) (Davis, 2001).

Research on PIU has also revealed significant relationships between internet use and the management of emotional difficulties and negative life outcomes (Caplan, 2002, 2010). This may imply that PIU, generally, and PSMU, more specifically, may emerge as dysfunctional coping mechanisms to help users manage their negative emotional and affective states (Kardefelt-Winther, 2014). Thus, people who use social media to help cope with adverse outcomes and existing difficulties (e.g., poor psychological well-being), may feel compelled to systematically use social media on a frequent basis (Radovic et al., 2017), rendering them potentially more vulnerable to developing PSMU due to increased duration of, and exposure to, social media (Brailovskaia et al., 2019b).

In order to help further advance current understanding of key PSMU risk factors, the aim of this study is to explore and empirically examine the role of key psychosocial predictors on PSMU, while accounting for potential confounding effects stemming from frequency of social media use and sociodemographic factors.

METHOD

Participants and Procedures

A cross-sectional study using an online survey was carried out to explore the role of motives for using social media, positive and negative affect, psychological well-being, and self-esteem in predicting PSMU in a convenience sample of English-speakers 759 social media users. An online survey hosted on Qualtrics was created and advertised from May to June 2017 on different social media platforms that included Facebook, Twitter, Instagram, and Snapchat where no form of incentives (e.g., financial) were

offered to potential participants. In the online survey, social media use was defined to all potential participants in terms of the following social media platforms: "*Facebook (including Messenger)*", "*Twitter*," "*Instagram,*" "*Snapchat*," and "*Others*" to ensure that the study would capture broad social media behavior. The online survey was brief and expected to be completed in ∼15 min on average.

All potential participants were informed about the nature of the study and required to provide online informed consent in order to partake in the study. Participants were provided with all the necessary information about the ethical aspects of this study (e.g., anonymity, confidentiality, right to discontinue participation, right to withdraw their data after completing the study). All participants were required to be aged at least 18 years old in order to be eligible to partake in the study. The present study has been granted ethical approval [*with the Nottingham Trent University*] Ethics Committee.

A total of 175 participants were excluded from analyses due to missing data, resulting in a final sample of 584 participants (M_{age} = 32.28 years, SD = 12.62 years), of which 67.81% (n = 396) were female. About 22.88% (n = 157) of the participants reported not being in a relationship. In terms of social media use, 96.58% (n = 564) reported accessing social media through a smartphone, and Facebook was reported to be the most used social media platform (55.82%, n = 326), followed by Instagram (20.03%, n = 117), with other platforms (e.g., Tumblr, Reddit) accounting for 3.91% (n = 23) of the responses. Furthermore, the majority of participants declared using only one social media platform (38.86%, n = 227) and about 34.76% (n = 203) of all participants reported accessing social media very frequently (i.e., on a daily basis). Finally, 6.68% (n = 39) of all participants could be classified as problematic users (see **Table 1**).

TABLE 1 | Structure of the sample, social media (SM) patterns of use and preferences, and descriptive statistics (n = 584).

Variable	
Gender (female, %)	396 (67.81)
Age (years) (*mean*, *SD*)	32.28 (12.62)
Not in a relationship (*n*, %)	157 (26.88)
Most used SM platform (*n*, %)	
Facebook (including "Messenger")	326 (55.82)
Instagram	117 (20.03)
Twitter	60 (10.27)
Snapchat	58 (9.93)
Other	23 (3.91)
Number Of SM Platforms Used Daily, (*n*, %)	
1	227 (38.86)
2	133 (22.77)
3	131 (22.43)
4	69 (11.81)
5	19 (3.25)
6 or more	5 (0.85)
Daily SM Use, (*n*, %)	
Very rarely	24 (4.11)
Rarely	88 (15.07)
Frequently	155 (26.54)
Very frequently	203 (34.76)
Access to SM via smartphone (*n*, %)	564 (96.58)
Daily SM occurrences (*mean*, *SD*)	18.58 (63.30)
Minutes spent per each session (*mean*, *SD*)	5.58 (38.76)
Problematic SM use (*n*, %)	
Non-problematic SM use	545 (93.32)
Problematic SM use	39 (6.68)
Descriptive Statistics for Overall Scale Scores	
Problematic SM use (*mean*, *SD*)	13.41 (4.98)
Psychological well-being (*mean*, *SD*)	79.30 (12.24)
Self-esteem (*mean*, *SD*)	28.33 (6.32)
SM use motivation: Surveillance (*mean*, *SD*)	19.65 (5.98)
SM use motivation: Network expansion (*mean*, *SD*)	12.59 (4.20)
SM use motivation: Intrapersonal motive (*mean*, *SD*)	17.26 (5.18)
SM use motivation: Relationship maintenance (*mean*, *SD*)	10.35 (2.70)
Positive Affect (*mean*, *SD*)	31.42 (7.29)
Negative Affect (*mean*, *SD*)	21.52 (7.52)

Problematic SM use risk was computed using a strict monothetic cut-off approach, which considered scores ≥ 4 on all six items of the Bergen Social Media Addiction Scale (BSMAS).

Measures

Sociodemographic and social media use characteristics were assessed with questions asking about participants' gender, age, relationship status, preferred social media platform, the number of social media platforms used daily, and whether the platforms were accessed via a smartphone. Additionally, frequency of social media usage was examined using a five-point Likert-scale ranging from very rarely (1) to very often (5), with the following questions: "*How many times during an average day do you use social media?*" and "*How many minutes on average do you spend per session of social media use?*."

Problematic social media use was measured using the Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2016). The BSMAS is a six-item tool measuring PSMU according to the core components of addiction (i.e., salience, mood modification, tolerance, withdraw symptoms, conflict, and relapse), without a specific timeframe. All six items are answered with a five-point Likert-scale ranging from very rarely (1) to very often (5). Participants were classified as problematic users using a strict monothetic cut-off approach (i.e., scoring four or above on all six items). Total scores on the BSMAS range from 6 to 30, with high scores denoting higher levels of PSMU. The BSMAS has been found to exhibit excellent psychometric properties (Andreassen et al., 2016; Chen et al., 2020). In the present study, the BSMAS exhibited adequate levels of internal consistency (α = 0.83).

Psychological well-being was assessed using the Scales of Psychological Well-Being (SPWB) test (Ryff and Keyes, 1995), which includes 18 items rated on a six-point Likert scale ranging from strongly disagree (1) to strongly agree (6), without a specific timeframe. Total scores can range from 18 to 108, with higher scores suggesting higher levels of psychological well-being. In the present study, the SPWB exhibited high levels of internal consistency (α = 0.83).

Self-esteem was assessed with the 10-item Rosenberg Self-Esteem Scale (RSES) (Rosenberg, 1965) rated on a four-point Likert scale ranging from strongly agree (1) to strongly disagree (4), without a specific timeframe. Total scores can range from 10 to 40, with higher scores indicating greater levels of self-esteem. In the present study, the RSES exhibited excellent levels of internal consistency ($\alpha = 0.92$).

Social media use motives were assessed using an adapted version of the Motivation for Twitter Use Measure (Lee and Kim, 2014) by replacing the strict term "Twitter" with "social media." This 14-item measure includes the following four subscales assessing different psychological motivations for using social media websites (without a specific timeframe) in general: *surveillance* (i.e., five items covering the motivation to discover pressing social issues, to obtain various interpretations/explanations on current affairs, to obtain professional knowledge and information, to befriend influential professionals, and to provide useful information to other people; *network expansion* (i.e., three items covering the motivation to provide information about interests to others, to express feelings and thoughts to others, and to befriend people); *intrapersonal motive* (i.e., four items capturing motivational aspects such as to forget the complications of everyday life, to remember what was done, to pass time, and to record everyday life); and *relationship maintenance* (i.e., two items covering the motivation to contact with friends and family, and to provide updates on current life to friends/acquaintances). All the 14 items were rated on a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7). In the present study, all subscales presented with adequate levels of reliability (surveillance $\alpha = 0.75$; network expansion $\alpha = 0.68$; intrapersonal motive $\alpha = 0.71$; and relationship maintenance $\alpha = 0.65$).

Positive and negative affect were measured using the 20-item Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988). The PANAS comprises 10 items assessing positive affect and 10 items to assess negative affect without a specific timeframe (i.e., trait-like affect). Participants were requested to indicate their levels of agreement with each item, using a five-point Likert scale ranging from very slightly or not at all (1) to extremely (5). Total scores for both positive and negative affect subscales ranged from 10 to 50, with higher scores indicating higher levels of positive or negative affect. In the present study, the PANAS has exhibited high levels of internal consistency (positive affect $\alpha = 0.84$ and negative affect $\alpha = 0.97$).

Statistical Analyses and Data Analytic Strategy

Statistical analyses comprised the following analyses: (i) descriptive statistics of the sample structure, characteristics, and patterns of social media usage; (ii) correlational analysis between the main variables of the study; (iii) independent sample *t*-tests to establish the profile of the sample in terms of PSMU; and (iv) a stepwise multiple linear regression analysis to investigate the role of potential predictors of PSMU (i.e., psychological well-being, self-esteem, social media use motives, and positive and negative affect), while controlling for the effects of age and gender. R^2 and Cohen's d (Cohen, 1988) coefficients were estimated for the assessment of goodness of fit of the multiple linear regression model and effect sizes. The analyses align with previous exploratory studies on social media behavior (e.g., Pontes et al., 2018).

Prior to collecting the data, sample size considerations were examined through a power analysis using G*Power (version 3.1.9.7) to calculate the minimum sample size needed for the analysis (Faul et al., 2009). This a priori test was based on (i) pre-set power ($1\text{-}\beta = 0.95$), (ii) medium effect size ($f^2 = 0.15$), and (iii) $\alpha = 0.05$, with eight predictors (i.e., psychological well-being, self-esteem, social media use motives, and positive and negative affect) and two sociodemographic and usage variables (age, daily SM use, gender). The results indicated that the required sample size was 172 participants, yielding a power of 0.95.

The procedures for data cleansing included examining the normal distribution, as well as univariate, and multivariate outliers in the dataset. No issues were detected after screening the data, so no further participants were excluded from analyses. The assumptions of the multiple linear regression analysis were examined in order to determine the suitability of the parametric approach. Potential multicollinearity issues were inspected using Variation Inflation Factors (VIF). All VIF values were less than or equal to 1.49, which is well-below the threshold of 10, indicating that there were no multicollinearity issues (Field, 2013). Finally, to minimize Type I errors, Bonferroni correction was applied (Bland and Altman, 1995). The analyses were carried out using IBM SPSS Statistics, Version 26.

RESULTS

Descriptive Statistics

All descriptive statistics with means and standard deviations of the variables of interest, can be found in **Table 1**. Beyond that, all sample characteristics are described in detail in **Table 1**.

PSMU Correlates and Profiles

Correlates of PSMU were analyzed with zero-order Pearson correlations (r) taking into account all the main variables of the study (see **Table 2**). Overall, PSMU was positively associated with intrapersonal motive ($r = 0.51$, $p < 0.01$), negative affect ($r = 0.37$), relationship maintenance motive ($r = 0.31$, $p < 0.01$), network expansion motive ($r = 0.29$, $p < 0.01$), and surveillance motive ($r = 0.25$, $p < 0.01$). Furthermore, PSMU was negatively associated with psychological well-being ($r = -0.30$, $p < 0.01$), self-esteem ($r = -0.27$, $p < 0.01$), and positive affect ($r = -0.08$, $p < 0.05$). Correlates for the respondents' age ranged from $r = -0.29$, $p < 0.01$ (problematic SM use) to $r = 0.19$, $p < 0.01$ (self-esteem). Correlates for $\text{gender}_{(\text{ref}:\,1=\text{female})}$ ranged from $r = -0.10$, $p < 0.01$ (network expansion) to $r = 0.15$, $p < 0.01$ (relationship maintenance).

Using a strict monothetic cut-off approach, about 6.68% ($n = 39$) of all participants could be classed as problematic users. Furthermore, key differences between problematic and non-problematic users emerged. It was found that problematic users accessed significantly more social media platforms than

TABLE 2 | Correlation matrix across the main variables of the study ($n = 584$).

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Problematic social media use	–	−0.30**	−0.27**	0.25**	0.29**	0.51**	0.31**	−0.08*	0.37**
2. Psychological well-being		–	0.78**	−0.04	−0.09*	−0.22**	0.01	0.45**	−0.52**
3. Self-esteem			–	−0.09*	−0.12**	−0.26**	−0.08	0.38**	−0.55**
4. Surveillance				–	0.40**	0.21**	0.17**	0.12**	0.13**
5. Network expansion					–	0.47**	0.49**	−0.01	0.13**
6. Intrapersonal motive						–	0.50**	−0.03	0.28**
7. Relationship maintenance							–	0.13**	0.10*
8. Positive affect								–	−0.08
9. Negative affect									–
Age	−0.29**	0.12**	0.19**	−0.13**	−0.10*	−0.28**	−0.16**	−0.09*	−0.25**
Gender	0.03	0.12**	−0.02	−0.09*	−0.10**	0.07	0.15**	−0.01	−0.03

*Social media use motivations subdimensions include surveillance, network expansion, intrapersonal motive, relationship maintenance; ** = zero-order Pearson correlation (r) significant at the 0.01 level (two-tailed); *zero-order Pearson correlation (r) significant at the 0.05 level (two-tailed); Gender ref=1 female.*

TABLE 3 | Main differences across social media (SM) users presenting with low and high risk of problematic social media use ($n = 584$).

Measure	Low risk mean (SD)	High risk mean (SD)	t-statistic	df	Mean differences	CI lower	CI upper	Cohen's d
Number of SM platforms used	2.15 (1.19)	2.90 (1.29)	−3.48	42.77	−0.74	−1.17	−0.31	0.60
Psychological well-being	4.43 (0.66)	4.00 (0.73)	3.64	42.66	0.44	0.20	0.68	0.61
Self-esteem	28.59 (6.19)	24.74 (7.19)	3.25	42.12	3.84	1.46	6.23	0.57
Surveillance	19.43 (5.90)	22.69 (6.22)	−3.17	43.05	−3.26	−5.33	−1.19	0.53
Network expansion	12.46 (4.19)	14.41 (3.91)	−3.00	44.47	−1.96	−3.27	−0.64	0.48
Intrapersonal motive	16.92 (5.07)	22.03 (4.38)	−6.95	45.62	−5.11	−6.58	−3.63	1.07
Relationship maintenance	10.28 (2.69)	11.38 (2.59)	−2.56	44.10	−1.10	−1.97	−0.24	0.41
Positive affect	31.52 (7.22)	30.03 (8.18)	1.11	42.35	1.49	−1.23	4.21	0.19
Negative affect	20.96 (7.16)	29.31 (8.22)	−6.17	42.23	−8.34	−11.07	−5.62	1.08

Results are statistically significant after applying Bonferroni correction to account for potential Type I error (i.e., $p < 0.006$); SD, standard deviation; df, degrees of freedom; CI, confidence interval.

non-problematic users (Cohen's d =0.60). Compared to non-problematic users, problematic users also showed increased levels of negative affect (d = 1.08), intrapersonal motive (d = 1.07), surveillance (d =*0.53*), network expansion (d =*0.48*), and relationship maintenance (d =*0.41*) motives. Finally, problematic users reported lower levels of psychological well-being (d = 0.61) and self-esteem (d = *0.57*), as compared to non-problematic users. Apart from positive affect ($p = 0.55$), all mean differences across the two groups were statistically significant (see **Table 3**).

Predictors of PSMU

A stepwise multiple linear regression was carried out to explore the predictors of PSMU using the main variables of the study. The final model estimated in the fifth step (see **Table 4**) included intrapersonal motive ($\beta = 0.37$, $t = 10.67$), negative affect ($\beta = 0.22$, $t = 6.66$), daily social media use ($\beta = 0.18$, $t = 5.37$), surveillance motive ($\beta = 0.12$, $t = 3.35$), and positive affect ($\beta = -0.09$, $t = -2.80$) as significant predictors of PSMU, contributing ∼37.3% of the total variance in PSMU scores. Among all predictors, intrapersonal motive ($\beta = 0.37$) provided the strongest predictive contribution ($\Delta R^2 = 0.009$; ΔF [1, 577] = 7.88, $p = 0.005$). The final model excluded the following predictors due to low, or non-statistically significant, predictive power: psychological well-being ($p = 0.10$), self-esteem ($p = 0.51$), network expansion motive ($p = 0.82$), and relationship maintenance motive ($p = 0.06$). Finally, the control variables age and gender emerged as non-significant predictors of PSMU ($p > 0.05$).

DISCUSSION

This study contributes to the growing field of PSMU by investigating the role of key correlates and predictors of PSMU, broadly defined. This is an important contribution to the field given that a relatively large amount of previous research has focused on problematic Facebook use specifically, and exclusively. Analyses of the data in the present study revealed that intrapersonal motive, negative affect, relationship maintenance, and psychological well-being were the strongest correlates of PSMU. Furthermore, intrapersonal motive explained about 26% of the total variance in PSMU, followed by negative affect (14%), and relationship maintenance (10%), respectively. Interestingly, broad social media use motives produced strong effects, which is in line with findings from uses and gratification theory (Blumler

TABLE 4 | The relationship between problematic social media use and key related predictors.

Predictors	***Step 1***			***Step 2***			***Step 3***			***Step 4***			***Step 5***		
	B	***SE***	***β***	***B***	***SE***	***β***	***B***	***SE***	***β***	***B***	***SE***	***β***	***B***	***SE***	***β***
Intrapersonal motive	0.50	0.03	0.51***	0.43	0.03	0.43***	0.39	0.03	0.40***	0.37	0.04	0.38***	0.37	0.03	0.38***
Negative affect				0.16	0.02	0.16***	0.16	0.02	0.24***	0.16	0.02	0.23***	0.15	0.02	0.22***
Daily social media use							0.79	0.14	0.19***	0.74	0.14	0.18***	0.77	0.14	0.18***
Surveillance										0.09	0.03	0.10**	0.10	0.03	0.12**
Positive affect													−0.06	0.02	−0.09**
Model summary															
Variance explained by the model	R^2 =0.263 (26.3%)			R^2 =0.320 (32%)			R^2 = 0.354 (35.4%)			R^2 = 0.364 (36.4%)			R^2 = 0.373 (37.3%)		
Change in variance by increasing step				ΔR^2 = 0.057 (57%)			ΔR^2 = 0.034 (34%)			ΔR^2 = 0.010 (10%)			ΔR^2 = 0.009 (0.9%)		
Statistical significance of the model	$F_{(1, 581)}$ = 207.66***			$F_{(2, 580)}$ = 136.36***			$F_{(3, 579)}$ = 105.79***			$F_{(4, 578)}$ = 82.72***			$F_{(5, 577)}$ = 68.54***		
Statistical significance of steps				$\Delta F_{(1, 580)}$ = 48.20***			$\Delta F_{(1, 579)}$ = 30.69***			$\Delta F_{(1, 578)}$ = 9.08**			$\Delta F_{(1, 577)}$ = 7.88**		

***$p < 0.001$; **$p < 0.05$.

The final model, i.e., Step 5 excluded the following variables due to low or non-significant predictive power: age and gender (control variables), psychological well-being, self-esteem, network expansion, and relationship maintenance. B, unstandardized regression coefficient; SE, standard error; β, standardized regression coefficient; R^2*, R square;* ΔR^2*, R square change.*

and Katz, 2020), for instance showing that among others, social motives play an important role in understanding social media use [both to predict intention to use (see Hossain, 2019) and continuance usage Hsiao et al. (2016)]. A recent work by Sariyska et al. (2019) also found support for the relevance of investigating the affiliative motive in the context of Facebook use, but findings might be also dependent on the cultural context. In general, these observations also fit with empirical findings from personality psychology, demonstrating that social media users tend to be slightly more extraverted than non-users (Marengo et al., 2020; Sindermann et al., 2020) and it is well-known that extraverts have a stronger urge to socially interact with other persons. Note that much research on diverse social media use motives has been conducted in the realm of normal or healthy social media use.

As one can see, previous research has considered the relationships between social media use motives and specific factors as described above, such as affiliation and communication confidence (Lee and Kim, 2014). Nevertheless, we believe the present study is among the first, to the authors' knowledge, to explore the relationship between broad social media use motives and PSMU. Moreover, these findings align with previous literature on social media use by supporting the relationship between PSMU with psychological well-being (Oh et al., 2014), self-esteem (Mei et al., 2016), and psychological affect (Caplan, 2002, 2010).

The findings obtained further indicated that about 6.68% of the sample recruited could be classed as problematic users due to their high-risk profile of PSMU. This result aligns with previous research reporting that social media related problems due to PSMU may range from 1.6% (Alabi, 2013) to 18% (Moghavvemi et al., 2017). Although epidemiological data on PSMU has been previously reported, additional research on this emerging phenomenon is warranted before any formal psychiatric recognition and further generalizations to the broader population can be made.

Notwithstanding this, the findings obtained in this study suggest that problematic users used significantly more social media platforms, and presented with increased levels of negative affect, intrapersonal, surveillance, network expansion, and relationship maintenance motives compared to non-problematic users. Furthermore, problematic users also presented with decreased levels of psychological well-being and self-esteem in comparison to non-problematic users. These findings contribute to the growing body of evidence linking PSMU with maladaptive cognition, increased psychiatric distress (Pontes et al., 2018), and decreased well-being (Kross et al., 2013; Satici and Uysal, 2015; Błachnio et al., 2016b).

In terms of key PSMU predictors, the most relevant factors related to intrapersonal motive, followed by negative affect, daily social media use, surveillance motive, and positive affect, which explained about 37.3% of the total variance in PSMU. This finding aligns with past research reporting that key predictive factors associated with PSMU are over and above the influence of commonly related sociodemographic variables such as gender and age (Pontes et al., 2018).

The intricate connection between intrapersonal motive for using social media and PSMU should be further

investigated beyond the linear relationship reported in this study. Intrapersonal motives comprise self-directed emotions associated with self-esteem, guilt, and shame (Weiner, 2001). This finding supports the notion that individuals using social media in an attempt to better understand themselves and their environment are likely to exhibit greater levels of PSMU, a contention that aligns with emerging research showing that trait emotional intelligence may be thought of as a risk factor for PSMU (Kircaburun et al., 2019; Süral et al., 2019). This idea needs to be supplemented by recent notions to better understand the detrimental aspects of social media use by distinguishing between active and passive use, whereas passively browsing seems to be associated with the aspects of overuse and negative affect (e.g., Escobar-Viera et al., 2018).

The current findings also indicated that PSMU may be explained by other social media use motives since they contributed to predicting PSMU in the present sample. Furthermore, the results indicated that self-esteem and the use of multiple social media platforms were linked to PSMU, which may highlight the users' need to improve their levels of self-image and self-esteem, particularly among problematic users (Błachnio et al., 2016a). In this context, it is worth mentioning the process of upward social comparison, which can be triggered by comparing the number of "Likes" with others or by comparing life styles (Vogel et al., 2014). Taken together, these findings may provide useful information with potential clinical implications about the way individuals use social media in the context of the coronavirus (COVID-19) pandemic as recent studies have reported that increased exposure to disaster-related information on social media may trigger negative affect, which can elicit mental health disorders (Zhao and Zhou, 2020), a contention that is aligned with the findings obtained since negative affect was a strong predictor of PSMU.

Despite its contributions, the current study presents with several potential limitations. Although this study found consistent associations between PSMU and psychological well-being, self-esteem, negative affect, and social media use motives, its cross-sectional nature does not allow for causal inferences to be made. Future research should adopt a longitudinal design to further examine the temporal role of key mechanisms underlying PSMU. Another potential limitation in the present study relates to the self-report methodology used, which is likely to have generated well-known biases and unreliable estimations of participants' objective social media use (Rozgonjuk et al., 2020c). Consequently, it is of high interest to also record behavior directly due to time distortions participants experience while using technology (e.g., Lin et al., 2015; Montag et al., 2015).

Importantly, the present study drew its conclusions on a relatively small sample that was sampled through convenience and self-selection sampling, further limiting the scope of the findings as any research question addressed with convenience sampling is limited to the sample itself (Bornstein et al., 2013). We also acknowledge that the *ad-hoc* cut-off approach of the BSMAS, despite being strict, lacks information about its diagnostic accuracy (e.g., sensitivity and specificity) using clinically diagnosed samples as a gold standard. Finally, another potential limitation related to the present study relates to the relatively limited number of possible social media use motives that have been investigated, therefore it is likely that different results would have emerged in light of different psychological motives.

Notwithstanding these potential limitations, this study helps advancing the field of PSMU by further elucidating its key correlates and predictors in terms of psychological well-being, self-esteem, social media use motives, and psychological affect. In conclusion, we found that PSMU was positively associated with intrapersonal motive, negative affect, relationship maintenance motive, network expansion motive, and surveillance motive and negatively associated with psychological well-being, self-esteem, and positive affect. Finally, key predictors of PSMU were related to intrapersonal motive, negative affect, daily social media use, surveillance motive, and positive affect.

DATA AVAILABILITY STATEMENT

The dataset presented in this article is not readily available due to limitations in the confidentiality as per the SREC's recommendations. Requests to access the datasets should be directed to Dr. Bruno Schivinski, bruno.schivinski@rmit.edu.au.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the School of Social Sciences Research Ethics Committee (SREC) Nottingham Trent University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

BS has performed all final statistical analyses of the study and helped drafting, revising, and reviewing the manuscript. MB-W, JS, and CM have all contributed extensively to revising the manuscript and writing its final version. ES was involved in the design of the study, preliminary statistical analyses, and recruitment of participants in addition to helping draft the manuscript. HP has designed the study, assisted with the preliminary statistical analyses, drafting, reviewing, and revision of all versions of the manuscript.

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Self-Reported Screen Time on Social Networking Sites Associated With Problematic Smartphone Use in Chinese Adults: A Population-Based Study

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Background: Problematic smartphone use (PSU) has been associated with screen time in general, but little is known about the effect of different screen-based activities. We examined the associations of self-reported time spent on overall and specific screen-based activities with PSU and its addictive symptoms in Hong Kong Chinese adults.

Methods: We analyzed data from 562 smartphone owners (56.5% female; 82.1% aged 25–64 years) in a population-based telephone survey in 2017. PSU was measured using Smartphone Addiction Scale-Short Version (range 10–60) which includes symptoms of daily-life disturbance, withdrawal, cyberspace-oriented relationship, overuse, and tolerance. Screen time was self-reported as average hours per day spent on the internet, online book/newspaper/magazine, online video, and social networking sites (SNS). Multivariable linear regression analyzed the associations of self-reported screen time with PSU severity and symptoms. Interaction effects of sex, age group, educational attainment, and monthly household income were examined.

Results: Self-reported time spent on overall screen-based activities was associated with PSU severity (β = 1.35, 95% CI 0.15, 2.55) and withdrawal and overuse symptoms, after adjusting for sociodemographic and health-related variables. Independent association was observed for self-reported SNS time with PSU severity (β = 1.42, 95% CI 0.35, 2.49) and symptoms of withdrawal and cyberspace-oriented relationship, after mutually adjusting for time on other activities. The strongest association between self-reported SNS time and PSU severity was observed in younger than older adults (β = 4.36, 95% CI 2.58, 6.13; *P* for interaction = 0.004).

Conclusions: The independent association of self-reported SNS time with PSU and core addictive symptoms highlighted the addiction potential of SNS use, particularly in younger users.

Keywords: screen time, screen-based activities, problematic smartphone use, addictive symptoms, social networking sites

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INTRODUCTION

Excessive use of the internet has raised concerns about its behavioral addiction potential (i.e., internet use disorders), among which online gaming disorder has been added in ICD-11 (1). Problematic smartphone use (PSU) is suggested as a subtype of internet use disorder (2) showing the similar neurobiological pathway of structural and functional brain abnormalities with addictive behaviors (e.g., gambling disorder) (3, 4). PSU could represent symptoms of salience, mood modification, withdrawal, tolerance, conflict, and relapse as posited in the behavioral addiction components model (5, 6). Such symptoms have a spectrum of severity that can be less or more significant to indicate pathological addiction (7). Core criteria of PSU were proposed to include symptoms related to withdrawal, tolerance, and functional impairments (of physical/psychological health, social relationship, or workplace/school performance) (7, 8). The diagnostic accuracy of the criteria has been shown in studies to distinguish online gaming disorder from non-pathological use (9). However, it should be noted that PSU is not an official diagnosis in ICD-11 or DSM-5 and may not be comparable to the established heroin and tobacco addictions on severity and/or associated health problems (7). Debates are ongoing on whether PSU qualifies for an addiction (10, 11). We used the term "PSU" as recommended to avoid over-pathologizing of everyday-life behaviors (12–14).

PSU is found to be associated with self-reported overall screen time (15, 16). The association was supported in studies objectively measuring smartphone use on different devices (Android and iOS) (17–19). The screen time can involve various activities differing in using motives categorized into process and social use (20–23). Process use is for news consumption, entertainment, or other nonsocial motives, such as surfing the internet/websites, reading online book/newspaper/magazine, and watching online videos, while social use is for social interaction motives, such as using social networking sites (SNS; e.g., Facebook, Twitter, WhatsApp, WeChat) (21).

Results are mixed on associations between different screen-based activities and PSU. Social-oriented activity was associated with PSU (15), particularly in females who might have greater sociality than males and younger people who might be more active on SNS (24). Exposure to social comparison information on SNS, such as a large amount of "Likes" and comments, perfect body images, and idealized lives, might reduce self-esteem and increase depression (25), which are consistently associated with PSU (26–28). Other research showed stronger associations of process-oriented activities with PSU adjusting for sex and age (20). Spending more time on process-oriented activities could be a mechanism for individuals with higher anxiety to deflect negative stressors (29), while anxiety and dysfunctional emotion regulation could lead to PSU (20). Little is known about the potential moderating role of educational attainment and income, despite that electronic literacy and pattern of engagement in screen-based activities may differ by socioeconomic status (30).

We used the Uses and Gratifications Theory (UGT) (31) and the Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors (32) to theoretically conceptualize the study. The UGT posits that individual differences motivate people to increasingly use specific types of electronic media to satisfy underlying needs (31). UGT was proposed for traditional media but has been widely applied to the advanced screen-based activities (20, 21, 26). Individual differences in the UGT can include sociodemographic and psychological characteristics such as anxiety and depression symptoms (21). The more comprehensive I-PACE model can be used to explain associations between specific screen-based activities and PSU (23, 33). Specific using motives plus general characteristics (e.g., sociodemographic and psychological characteristics) could predispose individuals to the onset and maintenance of PSU as posited in the I-PACE model (32).

Hong Kong, the most developed city in China, has one of the highest smartphone penetration rates worldwide (91.5% in 2019) (34). Our previous study showed a high prevalence of PSU (38.5%) in Hong Kong (35). We have also found that PSU was associated with impaired mental health and family well-being (36, 37). This study took advantage of a population-based survey in Hong Kong Chinese adults to examine the associations of time spent on overall and specific types of screen-based activities with PSU and its addictive symptoms. We also examined the potential interaction effects of sex, age group, educational attainment, and monthly household income on these associations.

MATERIALS AND METHODS

Design and Participants

The Hong Kong Family and Health Information Trends Survey (FHInTS) was a periodic territory-wide telephone survey on the general public's behaviors and views regarding information use, individual health, and family well-being, under the project "FAMILY: A Jockey Club Initiative for a Harmonious Society." We conducted five waves of FHInTS since 2009. The present landline telephone survey was part of the fifth wave of FHInTS from February to August 2017. Details of the study design have been reported elsewhere (30, 35). The target population was Cantonese-speaking Hong Kong residents aged 18 years or above. A two-stage probability-based sampling method was used to minimalize sampling bias. In the first stage of random-digit-dialing, telephone numbers were randomly generated using known prefixes assigned to telecommunication service providers by the Government Office of the Communications Authority, which covered nearly all households in Hong Kong. Invalid numbers were removed according to the computer and manual dialing records. Telephone numbers of respondents from previous waves were also filtered. In the second stage of within household sampling, once a household was successfully reached, an eligible family member whose next birthday was the closest to the interview day was invited for the survey. All telephone interviews were conducted by trained interviewers from Public Opinion Programme (POP) at the University of Hong Kong. Of 5,773 eligible subjects, 4,054 responded to the survey (response rate = 70.2%). Six hundred eighty-six respondents were randomly selected to answer questions on screen time and PSU. The final study sample comprised 562 smartphone owners, after excluding smartphone nonowners.

Measures

PSU was measured using the ten-item Smartphone Addiction Scale-Short Version (SAS-SV), with each item scoring on a six-point Likert scale (1 = strongly disagree to 6 = strongly agree) (38). A higher total SAS-SV score (range 10–60) indicates a higher PSU severity (38). The addictive symptoms of cyberspace-oriented relationship, overuse, and tolerance each have one item; symptoms of daily-life disturbance have three items; and withdrawal symptoms have four items (38). The average score of these multi-item symptoms was calculated (range 1–6). The Chinese version of SAS-SV was found reliable and valid in our previous study (35). Cronbach's alpha was 0.84 in the present sample. SAS-SV scores could be dichotomized into "non-PSU" and "PSU" using suggested cutoffs (male 31; female 33) (38). However, the cutoffs were established by receiver-operating characteristic analyses on adolescents (38), which may be less applicable to adults in the present study. Note that PSU has not been an official diagnosis but a behavior ranging from unproblematic to problematic (7). We hence used continuous SAS-SV scores for all analyses.

Respondents were asked that "In the past month, how many hours did you spend on…per day? [If <1 h, please probe how long, i.e., half an hour (0.5), 15 min (0.25), no (0)]." Process-oriented screen-based activities included surfing the internet; reading online book/newspaper/magazine; watching online video (e.g., YouTube); and social-oriented activity included using SNS (e.g., Facebook, Twitter, WhatsApp, WeChat). We categorized the amount of time as "0," ">0 to <1 hours per day," "≥1 to <2 hours per day," "≥2 to <3 hours per day," and "≥3 hours per day." The similar categorization was used in large-scale longitudinal studies on self-reported screen time (25, 39). Overall screen time was calculated by summing the amount of time spent on all four screen-based activities measured.

Sociodemographic characteristics included sex, age group, marital status, employment status, educational attainment (primary or below, secondary, or tertiary), and monthly household income (≤HK$ 19,999, 20,000–29,999, or ≥30,000; US $1 = HK $7.8) (the median household income was HK$ 24,900 in Hong Kong in 2016). Cigarette smoking (never smoker, former smoker, or current smoker) and alcohol drinking (never drinker, former drinker, occasional drinker, or monthly or more drinker) were examined, given the co-occurrence of substance use and addictive behaviors (40). History of doctor-diagnosed chronic diseases (e.g., cardiovascular diseases, respiratory diseases, liver diseases, allergies, and others) was dichotomized into none or any. Psychological characteristics were measured using the validated four-item Patient Health Questionnaire (PHQ-4) (41). Each item scores on a Likert scale (0 = not at all to 3 = nearly every day), with a higher total score (range 0–12) indicating higher symptom severity (41). Cronbach's α was 0.83 in the present sample. Cigarette smoking, alcohol drinking, chronic disease, and PHQ-4 score were grouped as health-related characteristics.

Statistical Analysis

All data were weighted according to sex, age, and educational attainment distributions of the Hong Kong general population to increase the sample representativeness. We examined the associations of time spent on overall and each of four specific screen-based activities with PSU severity and symptoms using bivariate and multivariable linear regression analyses adjusting for sociodemographic and health-related characteristics (Model 1). In Model 2, we repeated Model 1 with mutually adjusting time spent on other types of screen-based activities. The variance inflation factors (range 1.51–2.34, <10 acceptable) suggested the minimal multicollinearity among time spent on different types of screen-based activities in Model 2 (42). Dichotomized SAS-SV scores by suggested cutoffs were used for testing robustness of results in sensitivity analyses. We further tested whether any observed association of time spent on specific screen-based activity with PSU severity in Model 2 differed by sex, age group, educational attainment, and monthly household income by adding multiplicative interaction terms. An omnibus *P* for interactor was calculated using adjusted Wald tests. Missing data were handled by available case analyses as missing values for all variables were minimal (<2.0%). All analyses were conducted using STATA version/MP 15.1 (StataCorp., TX, USA). A two-side $P < 0.05$ was considered statistically significant.

RESULTS

The weighted sample ($N = 562$; 56.5% female; 82.1% aged 25–64 years) had a mean SAS-SV score of 27.8 [standard deviation (SD) 10.2], with the highest symptom score was observed for cyberspace-oriented relationship (mean 3.5, SD 1.6) (**Table 1**).

Nearly three-quarters of respondents (71.5%) reported spending over 3 h per day on overall screen-based activities (**Table 2**). The most prevalent activity (spent over 3 h per day) was surfing the internet, followed by using SNS, reading online book/newspaper/magazine, and watching online video.

Multivariable analyses showed that each hour of increase in time spent on overall screen-based activities was associated with higher symptom severity of withdrawal (adjusted β = 0.19, 95% CI 0.05, 0.34) and overuse (adjusted β = 0.20, 95% CI 0.02, 0.38) and higher PSU severity (adjusted β = 1.35, 95% CI 0.15, 2.55), after adjusting for sociodemographic and health-related characteristics (Model 1) (**Table 3**). Associations with higher PSU severity were also observed for each hour of increase in time spent on surfing the internet, reading online book/newspaper/magazine, watching online video, and using SNS in Model 1. After mutually adjusting for time spent on other types of screen-based activities (Model 2), these associations were attenuated and became nonsignificant except for time spent on using SNS. Each hour of increase in time spent on using SNS was associated with higher PSU severity (adjusted β = 1.42, 95% CI 0.35, 2.49) and higher symptom severity of withdrawal (adjusted β = 0.18, 95% CI 0.05, 0.32) and cyberspace-oriented relationship (adjusted β = 0.38, 95% CI 0.23, 0.53). The association of SNS time with PSU was found robust in sensitivity analyses (adjusted odds ratio = 1.40, 95% CI 1.08, 1.83) (**Supplementary Table 1**). Each hour of increase in time spent on surfing the internet was associated with higher symptom severity of daily-life disturbance (adjusted β = 0.13, 95% CI 0.02, 0.24). Each hour of increase in

TABLE 1 | Demographic characteristics and SAS-SV total and symptom score ($N = 562$).

	Nonweighted ($N = 497$)	Weighted[a] ($N = 562$)
	n (%)	*n* (%)
Sex		
Male	192 (38.6)	244 (43.5)
Female	305 (61.4)	318 (56.5)
Age group, years		
18–24	67 (13.5)	54 (9.6)
25–44	98 (19.8)	248 (44.1)
45–64	216 (43.5)	214 (38.0)
≥65	116 (23.3)	47 (8.3)
Marital status		
Unmarried	141 (28.4)	205 (36.5)
Cohabitated/married	303 (61.0)	318 (56.6)
Divorced/separated/widowed	53 (10.7)	39 (6.9)
Employment status		
Unemployed	20 (4.0)	32 (5.7)
In-paid employed	202 (40.6)	315 (56.0)
Retired	143 (28.8)	77 (13.6)
Housekeeper	85 (17.1)	98 (17.4)
Full-time student	47 (9.5)	41 (7.3)
Educational attainment		
Primary or below	61 (12.3)	90 (16.0)
Secondary	222 (44.7)	279 (49.6)
Tertiary	214 (43.1)	193 (34.4)
Monthly household income (HK $)[b]		
≤9,999	70 (14.1)	44 (8.0)
10,000–19,999	60 (12.1)	79 (14.1)
20,000–29,999	95 (19.1)	124 (22.0)
30,000–39,999	63 (12.7)	90 (16.1)
≥40,000	143 (28.8)	158 (28.1)
Unstable/refused to answer	66 (13.3)	67 (11.9)
Cigarette smoking		
Never smoker	409 (82.3)	438 (77.9)
Former smoker	51 (10.3)	68 (12.0)
Current smoker	37 (7.4)	57 (10.1)
Alcohol drinking		
Never drinker	220 (44.3)	228 (40.6)
Former drinker	19 (3.8)	23 (4.1)
Occasional drinker	181 (36.4)	217 (38.6)
Monthly or more drinker	77 (15.5)	94 (16.7)
Chronic disease diagnosis		
None	324 (65.2)	420 (74.7)
Any	173 (34.8)	142 (25.3)
PHQ-4 score, range 0–12, mean ± SD	2.0 ± 2.4	2.3 ± 2.7
SAS-SV score, range 10–60, mean ± SD	26.8 ± 9.7	27.8 ± 10.2
SAS-SV symptom score, range 1–6, mean ± SD		
Daily-life disturbance[c]	2.3 ± 1.1	2.5 ±1.2
Withdrawal[d]	3.0 ± 1.3	3.0 ±1.3
Cyberspace-oriented relationship	3.5 ± 1.6	3.5 ±1.6
Overuse	2.6 ± 1.4	2.8 ±1.5
Tolerance	1.9 ± 1.2	2.0 ±1.3

PHQ-4, 4-item Patient Health Questionnaire; SAS-SV, Smartphone Addiction Scale-Short Version; SD, standard deviation.
Reported by n (%), otherwise as indicated.
[a] *Weighted by sex, age, and educational attainment distributions of Hong Kong general population.*
[b] *US $1 = HK $7.8.*
[c] *The average score of the symptoms of daily-life disturbance that contains three items.*
[d] *The average score of withdrawal symptoms that contains four items.*

time spent on watching online video was associated with higher symptom severity of withdrawal (adjusted β = 0.13, 95% CI 0.004, 0.26).

We also examined the interaction effects of sex, age group, educational attainment, and monthly household income on the association of SNS time with PSU severity in Model 2 (**Table 4**). Younger respondents aged 18–24 years had the strongest association (adjusted β = 4.36, 95% CI 2.58, 6.13), compared with older respondents (25–44 years: adjusted β = 0.97, 95% CI −0.76, 2.69; 45–64 years: adjusted β = 1.69, 95% CI 0.35, 3.04; ≥65 years: adjusted β = 2.87, 95% CI 0.95, 4.80; *P* for interaction = 0.004). Sex appeared to have no interaction effect on the association of SNS time with PSU severity (male: adjusted β = 1.52, 95% CI 0.03, 3.02; female: adjusted β = 1.98, 95% CI 0.46, 3.51). Respondents with higher educational attainment tended to have the stronger association of SNS time with PSU severity (secondary: adjusted β = 1.46, 95% CI 0.11, 2.82; tertiary: adjusted β = 2.11, 95% CI 0.90, 3.33), but the interaction effect did not reach significance level (*P* for interaction = 0.06).

DISCUSSION

In a random sample of Hong Kong Chinese adults, self-reported time spent on overall screen-based activities was positively associated with PSU severity. This finding was consistent with studies showing that longer smartphone usage time was associated with higher PSU severity using the same SAS-SV in Swiss, Spanish, and Belgian populations (15, 16).

Our study added to the literature by exploring the associations of self-reported time spent on overall and specific types of screen-based activities with PSU and its addictive symptom. Specifically, we found that overall screen time was associated with overuse (i.e., "Using my smartphone longer than I had intended."). The self-awareness of excessive use was also reported in a qualitative interview in users with higher PSU severity (8). However, overuse has been identified as a necessary but insufficient condition of pathological addiction (43). Tolerance symptoms were proposed in the core criteria (7), but we observed no association of overall screen time with tolerance.

TABLE 2 | Hours per day spent on overall and specific types of screen-based activities ($N = 562$).

Time spent on screen-based activities, hours/day	Nonweighted ($N = 497$)	Weighted[a] ($N = 562$)
	n (%)	*n* (%)
Overall		
0	15 (3.1)	10 (1.8)
>0 to <1	46 (9.4)	38 (6.9)
≥1 to <2	63 (12.9)	51 (9.2)
≥2 to <3	51 (10.4)	59 (10.6)
≥3	314 (64.2)	397 (71.5)
Surfing the internet		
0	90 (18.1)	71 (12.7)
>0 to <1	66 (13.3)	63 (11.3)
≥1 to <2	94 (19.0)	109 (19.5)
≥2 to <3	74 (15.0)	80 (14.3)
≥3	171 (34.6)	237 (42.2)
Reading online book/newspaper/magazine		
0	204 (41.1)	211 (37.5)
>0 to <1	111 (22.4)	130 (23.1)
≥1 to <2	110 (22.2)	123 (21.9)
≥2 to <3	42 (8.5)	51 (9.1)
≥3	29 (5.9)	47 (8.4)
Watching online video		
0	219 (44.2)	214 (38.2)
>0 to <1	109 (22.0)	137 (24.5)
≥1 to <2	90 (18.2)	117 (21.0)
≥2 to <3	41 (8.3)	47 (8.4)
≥3	36 (7.3)	44 (7.9)
Using social networking sites		
0	35 (7.1)	26 (4.7)
>0 to <1	147 (29.9)	151 (27.1)
≥1 to <2	136 (27.6)	137 (24.6)
≥2 to <3	62 (12.6)	94 (16.9)
≥3	112 (22.8)	150 (26.8)

[a]*Weighted by sex, age, and educational attainment distributions of Hong Kong general population.*

This might be attributable to the failure of the single-item measure of tolerance in SAS-SV (i.e., "The people around me tell me that I use my smartphone too much.") to capture other aspects, including increases in financial costs, feelings of gratification, and achievement (e.g., game score/level and SNS "Like"/comment) (44). Overall screen time was also not associated with core addictive symptoms of daily-life disturbance or cyberspace-oriented relationship. In contrast, impairments of workplace/school performance and offline interactions were consistently observed in research into online gaming disorder, a specific form of internet use disorder (9).

Self-reported time spent on using SNS was independently associated with PSU and its core addictive symptoms, including withdrawal and cyberspace-oriented relationship. This association was observed after adjusting for time spent on reading online book/newspaper/magazine, watching online video, and surfing the internet. The findings showed that social- and process-oriented activity were not equally associated with PSU, which supported the UGT (31) and I-PACE (32). Some SNS has features to predispose users to excessive use to meet such higher levels of online social demands; Snapchat is an example that delivers messages only available for a short time after having been viewed by recipients (45). The ephemeral nature of Snapchat can risk users to PSU to avoid missing out the time-limited social connections (46). Our observed association of SNS time with withdrawal symptoms complemented the findings from an experimental study, which found that imagining no access to SNS for 48 h led to dysregulated emotions, depression, and stress (47). A potential mediator on this association might be social anxiety about missing out real-time posts, events, and interactions on SNS (48). The observed association of SNS time with cyberspace-oriented relationship suggested a trade-off between online and offline interactions in the displacement hypothesis (49), which was also supported by impaired family relationships associated with increased SNS time (50). The independent associations of self-reported SNS time with PSU highlighted the needs of specific measurements on problematic SNS use (51) and interventions to prevent and reduce SNS time.

Younger adults appeared to be the most susceptible to the association of self-reported SNS time with PSU in our subgroup analyses. A similar finding was reported in a cross-generation study showing the predictive effect of SNS time on PSU only in the younger group (52). Younger adults tend to be more active but have lower self-control than older adults in using SNS, which might explain the observed association (24). Early adulthood is a developmental stage of emotion change, self-control underdevelopment, and reward sensitivity, which are known risk factors for PSU (6). Neuroscience studies supported the notion by identifying the lateral orbitofrontal gray matter abnormalities in young people with PSU and particularly in those spent time on SNS, and the lateral orbitofrontal cortex is important in regulatory control and reward-related decision-making (3). The stronger association of SNS time with PSU was also observed in those with higher education in our study, although the interaction effect was not significant possibly due to insufficient sample size. Higher SES group may have more social capitals, but greater needs to develop and maintain social connections have been associated with increased SNS time (53).

Self-reported time spent on surfing the internet was associated with daily-life disturbance in our study. Internet has an array of contents for information seeking, shopping, gaming, pornography viewing, gambling, or aimless browsing, and some of which have been identified with addiction potential (e.g., gaming and gambling disorders) and were associated with impairments of school/work performance (54, 55). We found that time spent on watching online video was associated with withdrawal symptoms, which was consistent with a study showing anxiety symptoms associated with excessive use of process-oriented activity (20). The popular video-sharing and live-streaming SNS (e.g., TikTok, Twitch, and Facebook Live) suggested that social anxiety about missing out connections may

TABLE 3 | Associations of time spent on overall and specific screen-based activities with PSU and its addictive symptoms ($N = 562$).

Time spent on screen-based activities	Regression model	Association with SAS-SV score, β (95% CI)	Association with SAS-SV symptom score, β (95% CI)				
			Daily-life disturbance	Withdrawal	Cyberspace-oriented relationships	Overuse	Tolerance
Overall	Crude	1.23 (0.18, 2.29)*	0.12 (-0.01, 0.25)	0.11 (−0.03, 0.24)	0.08 (−0.08, 0.23)	0.27 (0.11, 0.43)**	0.06 (−0.09, 0.20)
	Model 1[a]	1.35 (0.15, 2.55)*	0.06 (−0.08, 0.20)	0.19 (0.05, 0.34)**	0.15 (−0.04, 0.34)	0.20 (0.02, 0.38)*	0.07 (−0.10, 0.23)
Surfing the internet	Crude	1.51 (0.67, 2.36)***	0.19 (0.10, 0.28)***	0.11 (−0.001, 0.22)	0.06 (−0.07, 0.18)	0.29 (0.17, 0.41)***	0.11 (0.005, 0.22)*
	Model 1[a]	1.76 (0.77, 2.76)**	0.16 (0.05, 0.27)**	0.19 (0.07, 0.32)**	0.12 (−0.02, 0.27)	0.23 (0.09, 0.38)**	0.14 (0.01, 0.28)*
	Model 2[b]	0.89 (−0.14, 1.91)	0.13 (0.02, 0.24)*	0.08 (−0.06, 0.22)	−0.03 (−0.19, 0.12)	0.12 (−0.04, 0.28)	0.08 (−0.07, 0.22)
Reading online book/newspaper/magazine	Crude	1.37 (0.37, 2.36)**	0.13 (0.02, 0.24)*	0.11 (−0.01, 0.24)	0.09 (−0.06, 0.23)	0.29 (0.16, 0.42)***	0.11 (−0.02, 0.23)
	Model 1[a]	1.55 (0.60, 2.49)**	0.10 (−0.01, 0.21)	0.17 (0.06, 0.28)**	0.17 (0.03, 0.32)*	0.24 (0.10, 0.38)**	0.14 (0.01, 0.27)*
	Model 2[b]	0.68 (−0.24, 1.60)	0.03 (−0.08, 0.13)	0.07 (−0.05, 0.19)	0.09 (−0.06, 0.24)	0.14 (−0.001, 0.28)	0.07 (−0.06, 0.20)
Watching online video	Crude	1.53 (0.58, 2.47)**	0.17 (0.05, 0.28)**	0.15 (0.02, 0.27)*	0.07 (−0.08, 0.23)	0.24 (0.10, 0.38)**	0.10 (−0.03, 0.22)
	Model 1[a]	1.39 (0.45, 2.34)**	0.07 (−0.04, 0.19)	0.20 (0.09, 0.31)**	0.10 (−0.05, 0.26)	0.15 (0.01, 0.29)*	0.10 (−0.05, 0.26)
	Model 2[b]	0.77 (−0.29, 1.83)	0.03 (−0.09, 0.15)	0.13 (0.004, 0.26)*	0.02 (−0.15, 0.17)	0.06 (−0.09, 0.21)	0.05 (−0.11, 0.21)
Using social networking sites	Crude	1.60 (0.70, 2.50)**	0.13 (0.02, 0.23)*	0.14 (0.02, 0.26)*	0.24 (0.10, 0.38)**	0.29 (0.16, 0.42)***	0.11 (−0.01, 0.23)
	Model 1[a]	1.99 (0.94, 3.05)***	0.10 (−0.02, 0.22)	0.24 (0.12, 0.36)***	0.38 (0.24, 0.51)***	0.24 (0.09, 0.40)**	0.14 (0.002, 0.28)*
	Model 2[b]	1.42 (0.35, 2.49)**	0.04 (−0.07, 0.15)	0.18 (0.05, 0.32)**	0.38 (0.23, 0.53)***	0.16 (−0.002, 0.32)	0.10 (−0.04, 0.24)

PSU, problematic smartphone use; SAS-SV, Smartphone Addiction Scale-Short Version.

All data were weighted by sex, age, and educational attainment distribution of Hong Kong general population.

**P < 0.05, **P < 0.01, ***P < 0.001.*

[a]*Adjusted for sex, age, marital status, educational attainment, employment status, monthly household income, cigarette smoking, alcohol drinking, chronic disease, and four-item Patient Health Questionnaire score.*

[b]*Additionally adjusted for time spent on other screen-based activities.*

TABLE 4 | Adjusted associations of time spent on using social networking sites with PSU by sex, age, educational attainment, and monthly household income ($N = 562$)[a].

	SAS-SV score, mean ± SD	Adjusted associations of social networking sites time with SAS-SV score	
		β (95% CI)	*P* for interaction
Sex			0.17
Male	28.0 ± 9.7	1.52 (0.03, 3.02)*	
Female	27.7 ± 10.5	1.98 (0.46, 3.51)*	
Age group, years			0.004
18–24	29.5 ± 8.6	4.36 (2.58, 6.13)***	
25–44	28.3 ± 6.8	0.97 (−0.76, 2.69)	
45–64	27.1 ± 11.6	1.69 (0.35, 3.04)*	
≥65	26.8 ± 16.9	2.87 (0.95, 4.80)**	
Educational attainment			0.06
Primary or below	30.5 ± 9.9	0.13 (−3.37, 3.63)	
Secondary	26.5 ± 9.5	1.46 (0.11, 2.82)*	
Tertiary	28.4 ± 10.6	2.11 (0.90, 3.33)**	
Monthly household income (HK $)[b]			0.06
≤19,999	28.0 ± 12.9	0.90 (−0.61, 2.42)	
20,000–29,999	27.9 ± 8.6	2.54 (0.41, 4.68)*	
≥30,000	27.6 ± 9.8	0.85 (−0.74, 2.44)	

PSU, problematic smartphone use; SAS-SV, Smartphone Addiction Scale-Short Version. All data were weighted by sex, age, and educational attainment distribution of Hong Kong general population.

$^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

[a]Adjusted for sex, age, marital status, educational attainment, employment status, monthly household income, cigarette smoking, alcohol drinking, chronic disease, four-item Patient Health Questionnaire score, and time spent on other screen-based activities.

[b]US $1 = HK $7.8.

also be a mediator in the pathway from online video time to withdrawal symptoms (56). Future studies would benefit from examining more detailed contents that are used on the internet and online video.

Our results have theoretical and practical implications. The different associations between time spent on social- and process-oriented activities and PSU informed future research to distinguish between using motives. This fits with the UGT (31) and I-PACE (32) which posit specific motives could predispose individuals to PSU. Prevention and intervention programs, particularly in younger adults, might target limiting SNS time to reduce PSU severity and symptoms. Technology providers could consider incorporate time limit setting into mobile devices or applications.

Our study has several limitations. The cross-sectional data restricted the inference of the temporal sequence of self-reported screen time and PSU. Reverse direction of the association is possible as people with PSU tend to have longer screen time to deflect negative emotions induced by PSU (57). Longitudinal, experimental, and intervention studies are warranted to clarify causal relations and potential mechanisms. Although we adjusted for several potential confounders consistently reported in the literature (24), residual or unmeasured confounders such as personalities of low self-control and social anxiety might explain the observed associations between screen time and PSU (6, 48). Landline survey excluding mobile phone-only group might not be representative for the entire population. Weighting can reduce the non-coverage bias but may not fully compensate for differences in screen time and PSU between landline and mobile surveys. The exclusion of individuals younger than 18 years might underestimate the findings as this age group tended to have longer screen time and higher risks for PSU (24). Self-reported screen time was subject to recall bias and social desirability bias and with uncertain reliability. Future research can use the reliable screen-time questionnaire (58) or objective smartphone use by longitudinal and repeated measures (17–19) to validate the results. The lacking data on other popular social- (e.g., email) and process-oriented activities (e.g., gaming, shopping, online banking) warranted more comprehensive measures in future research.

CONCLUSIONS

Self-reported screen time was positively associated with PSU severity in Chinese adults in Hong Kong, but the associations varied by types of screen-based activities. The independent associations of self-reported SNS time with PSU severity and core addictive symptoms of withdrawal and cyberspace-oriented relationship highlighted recent warnings about excessive SNS use. Younger adults were the most susceptible to the association of SNS time with PSU severity. Our study provided reminders to smartphone users of the addiction potential of screen time in particular on using SNS. The study could help SNS providers and policymakers to develop regulations to prevent excessive SNS use and PSU.

DATA AVAILABILITY STATEMENT

The data analyzed in this study is subject to the following licenses/restrictions: The data that support the findings of this study are available from the FAMILY project but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Hong Kong Jockey Club Charities Trust. Requests to access these datasets should be directed to FAMILY project, https://www.family.org.hk/en/about-us/contact-us-en/.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board of the University of Hong Kong/Hospital Authority Hong Kong West Cluster. All respondents provided verbal informed consent. Telephone

interviews were audio-recorded for quality checking with respondents' consent. Interview records were then erased 6 months after completing the survey. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

NG: formal analysis, data curation, writing—original draft, and writing—review and editing. TTL: writing—review and editing. MPW: conceptualization, methodology, and writing—review and editing, supervision. SYH: conceptualization, methodology, writing—review and editing, and supervision. DYTF: writing—review and editing and supervision. AW: project administration. SSC: conceptualization and methodology. THL: conceptualization, methodology, writing—review and editing, and funding acquisition. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2020.614061/full#supplementary-material

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In-game Social Interaction and Gaming Disorder: A Perspective From Online Social Capital

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Background and Aims: Social interaction in the online games has been found to predict gaming disorder, but little research has examined the mechanism of this association. Drawing on the social capital theory, the present study investigated the mediating role of online social capital on the relationship between in-game social interaction and gaming disorder and the moderating role of alienation on the relationship between online social capital and gaming disorder.

Methods: A sample of 457 Chinese massively multiplayer online role-playing game gamers was recruited to complete the In-game Social Interaction Questionnaire, Online Social Capital Scale, Alienation Scale, and Pathological Gaming Scale.

Results: The results showed that online social capital was a mediator in the relationship between in-game social interaction and gaming disorder. Moreover, for individuals with low alienation, the effect of online social capital on gaming disorder was weaker than for those with high alienation.

Conclusions: The present study provides new insight into the complex processes involved in the effect of in-game social interaction on gaming disorder, and the results have important theoretical and practical implications.

Keywords: in-game social interaction, online social capital, alienation, gaming disorder, moderated mediation model

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INTRODUCTION

Playing online games has become a highly prevalent activity, which, in some cases, engenders negative consequences, and becomes addictive (1, 2). The 11th edition of the *International Classification of Diseases* [ICD-11; (3)] recently includes "gaming disorder, predominantly online" as an official diagnosis, and the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* [DSM-5; (4)] also includes online gaming disorder as an emerging mental health issue that should be further investigated. At present, there is a lack of agreement as to the precise name and definition of the online gaming disorder, which always is referred to as game addiction (5), pathological online game use (6), or problematic online game use (7). The present study proposes to use the name gaming disorder, which means that excessive online gaming led to gamers developing addiction-like symptoms (e.g., overuse) and negative consequences on physical/psychological health (8–10). This term describes the quintessence of the phenomenon (i.e., the behavior is not only excessive but gaming-related problems) while avoiding the notion of dependency.

Past research showed that gaming disorder is associated with negative consequences on gamers' work, education, and their social relationships e.g. (11–14); the problem of gaming disorder and

factors influencing it have received much research attention. Gamers' personality, motives, and psychosocial characteristics have been shown to be predictors of gaming disorder [e.g., (15–17)]. However, little research has addressed the influence of structural characteristics of online games, such as character play, leveling up, and in-game social interaction (18), which are critical design factors leading to engagement (19) and a greater risk for developing gaming disorder (18).

The current study focused on the in-game social interaction as a predictor of gaming disorder. Though previous studies have confirmed the direct link between in-game social interaction and gaming disorder (18, 20, 21), little is known about the mechanisms underlying the relation. Addressing this question is important for better understanding on how in-game social interaction influences gaming disorder (mediating mechanism) and when the link is most potent (moderating factors). The present study fills this gap by utilizing a large sample of Chinese massively multiplayer online role-playing game (MMORPG) gamers to test a moderated mediation model in which: (1) in-game social interaction increases online social capital, which, in turn, increases gamers' gaming disorder and (2) the indirect association between in-game social interaction and gaming disorder is moderated by individual factors such as alienation.

In-game Social Interaction and Gaming Disorder

In MMORPG, social features mainly refer to collective play involving collaboration, community, and social interaction (22). Social interaction in MMORPG includes communication, cooperation, making friends with other gamers within the game context, belonging to a guild, clan, or group, and social support networks (23). Most MMORPGs encourage collective play and other forms of social interaction among gamers, which means that playing MMORPG is not a solitary activity but very much an intrinsically social activity (24).

The belongingness theory (25) suggests that people have a fundamental need to belong that motivates them to seek out social interactions and form close and meaningful relationships with others. The social features of video games provide opportunities for new meaningful and emotionally resonant relationships to develop, helping to satisfy the human need for affiliation and social support. Therefore, social need and developing online relationships are main motivations for online gaming (26), and the social elements of an online game shaped the gamers' desire to forge and maintain online relationships, which may play a considerable role in the initiation, development, and maintenance of gaming disorder (15). Consequently, the intensity of this social interaction has been known to be associated with gaming disorder (18, 20, 21).

The Mediating Role of Online Social Capital

Online social interaction and relationships established in MMORPGs are based on collaboration and shared gaming experiences in which gamers exchange emotional or substantial support (22). Social capital is defined as the beneficial consequence (e.g., support-based resources) of social interactions and relationships (27), which can occur both offline and online (28) and is always separated into two subtypes: bonding and bridging (29).

Unlike other online friendships created merely by online communication (e.g., online social network services or SNS), these newly established strong ties in MMORPGs are more likely to generate social capital because of the frequent in-game social interactions and enjoyable social experience (22). Research has revealed that participation in guilds, quests, and inter-player interactions, engaging in clan/guild administration, joining in game-related groups, and the number of communication channels used for social interaction among gamers are positively associated with one's bridging and bonding social capital (22, 27, 30).

High online social capital is indicative of a meaningful and emotionally supportive online community (31, 32). However, social capital can also result in negative consequences. According to the uses and gratifications theory (33), individuals' dependency on media is related to use gratifications. Online social capital derived from in-game social interaction satisfies the need for affiliation and social support, which, in turn, leads to excessive gaming (34). Another mechanism through which online gaming may affect gaming disorder is suggested by the displacement hypothesis (35). Because of the "inelasticity of time" (36), playing online games takes away time from face-to-face interactions with one's offline ties (37), which can lead to the displacement of offline social contacts for online ties (38). Therefore, gamers who are absorbed with in-game social interaction may have an overall smaller and weaker offline social circle as a result of excessive online gaming (39). Reliance on online social interaction reduces offline contact (40), further maintaining online friendships and interactions. As gamers grow closer to their in-game contacts and their online social capital increases, offline activities become displaced and online game play becomes more desirable. Consequently, online gamers who participate in online social interaction might develop close ties with other gamers and receive social support from them, which, in turn, might lead to their psychological dependency on the online relationship (41), and the reduced levels of offline social interaction encourage the development of gaming disorder (42). Collins and Freeman (43) found that problematic video game play was associated with significantly higher online social capital and lower offline social capital. Therefore, the benefits of in-game social interaction, namely, online social capital, can increase the risk for problematic behavior in the form of gaming disorder.

Based on extant research, we believe that online social capital generated from in-game social interactions is an important predictor of problematic gaming, and thus we propose hypothesis 1: *Online social capital could mediate the relationship between in-game social interaction and gaming disorder.*

The Moderating Role of Alienation

Although in-game social interaction may influence gaming disorder through the mediation effect of online social capital, it is possible that individuals are influenced differently by its effects. Therefore, it is necessary to examine moderators of in-game social interaction as it impacts gaming disorder. In the present study, we tested whether the direct and/or indirect association

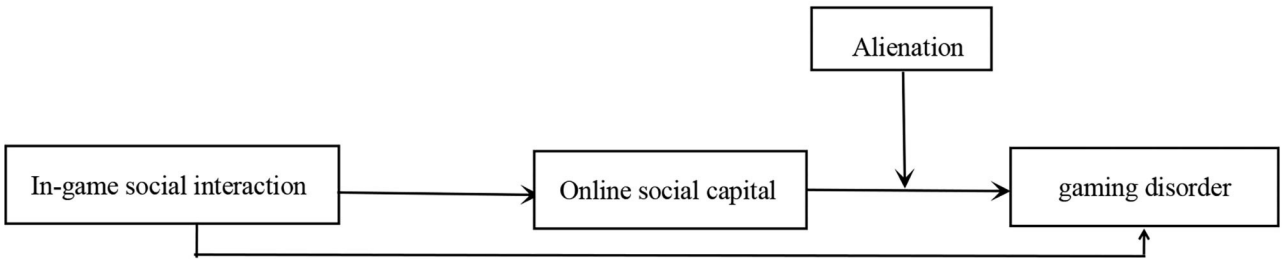

FIGURE 1 | The proposed moderated mediation model. Mediation and moderation effects were controlled for gender and age.

between in-game social interaction and gaming disorder was moderated by alienation.

Alienation is defined as the feeling of disconnectedness from social networks such as the family and peer group and an absence of social support (44). Individuals with high alienation often experience a sense of meaninglessness, helplessness, and loneliness (45). The compensatory Internet use model suggests that the Internet can provide opportunities for people to achieve some purposes that cannot be realized in real life (46). In the virtual online social environment, individuals can choose the groups to which they belong and gain opportunities to communicate with people based on their preferences, helping to compensate for the sense of helplessness and frustration experienced in real life (47). Therefore, university students with lower feeling of belonging to their surroundings may have been trying to compensate their need to belong *via* using excessive social networking. This result supported that belongingness is negatively associated with problematic social media use (48) and the relation between interpersonal dependency and gaming disorder (49). Thus, alienation appears to be an important risk factor for gaming disorder.

In addition, highly alienated individuals have difficulties in establishing effective connections with social groups and in maintaining relationships with others (45). According to the social skills deficit theory, individuals with a negative view of their own social competence are more likely to opt for the Internet to form and maintain their social relationships (50), and lonely individuals prefer online over offline interactions (51). Given that alienation may augment negative effect and increase the negative impact of behavior and environment on individuals (45), high levels of alienation might therefore serve as a risk factor that increases the potential negative effects of online social capital. In a sense, dependence on online social contacts for a sense of belonging may worsen offline social relationships, leading individuals to be more alienated from the offline social relationships maintained by traditional means of communication (52). Previous research has suggested that both offline and online social deficits are associated with gaming disorder, and offline social deficits can precede gaming disorder but then be exacerbated by the preoccupation with online social interactions and relationships (53).

Based on this review of the literature, we propose hypothesis 2: *Alienation would moderate the association between online social capital and gaming disorder. Specifically, the association would be stronger among individuals with high alienation than for those with low alienation.*

The Present Study

Earlier research has established a link between in-game social interaction and gaming disorder. The current study expanded this research by testing the role of social capital and alienation in this relationship. First, this study examined the mediating role of online social capital in this relation; we expected that in-game social interaction would be indirectly related to gaming disorder through its effects on online social capital. Second, this study examined whether the indirect relationship between in-game social interaction and gaming disorder through online social capital would be moderated by alienation; we expected that the indirect association would be stronger for those with high alienation. These two research questions form a moderated mediation model, which can address both mediation (i.e., how does in-game social interaction lead to gaming disorder) and moderation (i.e., when is the effect most potent) as processes affecting the relationship between in-game social interaction and gaming disorder. According to previous studies that have demonstrated that gender and age [e.g., (54)] are associated with gaming disorder, gender, and age were included as control variables in the multivariate multiple regression model. **Figure 1** illustrates the conceptual model.

MATERIALS AND METHODS

Sample

Based on the comprehensive consideration of research accuracy and cost, a total of 495 MMORPG gamers were recruited through convenience sampling method from four universities in China during the 2018 fall semester. After excluding invalid questionnaires (with incomplete data), 457 valid questionnaires were collected (62.4% male, 37.6% female); the effective rate was 92.32%. Their ages ranged from 18 to 23 years old (M = 19.81, SD = 1.36). The participants completed a survey to collect information regarding demographic variables, in-game social interaction, online social capital, alienation, and gaming disorder.

Measures

In-game Social Interaction

In-game social interaction often takes on the forms of communication with other gamers, guild, and group play

(23). Therefore, it can be measured by the frequency of communication with other gamers and the frequency of group/guild actions. In addition, it is necessary to evaluate the respondents' attitudes toward the guilds/groups, the leaders, and other members of the guild/group (23).

Based on this, Zhong (22) developed an online game collective play scale which includes two factors (i.e., the frequency of collective actions and evaluation to the life in guild/group). This scale has yielded good construct validity and reliability (22). We modified this scale to measure in-game social interaction, which consists of two subscales: three items focus on the frequency of collective actions (How often do you communicate with other gamers while playing game? How often do you participate in group actions in a week? How often do you participate in guild actions in a week?) ($\alpha = 0.82$) and were rated on a five-point scale (1 = never, 5 = always); the other three items relate to attitudes toward the life in guild/group (Are you satisfied with your guild/group? Are you satisfied with leader of the guild/group? Are you satisfied with members of the guild/group?) ($\alpha = 0.76$) and were also rated on a five-point scale (1 = not satisfied at all, 5 = very much satisfied). Summing up the item scores created a scale score, with higher scores indicating higher levels of in-game social interaction. We checked the structural validity by a confirmatory factor analysis. All factor loadings were significant and bigger than 0.44, with indices indicating that the two-factor model fit well (RMSEA =.05, GFI = 0.94, AGFI = 0.91, CFI = 0.92), and two factors were significantly correlated with each other ($r = 0.48$, $p < 0.01$). Cronbach's α in the current study was 0.75.

Online Social Capital

Online social capital was measured with a translated version of the Internet Social Capital Scales (55), which were modified to better fit the gaming context (e.g., Interacting with people in a game makes me feel like part of a larger community). Of the 20 items, 10 items focus on bonding social capital ($\alpha = 0.91$), and the other 10 items relate to bridging social capital ($\alpha = 0.87$). The participants responded to each question on a five-point scale (1 = strongly disagree, 5 = strongly agree). To establish structural validity, we conducted confirmatory factor analyses, and the indices indicated that the two-factor model fit well (RMSEA = 0.06, GFI = 0.96, AGFI = 0.93, CFI = 0.95). Cronbach's α for the online social capital scale was 0.96.

Alienation

Alienation was measured by the 15-item Alienation Scale developed by Yang et al. (56). The scale consists of three subscales: sense of loneliness (e.g., I always feel lonely) ($\alpha = 0.83$), alienation from family members (e.g., I have a sense of alienation from family members) ($\alpha = 0.79$), and sense of social isolation (e.g., I feel like the people around me are like strangers) ($\alpha = 0.85$). The participants rated each item on a five-point scale (1 = strongly disagree, 5 = strongly agree), with higher scores representing a higher sense of alienation. This scale has been validated in Chinese samples and has yielded good reliability (56). Cronbach's α for the alienation scale was 0.77.

Pathological Online Game Use

A translated version of the 11-item Pathological Gaming Scale (6) was used to assess the level of gaming disorder. This scale was developed based on the DSM—IV criteria for pathological gambling (e.g., Do you become restless or irritable when attempting to cut down or stop playing video games?) The participants rated the symptoms on a three-point scale (1 = never, 3 = always). Summing up the item scores created a scale score, with higher scores indicating higher levels of game-related behavioral problems. The convergent and divergent validity, as well as the reliability of the original scale, are acceptable (6), and the translated version of the scale has demonstrated good reliability and validity in Chinese samples (57). Cronbach's alpha in the current study was 0.81.

Procedure and Data Analysis

Surveys were conducted in classes by trained psychology graduate students after obtaining a written informed consent from participants. All participants were told that their participation was voluntary and that their privacy would be protected. The data collectors explained the requirements to the participants with standard instructions. At the end of the study, the participants were thanked for their participation. SPSS 21.0 was used for statistical analyses, descriptive statistics, correlational analyses, and examining the interaction effects and mediation effects.

Ethics

The study was approved by the institutional review board of the Institute of Education, Henan Normal University, China. Written informed consent was obtained from all participants prior to assessment. This study did not involve human and/or animal experimentation and conformed to all guidelines according to the Declaration of Helsinki.

RESULTS

Descriptive Analysis

The means, standard deviations, and Pearson correlational analyses for all variables are presented in **Table 1**. In-game social interaction was positively correlated with online social capital and gaming disorder ($r = 0.39$, $p < 0.01$; $r = 0.18$, $p < 0.01$). In addition, online social capital was positively correlated with gaming disorder ($r = 0.43$, $p < 0.01$). Finally, alienation was positively associated with gaming disorder ($r = 0.47$, $p < 0.01$).

Testing for Mediation Effect

To test the mediation effect of online social capital in the relationship between in-game social interaction and gaming disorder, this study followed MacKinnon's (58) four-step procedure to test for significant associations between (a) in-game social interaction and gaming disorder, (b) in-game social interaction and online social capital, (c) online social capital and gaming disorder while controlling for in-game social interaction, and (d) a significant coefficient for the indirect path between in-game social interaction and gaming disorder *via* online social capital. We used the macro PROCESS (model

TABLE 1 | Means, standard deviations, and correlations for variables ($n = 457$).

Variables	*M*	SD	1	2	3	4	5	6
Gender	0.62	0.49	–					
Age	19.77	1.42	−0.02	–				
In-game social interaction	3.72	0.62	0.03	−0.01	–			
Online social capital	3.86	0.37	0.04	−0.04	0.39**	–		
Alienation	3.16	1.19	0.04	0.01	0.03	0.04	–	
Gaming disorder	1.92	0.56	0.02	−0.03	0.18**	0.43**	0.47**	–

Gender was dummy coded such that 0 = female and 1 = male. False discovery rate method was used to correct p-values for multiple testing.
**p < 0.05; **p < 0.01.*

TABLE 2 | Testing the mediation effect of in-game social interaction on gaming disorder.

	Model 1 (gaming disorder)		Model 2 (online social capital)		Model 3 (gaming disorder)	
	β	*t*	*β*	*t*	*β*	*t*
Gender	0.03	0.34	0.05	0.53	0.02	0.14
Age	−0.02	−0.48	−0.03	−0.88	−0.01	−0.14
In-game social interaction	0.17	4.25**	0.39	8.04**	0.02	0.41
Online social capital					0.42	9.31**
R^2	0.18		0.39		0.43	
F	6.23**		23.62**		25.76**	

Gender was dummy coded such that 0 = female and 1 = male.
**p < 0.05; **p < 0.01.*

4) for SPSS (59) to examine the indirect effects. If the bias-corrected 95% confidence interval (CI) does not contain zero, the indirect effect is considered as statistically significant. This study included the participants' gender and age as covariates in all analyses.

Table 2 reports the results of the mediation analysis. Multiple regression analysis indicated that in-game social interaction was significantly associated with gaming disorder ($\beta = 0.17$, $p < 0.001$) and online social capital ($\beta = 0.39$, $p < 0.001$); when in-game social interaction was controlled, online social capital was significantly associated with gaming disorder ($\beta = 0.42$, $p < 0.001$). Finally, the bias-corrected percentile bootstrap method indicated that the indirect effect of in-game social interaction on gaming disorder through online social capital was significant, ab =.16, SE =.03, 95% CI= [0.11, 0.23]. Therefore, hypothesis 1 was supported.

Testing for Moderated Mediation

We expected that alienation would moderate the mediation effect of online social capital on gaming disorder. According to Muller et al. (60), the parameters for the three regression models should be estimated to test the moderated mediation hypothesis. This study specifically estimated the moderating effect of alienation on (1) the relationship between in-game social interaction and gaming disorder (model 1), (2) the relationship between in-game social interaction and online social capital (model 2), and (3) the relationship between online social capital and gaming disorder as well as the residual effect of in-game social interaction on gaming disorder (model 3). The specifications of the three models can be seen in **Table 3**. In each model, we controlled for relevant covariates (gender and age). All the predictors were standardized to minimize multicollinearity (61). Moderated mediation is established if either or both of thesee two patterns exist (59): (a) the path from in-game social interaction to online social capital is moderated by alienation and/or (b) the path from online social capital to gaming disorder is moderated by alienation.

As **Table 3** illustrates, model 1 showed that both in-game social interaction and alienation significantly predicted gaming disorder ($\beta = 0.18$, $\beta = 0.48$, $p < 0.01$), but the interaction effect was not significant ($\beta = 0.07$, $p > 0.05$). Model 2 indicated that the main effect of in-game social interaction on online social capital was significant ($\beta = 0.39$, $p < 0.01$), but the main effect of alienation and the interaction effect were not significant ($\beta = 0.04$, $\beta = 0.06$, $p > 0.05$). In model 3, alienation and online social capital both had a significant effect on gaming disorder ($\beta = 0.49$, $\beta = 0.34$, $p < 0.01$), and the interaction effect of online social capital and alienation on gaming disorder was also significant ($\beta = 0.31$, $p < 0.01$).

To facilitate the interpretation of this interaction effect, we plotted predicted gaming disorder against online social capital separately for low and high levels of alienation (1 SD below the mean and 1 SD above the mean, respectively; see **Figure 2**). Simple slope tests showed that, for individuals with high alienation, higher levels of online social capital were associated with higher levels of gaming disorder ($\beta_{\text{simple}} =.35$, $p < 0.001$). However, for individuals with low alienation, the effect of online

TABLE 3 | Testing the moderated mediation effects of in-game social interaction on gaming disorder.

	Model 1 (gaming disorder)		Model 2 (online social capital)		Model 3 (gaming disorder)	
	β	*t*	*β*	*t*	*β*	*t*
Gender	−0.01	−0.12	0.02	0.43	−0.02	−0.35
Age	−0.03	−0.69	−0.04	−0.95	−0.01	−0.30
In-game social interaction	0.18	4.47**	0.39	9.33**	0.08	2.24
Alienation	0.48	11.92**	0.04	1.01	0.49	14.44**
In-game social interaction × alienation	0.07	1.87	0.06	1.45	0.01	0.23
Online social capital					0.34	8.87**
Online social capital × alienation					0.31	8.49**
R^2	0.27		0.18		0.47	
F	34.59**		20.35**		59.20**	

Gender was dummy coded such that 0 = female and 1 = male.
**p < 0.05; **p < 0.01.*

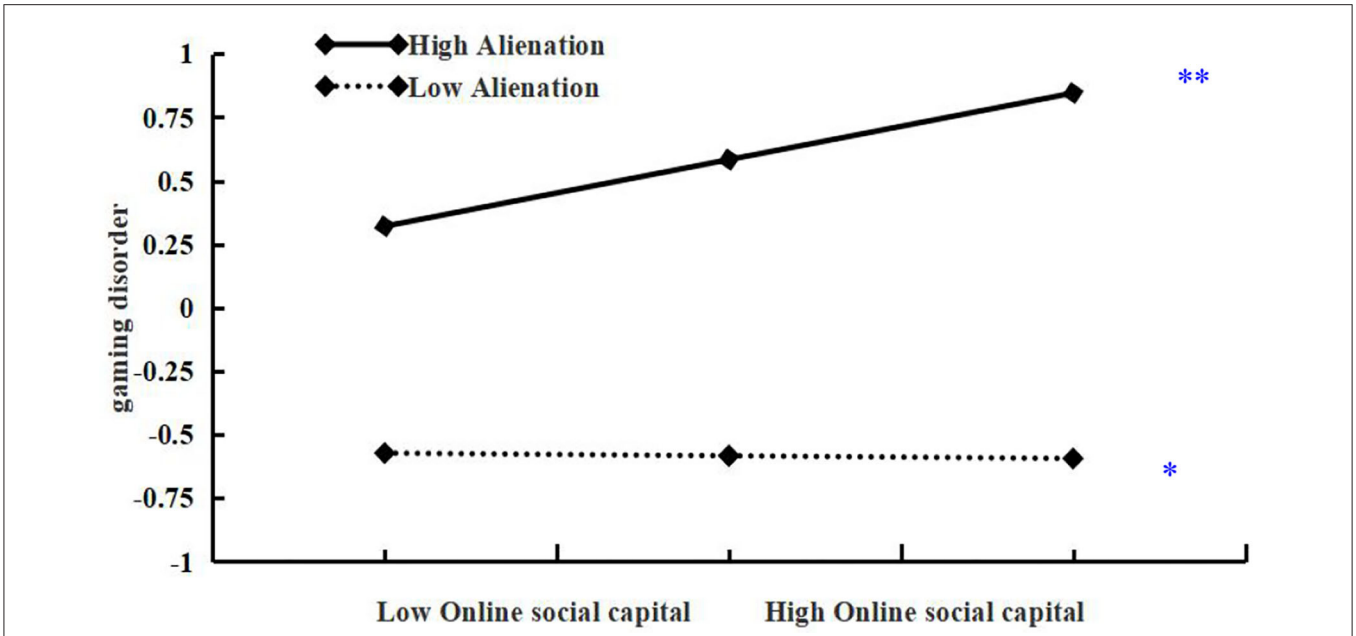

FIGURE 2 | Alienation as a moderator of the relationship between online social capital and gaming disorder. The moderating effect is graphed for two levels of alienation: one standard deviation above the mean and one standard deviation below the mean.

social capital on gaming disorder was still significant but much weaker ($\beta_{\text{simple}} = .06$, $p > 0.05$).

DISCUSSION

Although there is considerable empirical evidence of the impact of social features of online games on gaming disorder, the underlying mediating and moderating processes involved in this association have not been explored. The present study constructed a moderated mediation model to examine the mediating effect of online social capital in the association between social features of online game and gaming disorder and tested whether this indirect effect was moderated by alienation.

In-game Social Interactions and Gaming Disorder

This study found that frequent in-game social interactions in MMOGs are positively related to gamers' gaming disorder. The results were largely consistent with previous research that underlines the importance of social features in gaming disorder (18, 20, 62). The findings could suggest that social interactions in video games have a significant influence on gaming disorder.

Social need is an important motivation for playing online games (26), and the commonly reported reasons for gamers' interest and motivation to play have been shown to be related to social interaction, such as "grouping together with others"

and "being part of a guild" (21). The media system dependency theory (63) holds that the extent to which individuals depend on media is determined by the degree to which the media is useful in helping them to achieve their objective. Online games provide opportunities for new meaningful and emotionally resonant relationships to develop, helping to satisfy the human need for affiliation and social support. In addition, strong emotional bonds with fellow gamers may compensate for a lack of offline support and motivate further use (64). Consistent with this assumption, prior research showed that the social elements of an online game shaped the gamers' desire to forge and maintain online relationships but increased the risk for gaming disorder (62). The present study provides further evidence that searching the sense of fulfillment of human social need in MMORPG contributes to excessive game playing (34) that may further cause gaming disorder.

The Mediating Role of Online Social Capital

Previous studies have shown that online social capital directly impacts SNS addiction (65) and problematic video game play (43). It could also mediate the relationship between SNS use and SNS addiction (66). In line with previous studies, the present study not only found that both in-game social interaction and online social capital positively predicted gaming disorder but also revealed the mediating effect of online social capital in the association between in-game social interaction and gaming disorder. Therefore, online social capital was the mechanism underlying the effect of in-game social interaction on gaming disorder, which supported hypothesis 1.

In addition to the overall mediation result, each of the separate links in our mediation model is noteworthy. For the first stage of the mediation process, our findings support the premise that the intensity of in-game social interaction is positively correlated with online social capital, which is consistent with the findings of extant studies (22, 64). This further supports the claim that online games appear to serve best as "third places" for informal sociability, where people are able to establish and maintain social ties by interacting and collaborating with strangers (28). MMORPGs encourage collective play and social interactions, which facilitate interdependent relationships, social interactions, and teamwork, all of which are beneficial for the gamers' social capital (22).

For the second stage of our mediation model, the present study found that online social capital was positively associated with gaming disorder, which suggests problematic gaming gamers' reliance on online social support networks. This finding is congruent with previous research claiming that developing online relationships is a main motivation for online gaming (26), and strong emotional bonds with fellow gamers may compensate for a lack of support offline and motivate further use (64). The results provide further evidence that online social capital may result in negative consequences. To some extent, by providing gamers an opportunity to build social relationships with other gamers and the group, MMORPGs are potentially addictive applications in the same way as social network services are (41).

The Moderating Role of Alienation

Individual development is the result of an interaction between the effects of individual factors and environment (67). The present study tested the moderating effect of the individual factor of alienation in the relationship between online social capital and gaming disorder. The results showed that alienation was a risk factor of gaming disorder, which was in line with previous studies (51, 68–70). More importantly, alienation moderated the association between online social capital and gaming disorder.

The result showed that alienation from family, peers, and school was a significant and positive predictor of the level of gaming disorder. The primary socialization theory (71) suggests that individuals who have weak ties with prosocial institutions, such as family and school, often lack affiliation and turn to alternative social environments. For example, in one study, youth who were alienated from offline social relationships were eager to seek affection, friendship, and social support through participation in guilds and inter-player interactions (22). The virtual online environment provides more opportunity for communication and creates a sense of group identity, which provides a viable way for young people to seek a sense of belonging and to express their emotions (47). Individuals with higher alienation are often in a negative emotional state, such as estrangement, helplessness, loneliness, and meaninglessness (45). Studies have found that increased loneliness and lower social competence or greater social problems are associated with problematic game use (72, 73). These factors may increase the risk that alienated youth would excessively indulge in online gaming. Therefore, the effect of the Internet is a paradox because the social benefits of Internet use can have negative effects (74). The current results also showed that alienation enhances the facilitating effect of online social capital on gaming disorder. Compared with the online social capital of teenagers with a low level of alienation, the online social capital of highly alienated teenagers has a significant positive effect on gaming disorder.

According to the compensatory Internet use model (46), for individuals with higher alienation, excessive compensation for online social capital might displace offline social capital (35); the more they get from the online game, the more likely they are to rely on it and eventually show gaming disorder. This result is consistent with the "rich get richer" model: for those with more social support, using the Internet predicts better outcomes, but it predicts worse outcomes for those with less support (74).

Limitations and Future Directions

The limitations of the present study should be addressed. First, we use only a single score as the score of the in-game social interaction in this study. In theory, in-game social interaction contains two dimensions (frequency and attitudes) (23), which has good content validity. However, "frequency" and "attitudes" cannot be considered as a single construct according to the results of data analysis. Therefore, the use of a single score may make the results of this study less stringent. In future research, "frequency "and "attitudes" should be used as independent constructs, and the scores of the two dimensions should be calculated independently instead of summing up two-factor item scores created as a single scale score, which will make the

research results more rigorous. Second, the current study only examined the effect of online social capital on gaming disorder, but offline and online social capital are not mutually exclusive (75), and both of them may be related to gaming disorder. Future research should explore the fundamental social and psychological mechanisms that determine the relationship between combined online and offline social capital and gaming disorder. Third, in this study, we combine online bonding and bridging social capital as a single variable, but it is necessary to recognize that bridging and bonding social capital are not interchangeable (29). Therefore, future research may need to measure these two variables through a more valid and reliable method as well as explore how these different types of social capital are related to in-game social interaction, gaming disorder, and alienation. Fourth, future research is needed to explore other possible moderators and mediators that are important for refining our understanding of how in-game social interaction influences gaming disorder. Fifth, the sample of this study is comprised mainly of college students, with ages from 18 to 23 years; future research should focus on other age groups. Finally, our study was cross-sectional and cannot establish causality. Longitudinal data may provide a clearer understanding of the ways in which in-game social interaction can initiate, develop, and sustain online social capital and gaming disorder.

Theoretical and Practical Implications

This research has several important theoretical implications. First, the present study provided further evidence that in-game social interaction can influence gamers' problematic video game play (15). Second, previous studies tended to regard social capital as a predictor of users' positive outcomes (31, 32), but the results of our study indicate that online social capital is a significant predictor of gaming disorder. Third, although previous studies have confirmed the relationship between in-game social interaction and gaming disorder (62, 64), there are few studies that capture the essence of why an in-game social interaction increases the risk of gaming disorder. The present study extended previous research by examining the joint effect of in-game social interaction, online social capital, and alienation on gaming disorder, providing a more comprehensive explanation of the mechanisms that explain how in-game social interaction influences gaming disorder.

Aside from the theoretical contributions, this research also has important practical implications. First, this study confirms that online gaming is a double-edged sword (76). For some adolescents, the benefits of in-game social interaction and capital may be offset by psychological dependency on online relationship and gaming disorder. Therefore, gamers should invest more time in offline social activities and maintain good social relationships with their family, friends, and other persons in the real world. Second, our findings can help practitioners understand the detrimental effect of in-game social interaction on gaming disorder through online social capital. This relationship is stronger for individuals with high alienation than for those with low alienation, which provides some implications for targeted interventions. The findings showed that online social capital was positively related to gaming disorder, which may be an indication that problematic game gamers rely heavily on online social support and may lack the social support needed in offline environments (77). Therefore, encouraging offline social capital in gaming disorder may be an effective form of prevention, and interventions should aim at improving offline social relationships and support. In addition, we should pay more attention to alienated teenagers, who are more susceptible to gaming disorder; interventions aimed at reducing their alienation may protect them from this risk.

CONCLUSIONS

This study is an important step in unpacking how in-game social interactions relate to college students' gaming disorder. The findings suggest that the positive impact of in-game social interactions on gaming disorder can be partially explained by increased online social capital. Moreover, this indirect link was moderated by alienation in the second stage of the mediation process, such that the path from social capital to gaming disorder was stronger for more highly alienated individuals. This moderated mediation model is important because it provides a more comprehensive understanding of "how" and "when" in-game social interactions may increase gaming disorder.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The study was approved by the institutional review board of the Institute of Education, Henan Normal University, China. Written informed consent was obtained from all participants prior to assessment. This study did not involve human and/or animal experimentation and conformed to all guidelines according to the Declaration of Helsinki.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication. MW make substantial contributions to the acquisition, analysis, or interpretation of data for the work.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2020.468115/full#supplementary-material

The data sheet and data analysis result presentation has been shared on Open Science Framework (https://osf.io/gnqf7/).

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COVID-19 Stress and Addictive Social Media Use (SMU): Mediating Role of Active Use and Social Media Flow

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The ongoing COVID-19 pandemic is likely to enhance the risk of addictive social media use (SMU) as people spend more time online maintaining connectivity when face-to-face communication is limited. Stress is assumed to be a critical predictor of addictive SMU. However, the mechanisms underlying the association between stress and addictive SMU in crises like the current COVID-19 situation remain unclear. The present study aimed to understand the relationship between COVID-19 stress and addictive SMU by examining the mediating role of active use and social media flow (i.e., an intensive, enjoyable experience generated by SMU that perpetuates media use behaviors). A sample of 512 Chinese college students (M_{age} = 22.12 years, SD = 2.47; 62.5% women) provided self-report data on COVID-19 stress and SMU variables (i.e., time, active use, flow, addictive behavior) via an online survey from March 24 to April 1, 2020. The results showed that COVID-19 stress was positively associated with tendencies toward addictive SMU. Path analyses revealed that this relationship was significantly serially mediated by active use and social media flow, with SMU time being controlled. Our findings suggest that individuals who experience more COVID-19 stress are at increased risk of addictive SMU that may be fostered by active use and flow experience. Specific attention should be paid to these high-risk populations and future interventions to reduce addictive SMU could consider targeting factors of both active use and social media flow.

Keywords: active use, addictive social media use, addiction, COVID-19, disaster stress, social media flow

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INTRODUCTION

The ongoing global pandemic of COVID-19 caused by a novel coronavirus (SARS-CoV-19) has a significant impact on individual lifestyle. Due to policies to limit the spread of the virus, such as the "shelter-in-place" order (1), people, willing or not, are undergoing a transition from offline to online activities (2). In addition to remote work or remote learning, many people spent increased time on social media (SM), such as Facebook and Twitter, which could satisfy their need for disaster-related information, entertainment as well as interpersonal communication (3, 4). Despite the undeniable advantageous role that SM plays in an emergency like COVID-19 (5), escalations in the use of SM are likely to bring about addictive social media use (SMU). According to Andreassen (6), addictive SMU is defined as excessive and compulsive

use of social platforms. As a specific form of Internet addiction, addictive SMU entails six core components of a behavioral addiction model (7) including (1) being unduly concerned with or spending too much time on SM (salience), (2) using SM to regulate negative emotions or forget personal problems (mood modification), (3) feeling an urge to invest more time on SM to attain the same level of pleasure (tolerance), (4) feeling uncomfortable, restless, and irritable when prohibited from SM for a time (withdrawal), (5) causing harm to work, life and interpersonal relationship due to SMU (conflict), (6) trying to give up SMU but cannot manage it (relapse). It should be noted that additive SMU has not been formally recognized as a psychiatric disorder, though its definition is in line with diagnostic addiction criteria (8). Recent studies have suggested the increased tendency of Internet addiction following the pandemic onset (9, 10). However, little is known about the influence of COVID-19 on the development of addictive SMU as well as the underlying mechanisms.

People often resort to media use in response to daily hassles and stressful life events (11–13). In their stress and coping theory, Lazarus and Folkman (14) differentiated two types of coping strategies that people normally adopted to manage stress. One is problem-focused coping (i.e., engage in behaviors that could help solve problems) and the other is emotion-focused coping (i.e., regulate emotional responses to the problem without affecting the actual presence of stress). When confronted with challenges created by COVID-19, people are likely to turn to SM for both problem-focused coping (e.g., browsing health-related information) and emotion-focused coping (e.g., venting emotions for mood management, joining online communities for social support) (15). SM also promoted collective coping by becoming a venue for survivors to express feelings, document traumatic events, and reconstruct meaning in the aftermath of natural disasters (16). However, the reliance on SM for coping is not only associated with benefits. For example, recent research described that increased Internet use when coping with stress posed by the COVID-19 pandemic did not effectively enhance well-being among older adults (17). Although trauma-induced stress could be temporarily alleviated by certain online activities, it has the potential to lead to excessive SMU. Both cross-sectional and longitudinal studies have established a positive link between daily stress and addictive Facebook use (12, 18, 19). So far, however, there has been little discussion about the relationship between disaster-specific stress and addictive SMU. Along with the above theories and findings, it is therefore hypothesized that people who experience greater stress related to COVID-19 are at greater risk of addictive SMU.

Active use is a potential mediator explaining the effect of COVID-19 related stress on addictive SMU. Active use refers to activities that facilitate direct exchanges with others (e.g., commenting on posts of friends, tagging, "liking," posting a status update, sharing pictures or videos), while passive use involves activities, such as browsing news feeds or viewing posts of others without any direct exchanges (20). By differentiating the two types of SM activities, prior research suggested that active use could be beneficial in terms of enhancing social connectedness, subjective well-being and reducing loneliness (21–23). However, active use could be excessive when it is motivated to compensate for psychosocial problems (24). Following the theory of basic psychological needs (25), it might be possible that individuals who experience considerable stress related to COVID-19 (e.g., infection, quarantine) may feel that their basic psychological needs (i.e., autonomy, capacity, and relationships) are not satisfied and thus turn to active use of SM to compensate for their unmet needs. On the other hand, active SMU, such as broadcasting has been proved to be positively associated with addictive Facebook use (26). However, there are no studies that directly tested the mediating role of active use in the relationship between COVID-19 stress and addictive SMU.

Flow could be another antecedent of addictive SMU. Flow is a concept of positive psychology, which refers to a state of concentration that is so focused that people find themselves deeply absorbed in that activity (27). The state of flow is intrinsically self-reinforcing, in which people can experience feelings of joy, pleasure, and satisfaction and therefore can be motivated to repeat the ongoing activities (28). Researchers integrated the concept of flow into online activities (29). Specifically, Kwak et al. (30) proposed six elements to characterize the flow experience on SM: focused attention (i.e., high concentration on SM), enjoyment (i.e., pleasant experience due to SMU), curiosity (i.e., desire to know things happened on social media), telepresence (i.e., feeling the world created by SM is real), time-distortion (i.e., loss of a sense of time during SMU) and self-disclosure (i.e., revelation of personal information during SMU). In the media context, it has been suggested that flow experience resulted from repetitive behaviors through a desire to maintain positive feelings could raise the frequency and intensity of media consumption, and therefore, results in addictive behaviors (31). In line with this notion, previous studies proved that flow was a positive predictor of Internet addictive symptoms (32), Internet gaming disorder (33), and addictive Facebook use (34). Therefore, it seems plausible to hypothesize that flow is positively associated with addictive SMU.

As reviewed above, both active use and SM flow are associated with addictive SMU. Moreover, it is suggested that flow appears when people are engaged in SMU activities with characteristics of social interaction, such as communicating with others and receiving instant feedback (35). Therefore, it is reasonable to posit that SM flow mediates the relationship between active use and addictive SMU (i.e., active use → SM flow → addictive SMU). Previous studies on narcissistic individuals indicated that this pathway might possibly exist. Brailovskaia and Margraf (21) found that narcissistic individuals, driven by a need for self-representation, actively engaged in SM (e.g., uploading attractive photos, writing updates, and joining online discussion groups) to maintain a positive impression. However, this process involving active use further contributed to the risk of Facebook addiction through increasing flow experience (36). In the context of COVID-19, one of the antecedents of active use might be COVID-19 stress given that people who experienced more disaster-related stressful events may resort to active SMU for coping (15). Therefore, it is reasonable to assume that the serial mediation effect of active use and flow may exist between the relationship of COVID-19 stress and addictive SMU (i.e.,

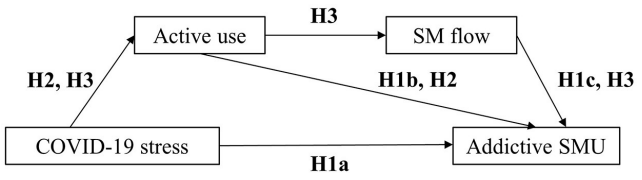

FIGURE 1 | The hypothesized model concerning the relationship between COVID-19 stress and addictive SMU: active use and SM flow as serial mediators.

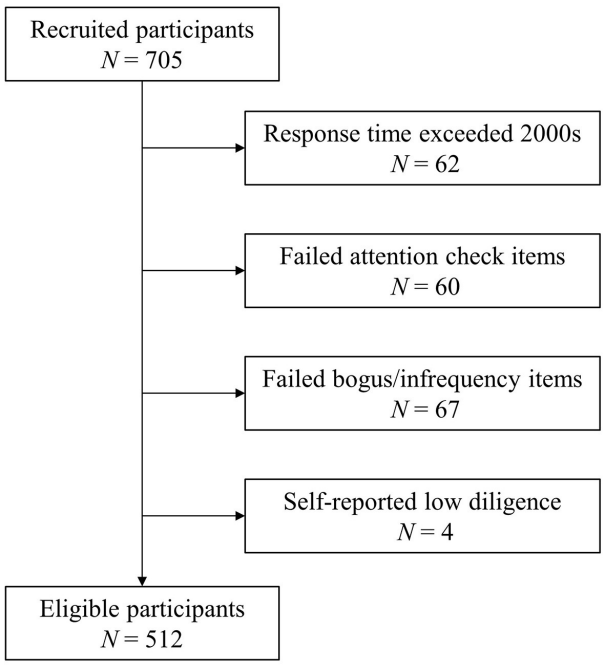

FIGURE 2 | Flow chart showing the steps involved in establishing the study sample.

COVID-19 stress → active use → SM flow → addictive SMU). However, this underlying mechanism has not been empirically tested to date.

The present study aims to clarify the relationships between COVID-19 stress, active use, SM flow, and addictive SMU. **Figure 1** illustrated the hypothesized model. To be specific, it is hypothesized that COVID-19 stress (Hypothesis 1a), active use (Hypothesis 1b), and flow (Hypothesis 1c) are all positively associated with addictive SMU; active use mediates the relationship between COVID-19 stress and addictive SMU (Hypothesis 2); active use and flow sequentially mediate the relationship between COVID-19 stress and addictive SMU (Hypothesis 3).

METHOD

Participants and Procedure

The study was approved by the Institutional Review Board of Peking University. From March, 24, to April, 01, 2020, an advertisement of the study was posted on Wechat, one of the most popular SM platforms in China. The post was shared and reposted hundreds of times. People who were willing to join the study could scan the quick response code on the poster, which directed them to online informed consent. Participants then spent ∼10 min to complete an online questionnaire via www.sojump.com.

A total number of 705 college students volunteered to participate in the study and completed the questionnaire. Following the recommendations of Curran (37), data of 192 participants were identified as invalid and removed before normal analysis (see **Figure 2**). The exclusion criteria included: (1) spent more than 2,000 s on the questionnaire ($N = 62$); (2) failed at least one of two attentional check items (e.g., "please answer with 'agree'"; $N = 60$); (3) failed at least one of two bogus items (e.g., "I have never used a mobile phone in my life," $N = 67$); (4) self-reported low diligence at the end of the questionnaire (e.g., "In your honest opinion, should we use your data in our analyses?"; $N = 4$). The final sample comprised of 512 college students. The age of the sample ranged from 18 to 30 years ($M_{age} = 22.12$, $SD = 2.47$). Most of the participants were female ($N = 320$, 62.5%) and of Han ethnic ($N = 480$, 93.8%). As for the educational attainment, 58% ($N = 297$) of the participants obtained a bachelor degree, 32.4% ($N = 166$) obtained a master degree and 9.5% ($N = 49$) obtained a doctor degree.

Measures

COVID-19 Stress

Adapted from the SARS-related stress by Main et al. (38), a checklist of ten items was used to assess participants' experience of COVID-19 related stressful events. Participants were asked whether or not they (1) confirmed or suspected infection; (2) experienced loved ones dying from infection; (3) witnessed others dying from infection; (4) worked with infectious patients; (5) volunteered for the disease prevention and control; (6) lacked food; (7) lacked masks or disinfectants; (8) had no access to medical care; (9) experienced the lockdown of Wuhan city; (10) stayed alone for a long time. Responses were "yes" (coded as 1) or "no" (coded as 0). The total number of events endorsed was computed to reflex the indexes of COVID-19 stress. The composite score ranged from 0 to 10, with a higher score indicating a higher level of COVID-19 stress.

Addictive Social Media Use

Addictive SMU was measured with the brief version of Bergen Facebook Addiction Scale [BFAS; (39)]. The 6-item scale assessed addictive SMU behaviors in six aspects (i.e., salience, mood modification, conflict, withdrawal, relapse, tolerance) with a 5-point Likert scale (1 = very rarely, 5 = very often). An example item is "How often do you become restless or troubled if you have been prohibited from using SM?" The sum score ranged from 6 to 30, with a higher score indicating a higher level of addictive SMU (Cronbach's $\alpha = 0.84$).

Active Use

Active SMU was measured with four items adapted from the assessment tool developed by Brailovskaia and Margraf (21).

TABLE 1 | Demographics and responses of participants ($N = 512$).

Variables	*N* (*M*)	% (*SD*)
Age	22.12	2.47
Gender (female)	320	62.5
Ethnic (Han)	480	93.8
Educational attainment		
Bachelor degree	297	58.0
Master degree	166	32.4
Doctor degree	49	9.5
COVID-19 stress		
Self or a close other confirmed or suspected COVID-19 infection	2	0.4
Experienced loved ones dying from COVID-19	1	0.2
Witnessed others dying from COVID-19	7	1.4
Worked with infectious patients	22	4.3
Volunteered for the disease prevention and control	77	15.0
Lacked food	43	8.4
Lacked face masks or disinfectants	326	63.7
No access to medical care	12	2.3
Experienced the lockdown of Wuhan city	15	2.9
Stayed alone for a long time due to COVID-19	167	32.6
SMU Time (h/day)		
Weibo	1.17	1.15
Wechat	1.48	1.36
QQ	0.42	0.82
Douban	0.11	0.48
Zhihu	0.47	0.74
Douyin	0.34	0.92
Kuaishou	0.07	0.39

SMU, social media use.

Participants were instructed to answer how often they engaged in each of four activities on SM since the COVID-19 outbreak on a 4-point Likert scale (0 = never, 3 = very often). Activities included: (1) updated status (including texts, photos, or short videos) about one's own life; (2) updated status about the COVID-19 pandemic; (3) liked, commented, or shared others' update; (4) liked, commented, or shared news about the COVID-19 pandemic. The sum score ranged from 0 to 12, with a higher score indicating a higher level of active SMU (Cronbach's $\alpha = 0.78$).

Social Media Flow

Flow experience related to SMU was assessed with a modified version of "Facebook flow" developed by Brailovskaia et al. (34). The scale included eleven items that captured five core aspects of flow experience (i.e., focused attention, enjoyment, curiosity, telepresence, and time-distortion). Items were rated on a 5-point Likert scale (1 = totally disagree, 5 = totally agree). An example item is "While using social media, I'm deeply engrossed." The sum score ranged from 11 to 55, with a higher score indicating a higher extent of SM flow (Cronbach's $\alpha = 0.82$).

TABLE 2 | Descriptive statistics and correlations between the main variables ($N = 512$).

Variables	1	2	3	4	5	6	7
1. Gender	—						
2. Age	0.01	—					
3. COVID-19 stress	0.03	−0.08	—				
4. Active use	−0.06	−0.08	0.15**	—			
5. SM flow	0.04	−0.03	0.13**	0.28***	—		
6. Addictive SMU	0.05	−0.05	0.16***	0.25***	0.46***	—	
7. SMU time	−0.05	−0.04	0.03	0.12**	0.15**	0.13**	—
Range	0–1	18–30	0–5	0–12	17–55	6–30	2–34
M	0.38	22.12	1.31	5.33	35.79	16.52	10.44
SD	0.49	2.47	0.94	2.88	6.49	5.44	5.61
Skewness	0.52	0.39	0.60	0.18	−0.05	0.11	1.22
Kurtosis	−1.74	−0.24	0.47	−0.35	0.14	−0.58	1.69

*Gender coded as 0 = female, 1 = male; SM, social media; SMU, social media use; M, mean; SD, standard deviation; **$p < 0.01$, ***$p < 0.001$.*

Covariate

SMU time was measured following the method of Lin et al. (40). Participants were instructed to recollect how many hours per day they spent on each of six widely-used SM platforms in China (i.e., Weibo, Wechat, Douyin, Kuaishou, Douban, Zhihu) during the period of severe pandemic (i.e., 20 January to 16 February 2020, characterized by a sharp increase in the number of infected from 258 to 70,635). Responses ranged from 0 to 12 h for each platform. Time spent on each platform per day was summed up to reflect the total daily hours of SMU time, with more hours indicating a higher level of SM consumption.

Statistical Analyses

Data were analyzed with SPSS 22.0 and PROCESS macro (41). First, descriptive statistics and correlations between the main variables were conducted. Second, to examine the relationship between COVID-19 stress and addictive SMU, a serial mediation was performed with COVID-19 stress as the independent variable, active use and SM flow as mediators in sequence, and addictive SMU as the dependent variable. The bootstrapping procedures in the Model 6 of PROCESS macro was used to test the significance of the serial indirect effects, with 5,000 times of random sampling. A 95% confidence interval (CI) of indirect effect that did not contain zero indicated a significant mediation effect at the 0.05 level. A reverse mediation model in which SM flow and active use interchanged positions was also tested.

RESULTS

Preliminary Analyses

Table 1 presented the demographics and responses of participants. Descriptive statistics and correlations between the main variables are presented in **Table 2**. Variables showed a univariate normal distribution with the skewness and kurtosis ranging from −2 to 2. COVID-19 stress was significantly positively correlated with active use, SM flow, and addictive

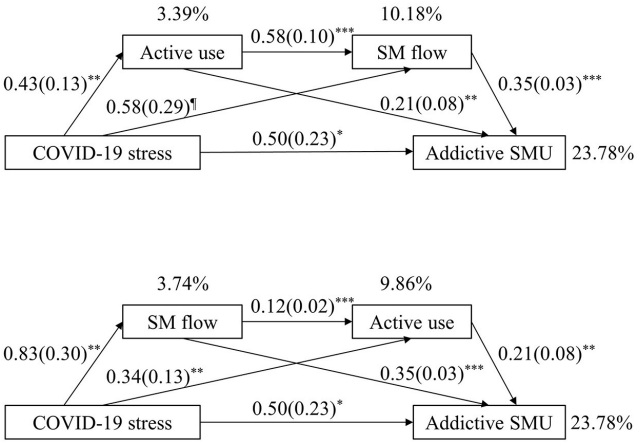

FIGURE 3 | Mediation model of the effect of COVID-19 stress on addictive SMU with active use and SM flow as mediators ($N = 512$). SM, social media; SMU, social media use. SMU time was controlled in the model as a covariate. Unstandardized coefficients and standard errors (SE) were reported. Percentages indicate the explained variance of each mediator and dependent variable in the model. All path coefficients were significant. ¶$p = 0.049$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

SMU. Active use was significantly positively correlated with SM flow and addictive SMU. SM flow was significantly positively correlated with addictive SMU. SMU time was significantly positively correlated with active use, SM flow, and addictive SMU, while COVID-19 stress was not significantly correlated with SMU time.

Serial Mediation Analyses

To investigate the relationship between COVID-19 stress and addictive SMU, serial mediation analysis was conducted with active use and SM flow as mediators using Model 6 of Hayes' PROCESS tool. Results are summarized in **Figure 3** and **Table 3**. Total effects of COVID-19 stress on addictive SMU was significant ($b = 0.88$, $SE = 0.25$, $p < 0.001$, 95%CI [0.3883, 1.3721]). The direct paths from COVID-19 stress to active use ($b = 0.43$, $SE = 0.13$, $p = 0.001$, 95%CI [0.1720, 0.6949]) and SM flow ($b = 0.58$, $SE = 0.29$, $p = 0.049$, 95%CI [0.0018, 1.1486]) were also significant. Meanwhile, the direct effects from mediators, namely active use ($b = 0.21$, $SE = 0.08$, $p = 0.007$, 95%CI [0.0590, 0.3619]) and SM flow ($b = 0.35$, $SE = 0.03$, $p < 0.001$, 95%CI [0.2776, 0.4125]) to addictive SMU were significant. Moreover, the path from the first mediator (active use) to the second mediator (SM flow) was significant ($b = 0.58$, $SE = 0.10$, $p < 0.001$, 95%CI [0.3920, 0.7700]). The indirect effect tests were significant for the first mediator (active use indirect $b = 0.09$, $SE = 0.05$, 95%CI [0.0129, 0.2047]), the second mediator (SM flow indirect $b = 0.20$, $SE = 0.10$, 95%CI [0.0052, 0.3961]), and both mediators in sequence ($b = 0.09$, $SE = 0.03$, 95%CI [0.0287, 0.1594]). When two mediators were included in the model, the direct effect of COVID-19 stress on addictive SMU was still significant ($b = 0.50$, $SE = 0.23$, $p = 0.027$, 95%CI [0.0581, 0.9491]), with active use, SM flow and addictive SMU accounted for 3.39, 10.18, and 23.78% of the total variance, respectively.

For the alternative reverse mediation model, the direct effects of COVID-19 stress, SM flow and active use on addictive SMU were exactly the same as those of original mediation model. The direct paths from COVID-19 stress to SM flow ($b = 0.83$, $SE = 0.30$, $p = 0.006$, 95%CI [0.2400, 1.4139]) and active use ($b = 0.34$, $SE = 0.13$, $p = 0.009$, 95%CI [0.0834, 0.5928]) were significant. Moreover, the path from the first mediator (SM flow) to the second mediator (active use) was significant ($b = 0.12$, $SE = 0.02$, $p < 0.001$, 95%CI [0.0778, 0.1528]). The indirect effect tests were significant for the first mediator (SM flow indirect $b = 0.29$, $SE = 0.10$, 95%CI [0.0850, 0.4908]), the second mediator (active use indirect $b = 0.07$, $SE = 0.04$, 95%CI [0.0077, 0.1681]), and both mediators in sequence ($b = 0.02$, $SE = 0.01$, 95%CI [0.0023, 0.0475]). SM flow, active use and addictive SMU accounted for 3.74, 9.86, and 23.78% of the total variance of the model, respectively.

DISCUSSION

The present study examined the relationship between COVID-19 stress, active use, SM flow, and addictive SMU in a sample of Chinese college students. Consistent with Hypothesis 1a, COVID-19 related stress was associated with a greater tendency of addictive SMU, higher level of active use, and SM flow experience. Both active use and SM flow were directly related to addictive SMU, confirming Hypothesis 1b and 1c. Consistent with Hypothesis 2, a mediating effect of active use was found between COVID-19 stress and addictive SMU. In addition, the present findings demonstrate that active use and SM flow in sequence mediate the relationship between COVID-19 stress and addictive SMU, confirming Hypothesis 3. However, the reverse mediation model with SM flow as the first mediator and active use as the second was also significant, which is contrary to our hypotheses. To sum up, the significant results in part confirmed our hypotheses and therefore allow a better understanding of why people who suffer from pandemic-related stress are at enhanced risk to develop addictive SMU.

Prior research suggests that stress and addictive SMU are positively related (12). Stress was considered to be a common risk factor of both chemical addictions [e.g., drug dependence; (42)] and behavioral addictions [e.g., excessive smartphone use; (43)]. Earlier studies found perceived daily stress to be positively related to addictive Facebook use (18) and Internet addiction (44). The current study adds value to the existing literature by measuring objective pandemic-related stress rather than subjectively perceived stress. The present results prove a positive association between stress and addictive SMU, which is in line with previous results (45). Given the fact that the prevalence of Internet addiction has increased during the COVID-19 pandemic (9, 10), it is imperative to identify individuals who are susceptible to addictive SMU. Our current findings suggest that people who experience extremely stressful events during the epidemic, such as quarantine, infection, or food shortages are at enhanced risk for developing addictive SMU.

TABLE 3 | Decomposition of the effect of COVID-19 stress on addictive SMU ($N = 512$).

	Mediation model				Reverse mediation model			
	β	*b*	*SE*	95%CI	*β*	*b*	*SE*	95%CI
Direct effect								
COVID-19 stress	0.09	0.50	0.23	(0.0581, 0.9491)	0.09	0.50	0.23	(0.0581, 0.9491)
Active use	0.11	0.21	0.08	(0.0590, 0.3619)	0.11	0.21	0.08	(0.0590, 0.3619)
SM flow	0.41	0.35	0.03	(0.2776, 0.4125)	0.41	0.35	0.03	(0.2776, 0.4125)
Indirect effects through								
Active use	0.02	0.09	0.05	(0.0129, 0.2047)	0.01	0.07	0.04	(0.0077, 0.1681)
SM flow	0.03	0.20	0.10	(0.0052, 0.3961)	0.05	0.29	0.10	(0.0850, 0.4908)
Active use and SM flow	0.02	0.09	0.03	(0.0287, 0.1594)			–	
SM flow and active use			–		0.004	0.02	0.01	(0.0023, 0.0475)

SMU, social media use; SM, social media.

Understanding the mediators of the association between COVID-19 stress and addictive SMU is important for identifying risky factors and developing prevention strategies for SM addiction. The current study revealed the mediating role of active use between COVID-19 stress and addictive SMU, which is in accordance with media use theories. According to the use and gratifications theory, people satisfy their unique social and psychological needs by exposure to mass media (46). A recent study suggested that people are motivated to use SM for several purposes, such as searching for information, seeking social interaction, beating boredom and pastime, escaping from negative emotions, and searching for positive emotions (47). When confronted with COVID-19-related stress, individuals are likely to actively engage in SM activities, such as disclosing personal feelings to relieve negative emotions. This behavior is likely to be reinforced since people receive empathetic responses and social support from online interactions, which creates a justification for further checking and posting on SM later on (48). Thus, it can be assumed that active SMU predicts addictive behaviors due to the negative reinforcement of mood alteration (49). Indeed, both empirical studies and meta-analysis suggest that individuals with the wish to escape from negative emotions caused by offline conflicts are at enhanced risk to develop addictive SMU (47, 50). Similarly, by proposing the concept of compensatory Internet use, Kardefelt-Winther (24) suggested that people use the online world to escape real life stress or to alleviate negative mood, which ultimately leads to negative outcomes. Therefore, the significant indirect path from COVID-19 stress to addictive SMU via active use implies that excessive active use acts as a maladaptive coping strategy in the time of the COVID-19 crisis. Another important finding is that active use independently or combined with flow explained the relationship between COVID-19 stress and addictive SMU. Furthermore, flow emerged as a stronger factor accounting for addictive SMU than active use, which is consistent with previous findings that people who experience flow (i.e., immersive pleasure) are particularly prone to behavioral addiction (32, 33).

However, findings from two serial mediation models suggest that the effects between active use and SM flow are likely bidirectional. Indeed, existed evidence on the relationships between SM use and flow is mostly correlational. Social network sites (SNS) flow was found to be predictive of increased SNS self-disclosure, a form of active use to build interpersonal connections (30). Another study also found that overall flow state enhanced the frequency of social media use (51). However, based on the flow theory and the psychological need framework, active use is likely to be proximal to COVID-19 stress as a way of coping whereas flow is proximal to addictive SMU in the serial mediation chain. In other words, it is more likely that individuals first adopt active SMU behaviors as a result of coping with stressful events and then fall into an immersed pleasant state through repeated use, which ultimately leads to SM addiction. Research on smartphone use revealed that people who use a smartphone for entertainment and sociability, especially to fight off negative feelings are more likely to achieve flow state, which is partly supportive of the sequence (52). Future studies should explore the trajectories of these various risk factors across time to uncover the directionality of active use and SM flow.

The current study extends our understanding of how COVID-19 stress is related to addictive SMU by uncovering the mediating roles of active use and flow experience. Although a clear answer to the order of two mediators cannot be given, our results may open new avenues for the prevention, identification, and intervention of addictive SMU behaviors. During the COVID-19 pandemic, it is crucial for people who are threatened by COVID-19 stress to be aware of potential maladaptive coping strategies and to refrain from excessive SMU. Furthermore, offline support from families or communities could be provided for those in need to encourage them to solve issues in the real life instead of getting immersed in the online world. Additionally, interventions may focus on fostering intentional awareness of one's state and exercising self-control over SMU, for example, by mindfulness practice to reduce addictive SMU (53).

Inevitably, this study has several limitations. First, the reliability of active use is relatively low, which limits the interpretations of the current results. Besides, self-report active SM activities may yield measurement bias. Future studies are recommended to obtain objective data that reflects individuals' SMU behaviors, such as the number of comments, "likes," status updates to improve the assessment accuracy (54). Second,

explanations for the relationship between stress and active use are conjectural since the motivation for active use was not measured in the present study. Therefore, it is unknown for what reasons people actively use SM (e.g., for social interaction, information seeking, or escape from negative emotions) when confronted with pandemic-related stress. Third, as an intrinsic rewarding state, SM flow seems to bring about negative consequences in our study. Future research could also investigate the potential positive psychological effects and benefits resulting from the optimal experiences while using SM. Fourth, the generalizability of the current findings is limited by the comparably young sample. It is also worth noting that the study did not find any sex-related differences. Therefore, it is necessary to replicate results in specific populations (e.g., adolescence) or in more balanced age composition of the sample. Fifth, confounding variables may possibly exist and should be taken into account in future research. For example, people with pre-existing psychopathology are both susceptible to external stress (55) and addictive Internet use (56). Finally, the correlational nature of the study allows only hypothetical conclusions about the causality of the described associations. Alternative explanations for the directionality of variables are possible. For example, previous research found that increase in SMU frequency can be predicted by SM addiction, which further facilitated future active use (57). Future work is encouraged to use a cross-lagged design or intensive repeated measures (e.g., experience sampling method) of active use, flow, and addictive SMU to see, whether the results of the present study can be generalized.

CONCLUSION

In sum, the study showed that COVID-19 stress was positively correlated with addictive SMU. Moreover, the relationship between COVID-19 stress and addictive SMU was significantly mediated by active use and SM flow, both individually and combined. Individuals who experienced higher level of COVID-19 stress were at a higher risk of developing addictive SMU as a result of increased level of active use and SM flow.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board at Peking University, School of Psychological and Cognitive Sciences. The patients/participants provided their online informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

NZ conceived of the present study, collected the data, conducted the statistical analyses, and drafted the manuscript. GZ supervised the study and helped to revise the manuscript. All authors read and approved the final manuscript.

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Association Between Anxiety Symptoms and Problematic Smartphone Use Among Chinese University Students: The Mediating/Moderating Role of Self-Efficacy

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Problematic smartphone use (PSU) is a novel manifestation of addictive behaviors. It is frequently reported to be correlated with anxiety symptoms among University students. However, the underlying mechanism has not yet been thoroughly studied. Whether the association between anxiety symptoms and PSU is mediated or moderated by self-efficacy remains unclarified. A cluster sampling cross-sectional study was thus conducted to explore the potential mediating or moderating effect of self-efficacy in Chinese University students. Participants (N = 1,113) were recruited from eight Universities in Shenyang, China. Of them, 146 did not effectively respond to the questionnaires. Thus, 967 participants were eligible for the final analysis. The mediating or moderating role of self-efficacy in the anxiety-PSU relationship was explored using hierarchical multiple regression. Then the mediation model was further verified using the SPSS macros program (PROCESS v3.0). Our results showed that anxiety symptoms was positively correlated with PSU (r = 0.302, P < 0.01), while self-efficacy was negatively correlated with anxiety symptoms and PSU (r = −0.271 and −0.181, P < 0.01). Self-efficacy partly mediated the relationship between anxiety symptoms and PSU, which accounted for ∼17.5% of the total effect that anxiety symptoms have on PSU. However, the moderating effect of self-efficacy on the anxiety-PSU relationship was insignificant. In summary, our findings suggested that self-efficacy partly mediates but not moderates the link between anxiety symptoms and PSU among Chinese University students. Therefore, multicomponent interventions should be made to restrict the frequency of smartphone usage, enhance the level of self-efficacy, and thus promote the mental health status of University students.

Keywords: University students, mediator, moderator, self-efficacy, anxiety symptoms, problematic smartphone use

INTRODUCTION

Background

A smartphone is no longer simply considered a "mobile phone" but rather a portable and omnipotent pocket computer. Owning smartphones enables us to keep in touch with our friends anywhere at any time, helps us to stay organized, guarantee stress-free travel through navigation apps, helps us to cope with emergencies, offers easy access to information and technology, and even promotes health through health-related apps (1). Given the convenience that smartphones provide to our daily lives, they have become pervasively used globally. According to a recent mobile user statistic report (2), the number of global smartphone users has reached 3.5 billion, increasing by 40% from 2016 to 2020. Therefore, smartphones have long been unconsciously and closely integrated into people's daily lives and gradually changed our lifestyles.

However, smartphone usage is a double-edged sword, as it helps to facilitate our daily lives but might also cause a series of worrisome problems due to problematic smartphone use (PSU). PSU has been previously defined as excessive use of a smartphone that is accompanied by functional impairments in daily living, and substance addiction-like symptoms (3). Youths, especially University students, are digital natives and the fastest adopters of electronic technologies (4). Unfortunately, they are usually mentally immature and lack the self-regulatory ability (5). Therefore, they are more vulnerable to PSU than older adults. It was demonstrated that PSU can have many detrimental effects, as it can cause academic distractions (6, 7), physical health hazards (including wrist pain, neck disability, and vision impairment) (8–10), and as well as elevated accident risk (11). Additionally, accumulating evidence has shown that PSU is closely related to poor mental health, particularly depression, anxiety, and perceived stress (12–15).

Anxiety is one of the most commonly investigated mental health variables related to PSU (15–17). A review by Elhai et al. revealed a small-to-moderate positive association between anxiety and PSU (15). A higher degree of anxiety symptoms was positively associated with more severe PSU. The prevalence of anxiety symptoms among University students with PSU was ∼1.78- to 2.31-fold higher than that among those without PSU (16). Several theoretical frameworks have been developed to help explain how psychological and psychopathological constructs such as anxiety could relate to PSU (17). The uses and gratifications theory (UGT) (18) proposes motivations (including psychological characteristics) for media usage. Based on the UGT, anxiety can drive people to use or overuse smartphones so as to satisfy or calm their anxiety. Another theoretical model that is more specific to psychopathological constructs is the compensatory Internet use theory (CIUT) (19). The CIUT assumes that excessive internet use, such as PSU, resulted from an attempt to alleviate negative emotions after experiencing stressful life events. A more plausible theoretical framework is the Interaction of Person-Affect-Cognition-Execution (I-PACE) (20, 21). Initially, the I-PACE model conceptualized personal background and predisposing factors such as anxiety symptoms as an important influence of problematic Internet use (PIU). The predisposing factors might cause an affective/cognitive response, and the latter also has a substantial impact on PSU. Under the framework of the I-PACE model, affective and cognitive response variables are usually conceptualized as mediators/moderators explaining the relationships between predisposing factors and PIU (20, 21).

Self-efficacy refers to individuals' beliefs in their own capabilities to execute behaviors necessary to produce specific performances (22). Belief in self-efficacy may have some impacts on an individual's cognitions, affects, and behaviors and may also help to deal with stressful situations (22). Evidence has shown that self-efficacy is negatively correlated with anxiety symptoms (23). A low level of self-efficacy is usually accompanied by a high level of anxiety symptoms. Similarly, a low level of self-efficacy was associated with a higher level of PSU severity (24, 25). According to the I-PACE model, self-efficacy could be regarded as a cognitive component; thus, it was reasonable to conceptualize self-efficacy as a potential mediating or moderating variable in the model. Actually, the mediating and buffering effect of self-efficacy on the relationship between PSU and other psychological variables such as academic procrastination and materialism has been previously reported (24, 25). Although numerous studies support the relationship between PSU and anxiety symptoms (17), whether self-efficacy can serve as a mediator or moderator on this relationship remains unknown.

Aims

Our primary aim was to clarify the role of self-efficacy in explaining the relationship between anxiety symptoms and the severity of PSU based on a sample of Chinese University students. We were particularly interested in the mediating and moderating effect of self-efficacy.

Theory

The most widely accepted theoretical framework underlying the PIU or PSU is the I-PACE model (17, 20, 21, 26–30). I-PACE proposes several categories of variables that influence excessive internet use. The first category includes personal predisposing variables such as personality, psychopathology, and internet use motive-based influences (28). The second category involves affective and cognitive response variables consisting of coping strategy, attention bias, mood dysregulation, and responses to environmental stressors (28). These response variables are usually conceptualized as mediators and moderators for the relationship between personal predisposing variables and PIU or PSU (20). Last, the I-PACE model assumes that response variables may have some impact on a person's decisions regarding a particular pattern of internet use, and thus may result in adaptive, problematic use. Based on the I-PACE model, anxiety-related psychopathology is what drives PSU, rather than the other way around. Self-efficacy fits well with the cognitive processes (or biases) in the affective and cognitive response variable category of the I-PACE model (20, 21). Therefore, it is reasonable to hypothesize that self-efficacy should mediate or moderate the anxiety-PSU relationship.

Hypotheses

H1. *Anxiety symptoms severity should be positively correlated with the severity of PSU.* The association between anxiety symptoms and PSU severity has been previously confirmed by many studies (15, 17, 27). Anxiety could be regarded as one of the individual's predisposing variables of the I-PACE model that can cause PSU (20, 21).

H2. *Self-efficacy should be negatively correlated with the severity of anxiety symptoms.* A low level of self-efficacy will lead to poor management of negative life events and thus result in anxiety symptoms (23).

H3. *Self-efficacy should be negatively correlated with PSU severity.* Several previous studies from Asia (24, 25, 31) support self-efficacy's negative relationship with PSU severity.

H4: *Self-efficacy should mediate the association between anxiety symptoms and PSU severity.* Self-efficacy can be considered as one of the affective and cognitive response variables in the I-PACE model (20, 21). A Korean study found that the relationship between depression and PSU could be fully mediated by self-efficacy (32).

H5. *Self-efficacy should moderate the association between anxiety symptoms and PSU severity.* As a potential affective and cognitive response variable in the I-PACE model, self-efficacy might moderate the association between anxiety symptoms and PSU as well.

MATERIALS AND METHODS

Study Design and Data Collection

The current study was a school-based cross-sectional study using a cluster random sampling strategy. From November 2018 to March 2019, students from eight universities were randomly selected from Shenyang city located in northeastern China. Participants came from medical universities, normal universities, and other majors. Their participation in our survey was voluntary, and they were free to withdraw at any time without being forced to complete the tasks. Electronic informed consent was obtained from each participant before the investigation, and then all participants were asked to answer self-rating questionnaires using the Wenjuanxing Online Survey System (https://www.wjx.cn/). Finally, a total of 1,113 undergraduate students were then randomly recruited. Of them, 146 were excluded due to incomplete responses, with at least 10% of the items not answered. Thus, only 967 subjects were eligible for the final analysis, resulting in an effective response rate of 86.9%. **Figure 1** showed the process of participant selection. Information obtained from all participants was ensured confidential and anonymous at all times. The study protocol was consistent with the ethical standards and was approved by the Ethics Committee of China Medical University.

Measures of Anxiety Symptoms

The Chinese version of the 20-item Self-Rating Anxiety Scale (SAS) developed by Zung was employed to assess the level of anxiety symptoms among University students during the past week (33). The SAS consists of 20 items that are rated on a 4-point Likert-like scale ranging from "1 = none or a little of the time (<1 day)" to "4 = most or all the time (5–7 days)." Of these items, 5, 9, 13, 17, and 19 items are reverse scoring questions. The summative score is obtained by multiplying the total score by 1.25 and taking an integer. Higher scores indicate more severe anxiety symptoms. The SAS scale has been proven reliable and of good internal consistency among the Chinese population (33, 34), with a Cronbach's alpha coe?cient of 0.806 in the current study.

Measures of Smartphone Addiction

The Smartphone Addiction Scale-Short Version (SAS-SV) (35) was employed to measure the severity of PSU. This self-rating scale contains 10 negative items. Each item is rated on a six-point Likert-type scale ranging from "1 = Strongly disagree" to "6 = Strongly agree" to reflect smartphone usage during the past month. Higher scores represent a higher risk of PSU. The total score ranged from 10 to 60. The Chinese version of the SAS-SV has been confirmed to have good reliability and validity (36). The Cronbach's alpha in our sample was 0.893.

Measures of Self-Efficacy

Self-efficacy was assessed using the General Self-Efficacy Scale (GSES) designed by Schwarzer et al. (37). The self-reported scale measures the degree of one's belief concerning ability and persistence to achieve the required performances. The questionnaire consists of 10 positive items, and the option for each item is scored according to a 4-point Likert scale from "1= strongly disagree" to "4=strongly agree." The theoretical score of the scale ranges from 0 to 40 points. Higher total scores indicate higher levels of self-efficacy. GSE scale has been widely used internationally. The empirical literature has shown that the Chinese version of the GSE also has good reliability and validity when applied to the Chinese population (38, 39). Cronbach's alpha was 0.818 in our study.

Statistical Analysis

All statistical analyses were performed using IBM SPSS Statistics for Windows (version 23.0; IBM Corp., Asia Analytics Shanghai). All tests were single-tailed, with $P < 0.05$ considered statistically significant. The group differences of continuous variables were tested by *t*-test or ANOVA as appropriate. The *post-hoc* analysis for multiple comparisons was conducted using Dunnett's *t*-test. A correlation matrix was examined using Pearson's correlation analysis among PSU, self-efficacy, and anxiety symptoms. Missing values were imputed by multiple imputation method.

The mediating or moderating role of self-efficacy in the anxiety-PSU relationship was explored using hierarchical multiple regression. All demographic variables that were significantly associated with PSU by univariate linear regression analysis served as control covariates. Category variables were transformed into dummy variables. Furthermore, continuous independent variables and mediator/moderator (self-efficacy) were centralized before hierarchical multiple regression. The covariates, independent variables, and mediator/moderator were sequentially included in the regression models in three steps. To explore the potential mediating role of self-efficacy, the covariates were added in step 1; anxiety symptoms was added as the independent variable in step 2; self-efficacy

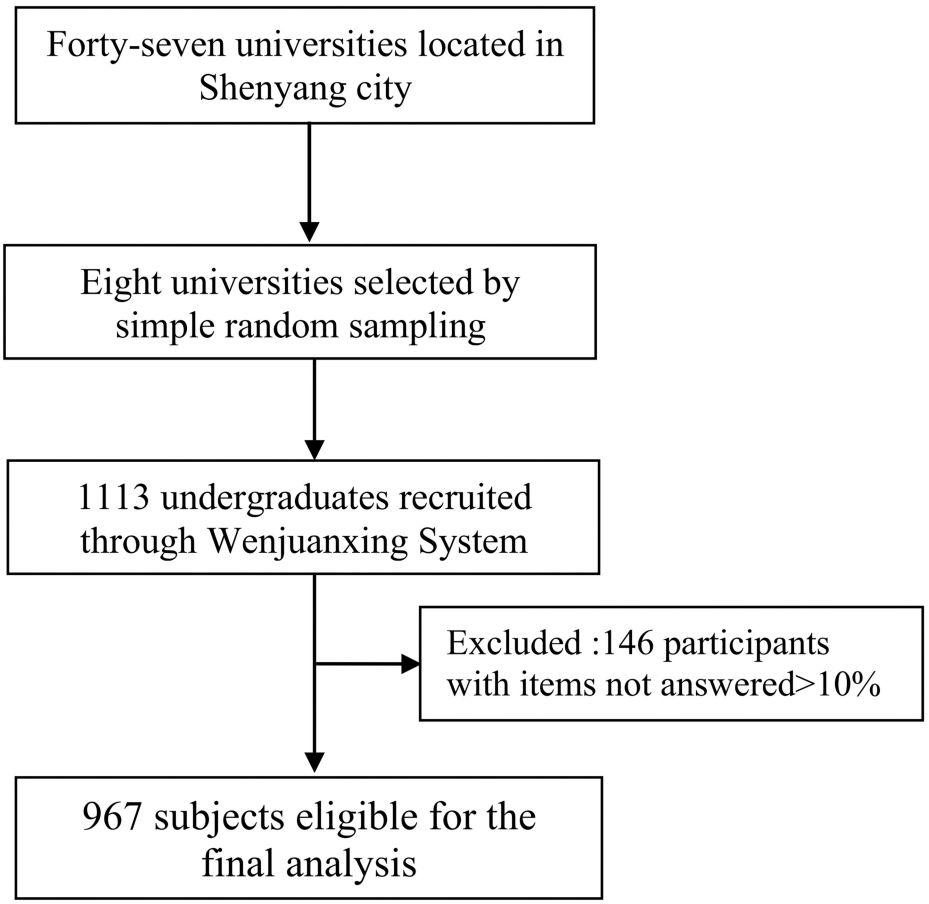

FIGURE 1 | Flow chart for participant selection.

was added as a mediator in step 3. Similarly, to explore the potential moderating role of self-efficacy, the covariates were added 1 in step 1. However, in step 2, both anxiety symptoms and self-efficacy were included. The product of anxiety symptoms and self-efficacy was added in step 3. Multicollinearity was examined by the variance inflation factor (VIF). A VIF value>10 indicated the existence of a serious multicollinear problem.

The potential mediating role of self-efficacy was further verified using the SPSS macros program (PROCESS v3.0 by Andrew F. Hayes) with 5,000 bootstrap sampling (40). The control covariates were the same as those used in the hierarchical multiple regression. Anxiety symptoms was treated as the independent variable, with PSU as the dependent variable, and self-efficacy as the mediator. Their total scores were standardized separately to eliminate the differences in scale scores. The total effect (path c), the direct effect (path c'), and the indirect effects (path a*b) were checked. The bias-corrected and accelerated 95% confidence interval (BCa 95%CI) for the indirect effect was also calculated. The mediating effect is considered statistically significant if the 95%CI of indirect effect (path a*c) does not contain zero.

RESULTS

Demographic Characteristics

The demographic characteristics of the study participants and group differences are shown in **Table 1**.

Female University students had higher PSU and anxiety symptoms than male University students (PSU: 39.65 vs. 37.89, $P < 0.01$; anxiety symptoms: 53.89 vs. 52.37, $P < 0.05$), but no sex difference was found regards to self-efficacy. The levels of PSU, self-efficacy, and anxiety symptoms significantly varied across the different grades of University students ($P < 0.01$). Monthly living expenses higher than 1,000 yuan were associated with elevated levels of PSU and self-efficacy, but not with anxiety symptoms. The PSU scores were significantly different between students from urban and rural areas (37.99 vs. 39.51, $P < 0.01$). Finally, University students who had no siblings tended to have higher levels of anxiety disorders than those who had siblings (54.06 vs. 51.90, $P < 0.01$).

TABLE 1 | Demographic characteristics of the study participants ($N = 967$) and univariate analysis for the factors related to the level of PSU, self-efficacy, and anxiety symptoms.

Variables	Number (%)	PSU (Mean ± SD)	Self-efficacy (Mean ± SD)	Anxiety symptoms (Mean ± SD)
Sex				
Male	490 (50.7)	37.89 ± 8.57	26.20 ± 5.12	52.37 ± 11.16
Female	477 (49.3)	39.65 ± 9.25**	26.34 ± 5.10	53.89 ± 9.89*
Grade				
Freshman	204 (21.1)	34.31 ± 8.50	25.06 ± 5.39	51.74 ± 10.91
Sophomore	249 (25.7)	37.43 ± 8.24**	25.44 ± 5.00	53.59 ± 12.12
Junior	415 (42.9)	41.32 ± 8.64**	27.18 ± 4.72**	52.79 ± 8.82
Senior	99 (10.2)	40.52 ± 8.79**	27.00 ± 5.59**	56.17 ± 11.91**
Monthly living expenses (yuan)				
<1,000	88 (9.1)	35.06 ± 7.61	24.62 ± 5.91	52.87 ± 12.88
1,000–3,000	671 (69.4)	39.46 ± 9.09**	26.33 ± 4.89**	52.86 ± 10.00
>3,000	208 (21.5)	38.07 ± 8.62*	26.76 ± 5.34**	54.06 ± 11.40
Residential area				
Urban	479 (49.5)	37.99 ± 9.02	26.06 ± 5.20	53.20 ± 10.73
Rural	488 (50.5)	39.51 ± 8.83**	26.47 ± 5.02	53.05 ± 10.43
Whether or not the only child				
Yes	546 (56.5)	38.44 ± 8.95	26.15 ± 5.11	54.06 ± 11.03
No	421 (43.5)	39.17 ± 8.96	26.41 ± 5.11	51.90 ± 9.85**

Missing values: grade, 4 cases; monthly living expenses, 5 cases; whether or not the only child, 4 cases; PSU, 2 cases; self-efficacy, 4 cases; anxiety symptoms, 3 cases.
**P<0.05, **P<0.01.*

TABLE 2 | The means, standard deviations, and bivariate correlations between continuous variables.

Variables	(Mean ± SD)	1	2	3
1. Age	20.36 ± 1.50	1		
2. Anxiety symptoms	53.12 ± 10.58	0.084**	1	
3. PSU	38.74 ± 8.94	0.148**	0.302**	1
4. Self-efficacy	26.27 ± 5.10	0.100**	−0.271**	−0.181**

*PSU, problematic smartphone use; SD, standard deviation. **P < 0.01.*

Correlations Among PSU, Self-Efficacy, and Anxiety Symptoms

The mean values and bivariate correlations between continuous variables are shown in **Table 2**. Anxiety symptoms was positively correlated with PSU ($r = 0.302$, $P < 0.01$). In contrast, self-efficacy was negatively associated with both anxiety symptoms and PSU ($r = -0.271$ and -0.181, $P < 0.01$).

Mediating Effect of Self-Efficacy on the Relationship Between Anxiety Symptoms and PSU Severity

As shown in **Table 3**, the control covariates in step 1 significantly explained PSU (adjusted $R^2 = 0.113$, $\Delta R^2 = 0.120$, $P < 0.01$). Among them, age, sex, grade, and monthly living expense were significantly related to PSU severity. In step 2, after adjusting for control covariates, anxiety symptoms was positively associated with PSU ($\beta = 0.292$, $P < 0.01$). Anxiety symptoms explained additional 8.3% of the variance of PSU. In step 3, self-efficacy was negatively associated with PSU ($\beta = -0.181$, $P < 0.01$), which accounted for additional 2.9% of the variance. When self-efficacy was added to the model, the absolute value of the regression coefficient of anxiety symptoms on PSU was decreased from 0.292 to 0.241. Therefore, self-efficacy might probably serve as a mediator in the association between anxiety symptoms and PSU among University students.

Regarding the implications of hierarchical multiple regression, the mediation of self-efficacy in the anxiety-PSU relationship was further validated using PROCESS v 3.0. **Table 4** demonstrated the results of the mediation analysis. First, the association between anxiety symptoms and PSU (c path) was calculated. Anxiety symptoms was positively associated with PSU ($c = 0.292$, $P < 0.01$). Second, the indirect effect of anxiety symptoms on PSU via self-efficacy was found statistically significant [path a*b, a = −0.282, b = −0.181, a*b(BCa 95%CI) = 0.051(0.029, 0.075)]. Since the confidence interval for indirect effect did not include the null value, then we could conclude that self-efficacy played a mediating role between anxiety symptoms and PSU. Finally, when self-efficacy was included in the model as a mediator, the direct effect of anxiety symptoms on PSU (path c′) remained statistically significant ($c' = -0.241$, $P < 0.01$). Therefore, self-efficacy had a partial mediating effect on the association between anxiety symptoms and PSU for University students. The mediation of self-efficacy accounted for ∼17.5% (a*b/c) of the total effect. The visualization of the model was demonstrated in **Figure 2**.

TABLE 3 | The mediating effect of self-efficacy on the relationship between anxiety symptoms and PSU severity among University students.

Variables	Block 1		Block 2		Block 3	
	β	VIFs	*β*	VIFs	*β*	VIFs
Step 1						
Age	−0.128**	2.502	−0.148**	2.507	−0.159**	2.511
Female vs. male	0.063*	1.034	0.040	1.041	0.042	1.041
Rural vs. urban	0.035	1.154	0.038	1.154	0.044	1.155
Grade 2 vs. grade 1	0.191**	1.910	0.174**	1.914	0.187**	1.919
Grade 3 vs. grade 1	0.460**	3.404	0.463**	3.404	0.508**	3.472
Grade 4 vs. grade 1	0.304 **	2.683	0.282**	2.688	0.314**	2.722
Monthly living expenses (yuan)						
1,000–3,000 vs. <1,000	0.117*	2.838	0.117*	2.838	0.133**	2.847
>3,000 vs. <1,000	0.057	2.981	0.048	2.982	0.073	3.003
Step 2						
Anxiety symptoms			0.292**	1.022	0.241**	1.113
Step 3						
Self-efficacy					−0.181**	1.137
F	16.351**		100.202**		36.049	
Adjusted R^2	0.113		0.196		0.224	
ΔR^2	0.120		0.083		0.029	

*Grade 1. Freshman; Grade 2, Sophomore; Grade 3, Junior; Grade 4, Senior; PSU, problematic smartphone use; VIF, Variance inflation factor. *P < 0.05; **P < 0.01.*

TABLE 4 | The results of the mediation analysis Path Coefficient/Effect *P*-value BCa 95% CI.

Path	Coefficient/effect	*P*-value	BCa 95%CI
c	0.292	<0.01	(0.235, 0.349)
a	−0.282	<0.01	(−0.342, −0.222)
b	−0.181	<0.01	(−0.241, −0.122)
a*b	0.051	-	(0.029, 0.075)
c′	0.241	<0.01	(0.182, 0.300)

BCa 95% CI the bias-corrected and accelerated 95% confidence interval; Age, gender, location, grade, monthly living expenses were covariates.

Moderating Effect of Self-Efficacy on the Relationship Between Anxiety Symptoms and PSU Severity

As shown in **Table 5**, in step 2, anxiety symptoms was positively associated with PSU after the adjustment of control variables ($\beta = 0.241$, $P < 0.01$), while self-efficacy was negatively associated with PSU ($\beta = -0.181$, $P < 0.01$). The model fits were significantly improved by anxiety symptoms and self-efficacy (adjusted $R^2 = 0.224$, $\Delta R^2 = 0.112$, $P < 0.01$). In step 3, the interaction term of anxiety symptoms and self-efficacy was not statistically significant ($\beta = 0.003$, $P = 0.98$). Thus, self-efficacy could not moderate the relationship between anxiety symptoms and PSU among University students.

DISCUSSION

Main Findings

The main findings of this study were as follows. A higher level of anxiety symptoms was significantly correlated with more severe PSU. There was a significantly negative association between self-efficacy and anxiety symptoms. Furthermore, self-efficacy can mediate the association between anxiety symptoms and PSU. Nevertheless, the moderating effect of self-efficacy on the association between anxiety symptoms and PSU was insignificant. To the best of our knowledge, this was the first study to explore the mediating/moderating effect of self-efficacy on the relationship between anxiety symptoms and excessive smartphone use in University students.

Our study reported a small to moderate positive correlation between anxiety symptoms and PSU among University students, which was consistent with findings from previous empirical studies (1, 17). Moreover, hierarchical multiple regression analyses showed that a high level of anxiety symptoms was an independent predictor of severe PSU. Our findings could be explained by some theoretical frameworks. The UGT treats anxiety as a motivator that drives people to overuse smartphones to calm their anxiety (18). The CIUT proposes that PSU results from people's attempt to relieve their negative emotions from stressful life events (19). The I-PACE model regards anxiety symptoms as predisposing factors that have an important influence on PSU (20, 21).

As expected, we found a negative correlation between self-efficacy and anxiety symptoms in our study. Self-efficacy, as one of the most important positive psychological qualities,

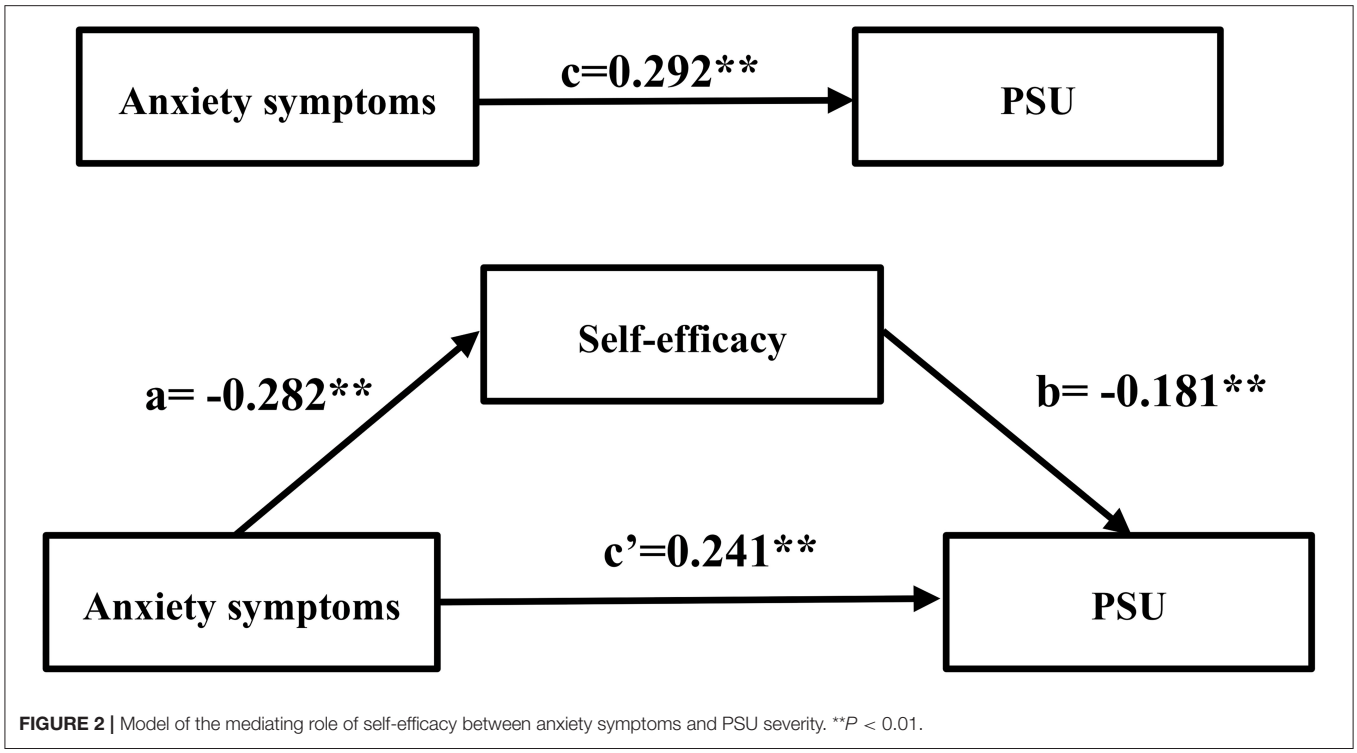

FIGURE 2 | Model of the mediating role of self-efficacy between anxiety symptoms and PSU severity. $^{**}P < 0.01$.

has become a plastic internal psychological resource and can serve as a buffer against mental disorders (41–43). CL Liu et al. demonstrated that self-efficacy was negatively correlated with the levels of both depression and anxiety among doctoral students (44). Self-efficacy training has been confirmed effective in reducing mental problems, such as anxiety and depression (45). Similarly, the negative correlation between self-efficacy and PSU was validated by our study. A previous study showed that a high level of self-efficacy might serve as a buffer to addiction-like behaviors such as problematic gambling, resulting in a weakened relationship (46). Additionally, randomized controlled trials by improving self-efficacy have been proven to be effective in the treatments of tobacco, alcohol, and drug addictions among college students (47, 48).

Our findings suggested that self-efficacy could act as a mediator between anxiety symptoms and PSU among University students. The mediating effect of self-efficacy could explain ∼17.5% of the total effect that anxiety symptoms have on PSU. Nevertheless, the moderating effect of self-efficacy on the anxiety-PSU relationship was insignificant. As mentioned in the Introduction section, self-efficacy can be treated as one of the affective and cognitive response variables of the I-PACE model (20, 21). Therefore, it is not surprising that self-efficacy can mediate the relationship between anxiety symptoms and PSU. Similar findings were reported in a population of Korean nursing students (32). They found that self-efficacy could fully mediate the relationship between depression and PSU. The potential mediating mechanisms of self-efficacy in preventing and reducing other addictive behaviors such as Internet and gambling addictions have been previously reported (46, 49).

However, no studies have investigated the mediating or moderating role of self-efficacy in the anxiety-PSU relationship. We believe that students who perceive a higher level of self-efficacy usually possess more confidence and perseverance to cope with interpersonal troubles and have a higher level of self-control over their impulsivity to pursue pleasure through smartphones, resulting in decreased exposure to PSU compared to those with a lower level of self-efficacy (50). Meanwhile, self-efficacy, as a well-known positive psychological resource, can also help to reduce adverse anxiety psychological problems effectively (51). Given the mediating role of self-efficacy in our findings, this model should be applied to provide a possible framework for the development of health education and health-related inventions. Effective strategies should be taken to resist the psychological dependence of smartphone usage, improve the level of self-efficacy, and thus relieve mental health disorders among University students.

Limitations

Several limitations should be taken into account in this study. First, data were collected at just one timepoint instead of longitudinally which limited the ability to establish the causal inferences or determine the direction of the causal relationships. Future prospective studies with a large sample size are warranted to validate our findings. Second, the survey was conducted using self-report questionnaires, which might not objectively reflect the actual smartphone usage and psychological exposures. Third, other psychiatric disorders such as depression personality disorders and medications for

TABLE 5 | The moderating effect of self-efficacy on the relationship between anxiety symptoms and PSU severity among University students.

Variables	Block 1		Block 2		Block 3	
	β	VIFs	*β*	VIFs	*β*	VIFs
Step 1						
Age	−0.128**	2.502	−0.159**	2.511	−0.159**	2.511
Female vs. male	0.063*	1.034	0.042	1.041	0.042	1.043
Rural vs. urban	0.035	1.154	0.044	1.155	0.043	1.155
Grade 2 vs. grade 1	0.191**	1.910	0.187**	1.919	0.186**	1.922
Grade 3 vs. grade 1	0.460**	3.404	0.508**	3.472	0.507**	3.479
Grade 4 vs. grade 1	0.304 **	2.683	0.314**	2.722	0.314**	2.722
Monthly living expenses (yuan)						
1,000–3,000 vs. <1,000	0.117*	2.838	0.133**	2.847	0.133**	2.849
>3,000 vs. <1,000	0.057	2.981	0.073	3.003	0.074	3.006
Step 2						
Anxiety symptoms			0.241**	1.113	0.241**	1.122
Self-efficacy			−0.181**	1.137	−0.181**	1.159
Step 3						
Interaction item					0.003	1.032
F	16.351**		69.961**		0.013	
Adjusted R^2	0.113		0.224		0.224	
ΔR^2	0.120		0.112		0	

*Grade 1, Freshman; Grade 2, Sophomore; Grade 3, Junior; Grade 4, Senior; PSU, problematic smartphone use; VIF, Variance inflation factor; *P < 0.05; **P < 0.01.*

psychiatric reasons were not investigated, which would prevent us from fully understanding the mechanisms between various psychological factors and problematic smartphone use. Fourth, a sample of adolescent Chinese students may disable the external generalization of our findings. More representative samples of general smartphone users are needed. Finally, as an observational study, the mediating effect of self-efficacy on the relationship between anxiety and PSU should be confirmed by randomized controlled trials. Future research on interventions should be extensively conducted to verify our hypothetical models and radically prevent addictive behaviors among college students.

CONCLUSION

PSU can cause many detrimental psychological disorders such as anxiety symptoms. It has become a mental health threat to University students. The current study is the first to provide evidence that self-efficacy can partly mediate the association between PSU and anxiety symptoms in Chinese University students. Considering the increasing prevalence of PSU among University students, multicomponent interventions, from the joint efforts of school-family-students, should be made to restrict the frequency of smartphone usage and increase the level of self-efficacy to thus promote the mental health of University students.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of China Medical University. The patients/participants provided their electronic informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

YL and M-LY contributed to data collection, statistical analysis, and revision of the manuscript. YL drafted the manuscript. Y-TQ and C-LL contributed to organizing the survey and interpretation of the data. HW and G-XL contributed to the study design, data collection, and revision of the manuscript. All authors read and approved the final version of the manuscript for submission.

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Exploring the Dimensions of Smartphone Distraction: Development, Validation, Measurement Invariance, and Latent Mean Differences of the Smartphone Distraction Scale (SDS)

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Background: Distraction is a functional emotion regulation strategy utilized to relieve emotional distress. Within the attention economy perspective, distraction is increasingly associated with digital technology use, performance impairments and interference with higher-order cognitive processes. Research on smartphone distraction and its association with problematic smartphone use is still scarce and there is no available psychometric assessment tool to assess this cognitive and emotive process parsimoniously.

Method: The present study reports the development and evaluation of the psychometric properties of the Smartphone Distraction Scale (SDS) through exploratory and confirmatory factor analysis, construct validity, gender invariance, and latent mean differences. The study was conducted in a sample of British university students ($N = 1{,}001$; $M = 21.10$ years, $SD = 2.77$).

Results: The 16-item SDS was best conceptualized in a four-factor model solution comprising *attention impulsiveness, online vigilance, emotion regulation*, and *multitasking*. Construct validity was established using relevant psychosocial and mental health measures, with SDS scores being moderately associated with deficient self-regulation and problematic social media use. Gender measurement invariance was achieved at the configural, metric, and scalar levels, and latent mean differences indicated that females had significantly higher means than males across all four SDS latent factors.

Discussion: The SDS presents with several strengths, including its theoretical grounding, relatively short length, and sound psychometric properties. The SDS enables the assessment of distraction, which appears to be one of the pathways to problematic smartphone use facilitating overuse and overreliance on smartphones for emotion

regulation processes. The assessment of distraction in relation to problematic use in vulnerable populations may facilitate interventions that could encourage metacognition and benefit these groups by allowing sustained productivity in an increasingly disrupted work and social environment.

Keywords: smartphone use, distraction, attention, social media use, smartphone distraction scale

INTRODUCTION

Attention is a scarce finite resource implicated in a variety of cognitive processes determining individual action and volition (1) that can be deployed externally (e.g., focus on the shape of a certain stimulus) or internally (e.g., focus on neutral or positive thoughts) (2). In the digital age, and particularly in the current pandemic era, which has shifted education and employment to remote learning and working, respectively, attentional resources are consistently challenged for engagement (3, 4). Concerns have been raised that the increased pressures for digitally juggling remote working with social, recreational, and information demands may be contributing to difficulties maintaining a healthy work-life balance (5) and the onset of mental health difficulties such as occupational burnout (6, 7). Additionally, online social spaces are influencing users with persuasive design (i.e., rolling feeds), prompting high cue reactivity and prolonged use of and overreliance on digital devices (8–11). Multitasking, multiple device use, and frequent attentional shifts are salient behaviors potentially leading to digital information overload (12–14).

Smartphones are ubiquitous digital devices that offer multiple communication affordances to half of the world's population (15), and may interfere with how attentional resources are allocated, constituting an emerging area of research (16–19). Increasing evidence suggests that smartphone use triggers frequent interruptions and breaks from main tasks, further interfering with cognitive processes and ability (20–24), cognitive functioning (25–28), and associated with distraction and compromised performance (26–28) resulting in sub-optimal learning among young people (29, 30). Disruption from smartphone use is even more prominent within classroom environments (31–33), hindering academic achievement due to interference with primary tasks (12, 34) and in less engaging academic contexts, prompting lower motivational levels and comprehension (12, 35, 36), task performance (37), and chronic media multitasking (12). Smartphone interruptive notifications are frequent external triggers (38) which disrupt daily activities and have even been associated with mood disorders mediated by boredom proneness (39).

Given the numerous advantages of smartphones which provide constant internet accessibility, distraction has become frequent and endemic among smartphone users, potentially reinforcing more habitual or compulsive smartphone use (40). Distraction has been traditionally defined as an emotion regulation coping strategy implicated in shifting focus to a non-threatening situation or thought to reduce emotional distress and negative affect (41–45). Smartphone distraction (SD) may be caused by external triggers, such as notifications, intrusive thoughts, or cognitive salience of smartphone-related content to avoid or regulate emotions (26, 46–48). Fear of missing out (FOMO: missing out on positive recreational experiences of others) appears to be a main driver for several forms of problematic technology use (49), including smartphone use (50) currently exacerbated by the impact of the pandemic and social isolation (51) and driving attentional bias and distraction from online content to fulfill control needs (52).

One of the most prominent models of attention and its orientation has been proposed by Posner (53), viewing the attentional system as having the possibilities to shift, orient, and disengage as a biased response. Based on Posner's attention networks model (53), as adapted by Wu and Cheng (54) for educational contexts (see **Figure 1**), SD is conceptualized within the present study as the result of a reaction to exogenous (orienting system) or endogenous cues (alerting system) or as the result of a conflict amongst these two networks that are competing for attentional resources. For the occurrence of distraction, the exogenous cues (orienting system) are triggered by auditory/visual signals, which can take the form of smartphone notifications in smartphone use. The endogenous cues (alerting system) are the bottom-up signals in the form of expectancies, worries, and lingering thoughts leading to distraction or daydreaming. The executive system is implicated when conflict arises between the exogenous and endogenous cues, leading to attention discontinuity and therefore poor attention deployment, prompting inhibitory or executive control difficulties (55). Distraction appears therefore to be the result of disruptions or interruptions in one of the three attention networks mediated by smartphone use (29, 39, 54).

Distraction may be psychologically explained by the control model of engagement (52), a theoretical model integrating elements from distraction conflict theory (56), theory of social facilitation (57), and perceptual control theory (58), supporting that online engagement partially occurs to control online content, relationships and presentation online, causing attentional bias toward online stimuli and distraction from daily activities. Distraction may be facilitated by the presence of others online (56, 59), prompting interaction and leading to heightened engagement or shallow processing when involved in parallel cognitively demanding tasks. Beyond perceptual conflicts (12, 34) associated with lowered levels in well-being and productivity or lowered academic achievement amongst young people (31, 60–63) due to excessive social media and smartphone use (64–66), these constant disruptions may be associated with hyperactivity levels (67), negative affect, sensitivity to evaluation, poor emotion regulation, and problematic smartphone use

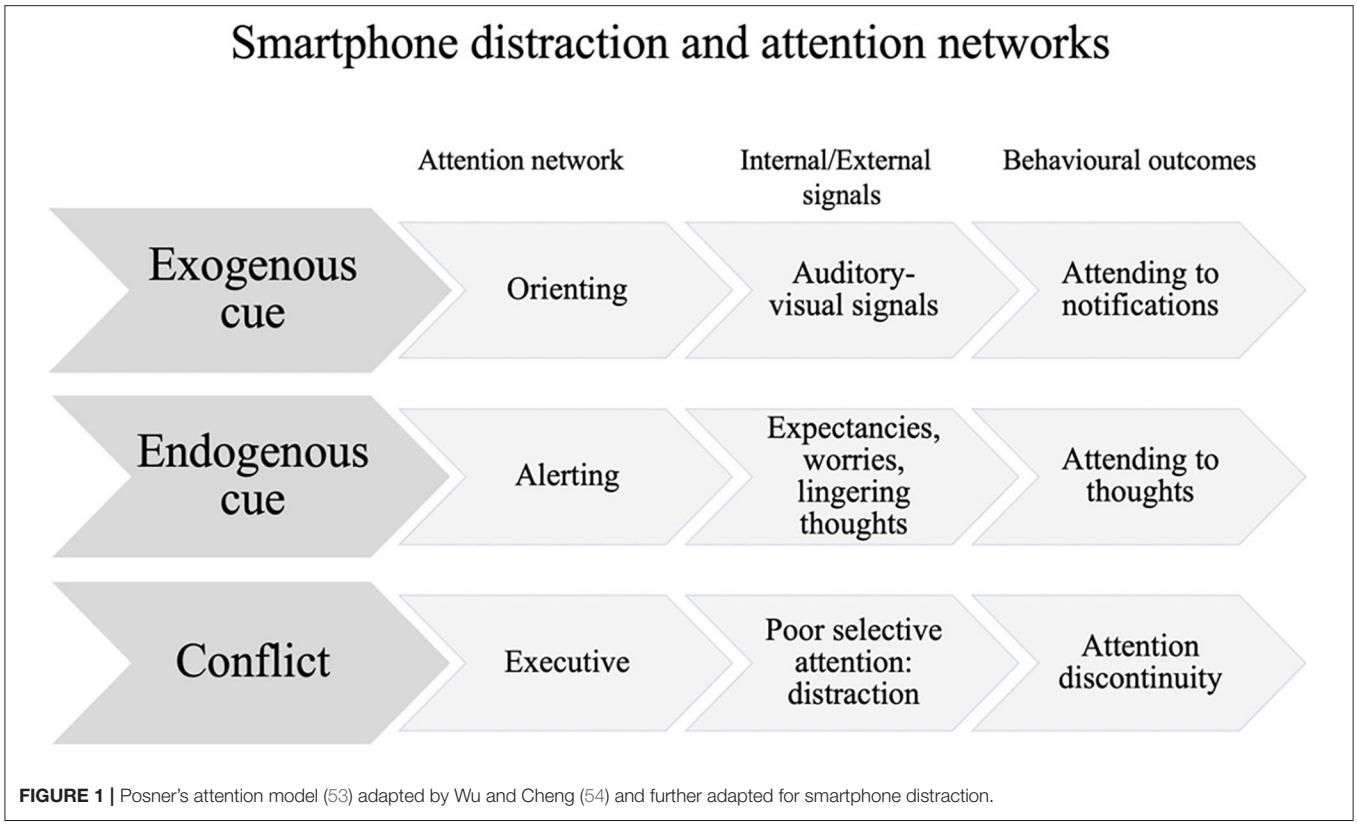

FIGURE 1 | Posner's attention model (53) adapted by Wu and Cheng (54) and further adapted for smartphone distraction.

(68–74). Attempting to achieve relief from negative emotions elicited smartphone use is reinforced (75, 76), leading to poor metacognition (77). However, despite accruing evidence for emotional and behavioral consequences of problematic smartphone use, the processes leading to addictive use (78) remain conceptually unclear and methodologically questionable partially due to the constantly evolving nature of products and services (17, 79–82) alongside the wide range of contents (social, information) smartphones provide access to.

Research on distraction and its association with problematic smartphone use is still scarce and there are no available psychometric assessment tools within the smartphone and social media literature to assess this cognitive and emotive process parsimoniously. Subscales within attention scales, executive function scales, and problematic internet use scales partially assess the role of distraction as a cognitive mechanism occurring in the digital environment (83–85). However, many of the existing psychometric scales are limited to a few items only, and therefore are neither comprehensive nor representative of the complexity involved in smartphone use experience, frequent attentional loss, and the associated processes experienced by smartphone users (i.e., urge to check, cue reactivity). Given that frequent attentional loss has been reported to affect executive function areas, critical for paying attention, decision-making, planning, organization, higher-order thinking, and regulating emotions (86, 87), it is important to assess distraction within the smartphone context with accuracy. Thus, the psychological function of distraction in the online environment should be further scrutinized since distraction is not a unitary process, but rather a multidimensional construct associated with both adaptive and maladaptive functions, rendering the development of such psychometric test timely due to the need to further understand this phenomenon and its relationship to problematic smartphone use as a psychological experience.

SMARTPHONE DISTRACTION AND RELEVANT PSYCHOLOGICAL CONSTRUCTS

Smartphone distraction among young people primarily occurs due to social media content. Smartphone use and social media use are inextricably interwoven for young people due to the prominent social element in smartphone use (88) leading to distraction and academic work conflict (89). More specifically, the rationale for the development of this scale was based on the premise that distractive smartphone use appears to be driven primarily by the cognitive preoccupation with social media content in order to attend to needs for validation and control (of content, self-presentation, and relationships). This preoccupation and urge to check (90) or interact, in turn, prompts emotional reactivity and behavioral activation in the form of distraction (40, 91), amplified by FOMO and the need to control self-presentation and others' perceptions or seek reassurance (92). This process could also be experienced from non-social use (73, 93) because smartphones are multi-purpose

devices and recent studies suggest that process use (e.g., watching videos, browsing online) is widespread as much as social use (73) and with stronger associations with problematic smartphone use (92, 94). In the present study, it is contended (and supported by empirical studies) that social media content is largely responsible for the attentional drift associated with frequent and prolonged smartphone engagement among young adults (95, 96). A smartphone is therefore viewed as the medium providing access to the desired content reflecting the attachment formed to the device among young adults (97–103) and intensified by experiences of nomophobia (NOMO; the fear of being without a smartphone) (104–107) and FOMO (29, 108, 109). However, the assessment of the relative role of process smartphone use and its relationship to smartphone distraction requires further exploration. Given the increasing mobile connectivity, providing access to social media via smartphones (110), and the frequent engagement with social content by emergent adults (111, 112), the use of social media measures (metacognitions and problematic social media use) were deemed appropriate to support the validity of the new measure.

Metacognitions

Metacognitions refer to higher order cognitive states and coping mechanisms to regulate those cognitions (113). These refer to *positive* cognitive-affective regulation (i.e., "*Smartphones distract me from worries*") and negative metacognitions (i.e., "*I am unable to control my distraction*") which denote the inability to control a cognition or a behavior and may amplify maladaptive engagement (113). A bi-directional association between distraction and metacognition has been established for auditory distractions, suggesting interference of distraction in metacognition and vice versa (114). Within the context of gambling, negative metacognitions have been associated with attention focusing and attention shifting and have been suggested as partially influencing the control of attention (115). As recently evidenced in the literature, both positive and negative metacognitions for emotion regulation, social benefits, and inability to control behavior have been found to predict problematic smartphone use (116) and have been associated with problematic social media use (113, 117) and problematic internet use (118). Metacognitive processes were chosen for construct validity due to evidence implicating such processes in problematic smartphone use and because they may also serve as a potential pathway to controlling problematic social media use (113) through positive beliefs about cognitively controlling attention (115).

Problematic Social Media Use

Problematic social media use, reflects a prolonged pathological engagement with social media content (119), which may be mediated by distraction and constant checking (11, 40, 83, 120). The current literature suggests that frequent smartphone checking behaviors (91, 121) have been associated with distraction (46, 122, 123) and habitual use (94, 121) fueled by FOMO, neurotic tendencies (124) and online vigilance (i.e., preoccupation with salient online content) (91). Therefore, experiences of FOMO and NOMO appear to be associated with distraction and may be driving checking behaviors (125), reflecting the cognitive preoccupation and interpersonal attachment via digital devices (10, 68, 126–131). Positive metacognitions also appear to mediate the relationship between FOMO and problematic social media use (132). Therefore, within smartphone use, distraction reflects a salient cognitive and emotive coping strategy, mediating or facilitating other potentially problematic processes in smartphone use (e.g., checking behaviors) or facilitating higher engagement for emotion regulation (40). Therefore, investigating the role of SD alongside its role in distress and problematic smartphone use (133) via problematic social media use (95, 134–136) and its differentiation from similar constructs (i.e., mind-wandering, interruptions) (137, 138), is timely because it is the context (smartphone use) and the function which accounts for the renewed scientific interest in the construct. The present authors utilize the term "problematic social media use" (similarly to "problematic smartphone use") instead of "social media addiction" given that the latter is not currently a formally accepted diagnostic construct (139) and respective screening measures reflect problematic engagement. "Social media addiction" as a term will only be used in the present manuscript where referenced in other studies. Social media addiction is a construct used by scholars to denote a state of addictive proclivity to social media when meeting criteria for addiction (140) with an evolving literature base regarding its nature and impact cross-culturally and longitudinally (141–144).

GENDER DIFFERENCES IN SMARTPHONE USE

Prior studies have confirmed gender differences in emotional distraction and reactivity (145). Within smartphone use, emergent evidence has also demonstrated gender-based differences with empirical studies to date presenting with mixed results concerning gender differences in smartphone use (124, 146–154). Gender has also been arguably identified as a potential risk factor for the development of problematic smartphone use with more females reporting higher problematic smartphone use than males but also gender differences in social media and other smartphone-related behaviors (155–157). However, given the novelty of the construct, gender differences have not been examined in relation to smartphone distraction. Therefore, a multiple group confirmatory factor analysis was undertaken to assess measurement invariance (configural, metric, and scalar) of the Smartphone Distraction Scale (SDS) across gender, and investigate gender-related latent mean differences across all the identified latent factors. Based on the analysis of the current literature, higher scores for smartphone distraction were expected for females than for males.

The present study therefore aimed to develop and empirically validate a psychometric scale to assess smartphone distraction (SD), the SDS. This was developed to identify its latent dimensions while accounting for the smartphone context, the extant empirical evidence, and the theoretically-relevant frameworks suggested (52, 58). More specifically, the present

study aimed to fulfill the following primary objectives: (i) examine the factorial validity and reliability of the SDS using exploratory and confirmatory factor analysis, and (ii) investigate the convergent and divergent validity by examining the relationship between the SDS and problematic social media use, metacognition, mindful attention, stress and smartphone-related psychological constructs. To achieve the aforementioned objectives, it was hypothesized that: (i) the SDS would show robust psychometric properties; and (ii) those with higher levels of distraction would present higher scores of problematic social media use, stress, and other relevant psychological constructs (i.e., self-regulation). It is envisaged by the present authors that the development and psychometric validation of a scale for SD will contribute to its assessment in academic institutions and work-related environments, generating further multidisciplinary scientific knowledge about this disruptive construct and its relationship with mental health correlates in smartphone use.

METHODS

Scale Development

The psychological dimensions of SD informed the item pool reflecting the following dimensions: (i) behaviors related to attention impulsiveness due to notifications or even the mere presence of a smartphone, (ii) preoccupation with online content, frequent checking, FOMO and NOMO, (iii) use of a smartphone to regulate distress, and (iv) multitasking and interference in daily activities and face-to-face interactions. This psychometric test was developed primarily for use with young adults (i.e., university students) who are the most frequent users of smartphones and therefore the most likely to experience academic disruption caused by smartphones with heightened distraction levels in University settings (34, 61, 158, 159) and subsequent attentional losses due to smartphone use (31, 34, 160).

An initial pool of 36 items was generated with attention to double-barreled items, leading questions, reverse-scored items, and clear short item presentation (161). Items were reviewed in terms of their conceptual relevance, coherence, linguistic clarity, and adequacy, by: (i) a panel of expert psychologists from the fields of cyberpsychology, behavioral addictions, clinical psychology, and psychometrics, respectively, and (ii) a pilot-testing among 35 university students to assess face validity, comprehension, and relevance of the items. A final pool of 33 items (in **Appendix 1**) formed the scale with each item rated on a 5-point Likert scale ranging from 1 (*almost never*) to 5 (*almost always*), which corresponded to four hypothesized factors. Following this initial step, the scale's dimensionality, validity, reliability and invariance was psychometrically assessed, following a stepwise approach as suggested by scholars (162, 163).

Participants and Procedure

An initial sample of 1,129 English-speaking university students from the United Kingdom (UK) were recruited online using snowball sampling. After data cleaning (see the "Statistical analyses" subsection), the sample was randomly split into two subsamples; the first sub-sample (Sample 1, $n = 501$) was used in Exploratory Factor Analysis (EFA) and the second one (Sample 2, $n = 500$) in Confirmatory Factor Analysis (CFA) to assess for population cross-validity (164, 165). Participant recruitment took place through university lectures in exchange for university credit as well as on social media with a potential financial compensation in the form of a prize draw of *Amazon* vouchers through a pool of eligible participants. The online survey was developed and administered via the survey platform *Qualtrics* (Provo, UT, USA) and included an information sheet, a consent form, and self-report questions to assess eligibility. Ethical approval for the present study was granted study by the University's Ethics Committee (No. 2018/226), and only participants who met the following inclusion criteria were able to complete the survey: (i) owning and using a smartphone with internet connection regularly for at least a year, (ii) using social media platforms on a daily basis, and (iii) being at least 18 years old. The survey took ∼25 min to complete.

Measures

Socio-Demographics and Media Use Habits. Socio-demographic and usage data were collected (gender, age, educational level, and relationship status) alongside data asking participants to indicate smartphone and social media use (average number of hours per day) on a multiple choice or open response format. Individuals also completed additional psychometric tests in order to assess the predictive ability of the new scale being developed (criterion-related validity).

The Attentional Control Scale (ACS) (166) is a 20-item self-report scale which assesses differences in the control of the orientation of attention as defined by three factors: attention focusing, attention shifting, and flexible control of thought (166, 167). Sample items in the scale include "*It is easy for me to read or write while I'm also talking on the phone,*" and "*I can become interested in a new topic very quickly when I need to.*" Items are rated on a 4-point Likert scale ranging from 1 (*almost never*) to 4 (*always*) with higher scores indicating greater difficulty to focus attention. Focusing attention has been associated with high anxiety and shifting attention with depression (166, 168). The ACS demonstrated adequate psychometric qualities in the present study (Cronbach's $\alpha = 0.80$).

The Mindful Attention Awareness Scale (MAAS) (169) is a 15-item assessment scale that assesses the dispositional mindfulness of being open and receptive in what is occurring in the present. The construct has been psychometrically and experimentally validated on various demographics and has been associated with various well-being constructs (169, 170). Item statements assess mindfulness within everyday situations reflecting cognitive, emotional, and behavioral aspects of the construct. Items are rated on a 6-point Likert scale from 1 (*almost always*) to 6 (*almost never*) with higher averaged scores indicating higher levels of dispositional mindfulness. Sample items include "*I do jobs or tasks automatically, without being aware of what I'm doing*" and "*I find myself doing things without paying attention.*" The construct has demonstrated a high degree of internal consistency in the present study (Cronbach's $\alpha = 0.90$).

The Perceived Stress Scale (PSS) (171) is a widely used 10-item scale assessing the degree of appraisal of life situations as unpredictable and beyond control causing additional burden

to an individual. The construct has been associated with more severe negative affective states and the onset of diseases (172). All items are rated on a 5-point Likert scale from 0 (*never*) to 4 (*very often*) with sample items such as "*In the last month, how often have you felt nervous and stressed?*" and "*In the last month, how often have you been able to control irritations in your life?*" Higher scores indicate greater levels of perceived stress. The scale possesses good psychometric properties (173) and had adequate internal consistency in the present study (Cronbach's $\alpha = 0.68$).

The Barratt Impulsiveness Scale-Alternative Version (BIS-8) (174) is an abbreviated version of the 11-item BIS scale (174) containing eight items assessing individuals' predisposition to fast and unplanned reactions with lack of control, and it is a construct associated with poor self-regulation and maladaptive behaviors (175). In previous studies the BIS-8 has presented with adequate levels of construct and concurrent validity among young populations (176, 177). Items are rated on a 4-point Likert scale ranging from 1 (*do not agree*) to 4 (*agree very much*) and higher mean scores indicate a higher degree of impulsiveness. Sample items include: "*I say things without thinking*" and "*I plan tasks carefully*." In the present study, the BIS-8 had adequate levels of reliability (Cronbach's $\alpha = 0.77$).

The Deficient Self-Regulation Measure (DSR) (178) is a 7-item scale assessing poor self-regulation in video game playing adapted for smartphone use (40) and unregulated internet use (179). This measure has been shown to exhibit sound psychometric properties (178), with sample items in the scale adapted for smartphone use including "*I get strong urges to use social media*" and "*I feel my social media use is out of control.*" Items are rated on a 7-point Likert scale ranging from 1 (*almost never*) to 7 (*almost always*), with grater scores suggesting higher levels of deficient self-regulation toward smartphone use. In the present study, the scale had adequate levels of reliability (Cronbach's $\alpha = 0.89$).

The Bergen Social Media Addiction Scale (BSMAS) (180–183) is a 6-item scale assessing the risk of problematic and addictive social media use severity based on the framework of the components model of addiction (salience, mood modification, tolerance, withdrawal, conflict, and relapse) (140). Items are rated on a 5-point Likert scale ranging from 1 (*very rarely*) to 5 (*very often*), producing a composite score ranging from 6 to 30, with higher scores indicating greater risk of social media addiction severity. A cut-off score $\geq$19 indicates problematic social media use (184). Sample items from the BSMAS is "*How often during the last year have you … used social media in order to forget about personal problems?*" and "*How often during the last year have you… become restless or troubled if you have been prohibited from using social media?*" The BSMAS has demonstrated sound psychometric properties (180–183, 185). In the present study, the BSMAS had excellent levels of internal consistency (Cronbach's $\alpha = 0.84$).

The Metacognitions about Gaming Questionnaire (MGQ) (186) was adapted for social media use for the present study. The 12 items are rated on a 4-point Likert scale ranging from 1 (*do not agree*) to 4 (*agree very much*). The MGQ includes two latent factors: positive metacognitions and negative metacognitions about social media use. Negative metacognitions refer to the difficulty in controlling social media use, content-related thoughts, and positive metacognitions to adaptive reflective beliefs related to cognitive and emotional responses to social media use. Sample items include "*Thoughts about social media interfere with my functioning*" and "*Social media stops me from worrying.*" Higher scores represent greater levels of metacognitions about social media use. The scale has demonstrated adequate psychometric properties in previous research (186). Internal consistency in the present study was excellent: for the positive metacognition subscale (Cronbach's $\alpha = 0.90$) and for the negative metacognition subscale (Cronbach's $\alpha = 0.89$).

The Generalized Self-Efficacy Scale (GSE) (187) is a widely used 10-item scale assessing perceived self-efficacy and is associated with both positive (i.e., optimism, work satisfaction) and negative outcomes (i.e., depression, stress, and anxiety). Sample items include: "*If I am in trouble, I can usually think of a solution*" and "*I can always manage to solve difficult problems if I try hard enough.*" All items are rated on a 4-point Likert scale ranging from 1 (*not at all true*) to 4 (*exactly true*). The GSE has demonstrated satisfactory internal consistency and validity in previous research (188, 189), and also high levels of internal consistency in the present study (Cronbach's $\alpha = 0.86$).

Statistical Analyses

The two subsamples were tested for equivalence with the use of independent samples *t*-tests and chi-square tests for socio-demographic variables. The constructs assessed indicating independence and Cohen's *d* designated trivial effect sizes. Statistically significant differences were found for age, gender, education, social media use, and problematic social media use (social media addiction). However, given the high sample size utilized in both subsamples, statistical significance may be inflated (190). Data cleaning involved identifying missing values above the 10% threshold for incomplete data, which resulted in 117 cases being excluded with listwise deletion based on literature suggesting that retaining data with missing data above this threshold may render biased results (191). To assess similar and repetitive patterns of responses (i.e., acquiescence bias) across the scales, Little's Missing Completely at Random (MCAR) test determined that data were missing completely at random ($p = 0.617$) in the remaining dataset. Multiple imputation was used to handle missing data. Univariate normality of all 33 items of the SDS was assessed by examining skewness and kurtosis values for each item. Three data points on the SDS had absolute values of skewness >3.0 and kurtosis > 8.0 (192), which were further removed from the dataset. Tolerance and Variance Inflation Factor (VIF) values suggested that there were no multicollinearity issues in the data. Mahalanobis distances and critical values for each case were used to check for multivariate outliers, resulting in eight cases being excluded from the dataset. Therefore, the final sample size for all subsequent analyses included 1,001 participants. Finally, to examine whether the assumption of multivariate normality was met, the Mardia index of multivariate skewness and kurtosis was applied. The Mardia's skewness for this data set was 253.44 and the Mardia's kurtosis 1,271.86. Both values are above the acceptable thresholds (i.e., 10

for multivariate skewness and $p(p+2)$ for multivariate kurtosis, which for our data was 288), indicating that the data were not multivariate normally distributed (193). All analyses were performed using Mplus v.8.3 (194).

Exploratory and Confirmatory Factor Analysis, Reliability, and Validity of the SDS

Statistical analyses involved: (i) estimation of descriptive statistics of the sample, (ii) an EFA to explore the underlying structure of the SDS, and (iii) CFA to ascertain the latent dimensions of the main construct, and to estimate the fit of the latent factors as defined by the EFA (195). This was decided because even though the items of the SDS being tested were defined *a priori* (based on the literature review of general distraction, the smartphone literature, and the expert comments), the lack of any relevant scale assessing this construct demanded an initial exploration of hypothesized theoretical factors, which would be further tested for their validity. In the EFA, Principal Axis Factoring extraction method was used with Promax (oblique) rotation due to the assumption that the factors are correlated, based on the underlying conceptual framework assumed (196). To measure sampling adequacy and suitability of the data for factor analysis, Bartlett's test of sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) measure were computed (197). A scree plot was also used to visually determine the number of factors to be retained (198) using the Kaiser criterion [retaining all factors with eigenvalues >1; (199) to obtain the most viable factor solution] (200, 201). To address criticisms of the Kaiser criterion technique (200, 202, 203) related to overestimation of the true number of factors (204), Horn's Parallel Analysis (205) was also performed since it is considered one of the most accurate factor retention methods and a better technique (206) based on the Monte Carlo simulation process, simulating random samples that parallel the observed data (207).

For the CFA, the following recommended fit indices with the conventionally accepted cut-off values were used to assess the fit: Root Mean Square Error of Approximation (RMSEA) [0.05;0.08], Standardized Root Mean Square Residual (SRMR) [0.05;0.08], Comparative Fit Index (CFI), Tucker-Lewis Fit Index (TLI), and Goodness of Fit Index GFI [0.90;0.95]. Maximum likelihood with robustness to non-normality and non-independence of observations (MLR; [194]) was used as the method of estimation for all models. Analysis of the reliability of the SDS was performed using two different indicators of internal consistency (McDonald's Omega and Cronbach's alpha). The validity of the scale was evaluated using several types of validity indicators such as criterion, convergent and discriminant validity (162, 163) by assessing the association between the SDS and measures of relevant psychological constructs (i.e., attentional control, and generalized self-efficacy).

Gender Invariance and Latent Mean Differences

Gender invariance was performed to assess similarity or divergence in the interpretation of the construct across gender and identify any latent mean differences across the factors. The present study also tested alternative models of fit by testing for invariance across gender, which was deemed critical given the multidimensional nature of the construct, influenced by individual differences in smartphone use (148, 154, 208). The invariance testing process begins with a well-fitting baseline model and involves the testing of equality of sets of parameters through several ordered and progressively more restrictive steps in measurement invariance by testing equality (209, 210). To assess gender invariance, a multi-group CFA (MGCFA) was conducted with maximum likelihood estimations to assess model fit by comparing fit indices amongst the models (209). Invariance may be achieved if there is an adequate fit to the data across groups with only a negligible change in values for fit indices (e.g., ΔCFI and ΔRMSEA, or ΔSRMR) (211). Three models—configural invariance, metric or weak invariance, and scalar or strong invariance—were estimated.

Traditionally, gender differences have been investigated using *t*-tests or analysis of variance comparing composite scores. However, a superior analytical method to examine gender differences is the latent mean analysis, which considers comparisons across groups based on a construct's latent factors, which cannot be directly measurable (212). In a SEM framework, to estimate the difference between two group means at a latent level, one of the groups should be served as a reference group and its mean should be fixed to zero. In this case, the latent mean of the other group represents the difference between the latent means of the two groups. "Males" was chosen as a reference group (coded as 0). In practice, the difference between the two group means on each latent variable equals the mean of the non-reference group (females) on the latent construct. Thus, a significant mean of a compared group would indicate that this group has a different level of the latent construct relative to the reference group. It is important to note that (full or partial) scalar invariance is a prerequisite in order to test for latent mean differences (212, 213).

RESULTS

Descriptive Statistics

The final sample of 1,001 English-speaking smartphone and social media users was predominantly female (69%, $n = 690$), 30% male ($n = 300$), and 1% other ($n = 11$) with an age range from 18 to 30 years ($M_{age} = 21.10$ years, $SD = 2.77$). A total of 730 participants (72.9%) were undergraduate students, 95 were graduate and post-graduate students (9.4%), 76 (7.6%) were employed and 28 (2.8%) participants were unemployed, whereas 72 (7.2%) were both students and employees. Sample 1 ($n = 501$) consisted of 88 (17.6%) males, 411 (82.2%) females, and two (0.2%) participants who declared as gender-free, whereas Sample 2 ($n = 500$) consisted of 212 (42.4%) males, 279 (55.8%) females, and nine (1.8%) participants who declared as gender-free. The two samples presented with the following composition in terms of ethnicity Sample 1 ($N = 501$), White, 369 (73.7%), Black, 44 (8.8%), Asian 30 (6%), and other 58 (11.6%). Sample 2 ($N = 500$), had a similar composition, White, 320 (64%), Black, 56 (11.2%), Asian 45 (9%), and other 79 (15.8%). More than half of the participants ($n = 524$, 52.3%) were in a relationship and reported different levels of daily smartphone usage: 305

TABLE 1 | Summary of the results from the Exploratory Factor Analysis (EFA) on the SDS 33 items obtained from Sample 1 ($n = 501$).

Items	Factor Loadings				Communalities	
	F1 ($\omega = 0.78$) ($\alpha = 0.84$)	F2 ($\omega = 0.74$) ($\alpha = 0.80$)	F3 ($\omega = 0.83$) ($\alpha = 0.74$)	F4 ($\omega = 0.63$) ($\alpha = 0.75$)	Initial	Extraction
Factor 1: Attention Impulsiveness (F1)						
Dis2: I get distracted by my phone apps	0.796				0.488	0.532
Dis1: I get distracted by my phone notifications	0.735				0.509	0.605
Dis3: I get distracted by just having my phone next to me	0.720				0.485	0.560
Dis4: I get distracted by my phone even when my full attention is required on other tasks	0.622				0.531	0.575
Factor 2: Emotion Regulation (F2)						
Dis30: Using my phone distracts me from tasks that are tedious or difficult		0.782			0.497	0.620
Dis27: Using my phone distracts me from doing unpleasant things		0.688			0.374	0.433
Dis28: Using my phone distracts me from negative or unpleasant thoughts		0.637			0.347	0.395
Dis31: Using my phone distracts me when I'm under pressure		0.634			0.405	0.445
Factor 3: Online Vigilance (F3)						
Dis16: I get distracted with what I could post while doing other tasks			0.690		0.386	0.488
Dis7: I get anxious if I don't check messages immediately on my phone			0.643		0.369	0.416
Dis13: I think a lot about checking my phone when I can't access it			0.641		0.455	0.516
Dis17: I get distracted thinking how many likes and comments I will get while doing other tasks			0.553		0.311	0.342
Factor 4: Multitasking (F4)						
Dis25: I often talk to others while checking what's on my phone				0.736	0.318	0.545
Dis24: I often walk and use my phone at the same time				0.467	0.268	0.352
Dis21: I can easily follow conversations while using my phone				0.406	0.201	0.310
Dis19: I use several applications on my phone while working				0.334	0.363	0.418

Percentage of the Total Variance Explained =59.62%. Four factors were extracted from the EFA after 6 iterations.
Removed items from each subscale due to low loadings:
F1: Dis5, Dis6.
F2: Dis26, Dis29,Dis32, Dis33.
F3: Dis8, Dis9, Dis10, Dis11, Dis12, Dis14, Dis15, Dis18.
F4: Dis20,Dis22,Dis23.
SDS, Smartphone Distraction Scale; ω, McDonald's Omega; α, Cronbach's Alpha; Dis, Items (i.e., Dis1, Dis2); F1, Factor 1; F2, Factor 2; F3, Factor 3; F4, Factor 4.

(30.5%) from half an hour to 3 h (0.5–3 h), half of the participants ($n = 503$, 50.2%) reported 3–6 h of smartphone use (3–6 h), 158 (15.8%) participants (6–10 h), and 35 (3.5%) of participants reported (10h+) of smartphone use.

Psychometric Properties of the Smartphone Distraction Scale

Exploratory Factor Analysis

An EFA was conducted on all SDS items in Sample 1 ($n = 501$) to examine the factorial structure and construct validity (195, 196) of the scale. Sample 2 ($n = 500$) was utilized to conduct the CFA for testing the findings from the EFA and to corroborate the factor structure emerging from the EFA (196). Results indicated that the proportion of variance in the variables explained by underlying factors was sufficient to indicate a strong relationship and conduct a factor analysis on the data (KMO = 0.854; BTS [$\chi^2[120, 501] = 2.597{,}36$, $p < 0.001$). Following conventions in EFA, items with factor loadings <0.40 were not retained (214). The communalities suggested that each item shared some common variance with other items and ranged from 0.20 (i.e., Item 21) to 0.62 (i.e., Item 30), meeting the thresholds to retain items and interpreted to be indicative of that factor (215).

The initial eight-factor solution was not retained as it rendered factors with fewer than three indicators and was an overestimation of the factors with no meaningful theoretical interpretation (196, 201). Parallel analysis also indicated a

four-factor solution. Furthermore, the EFA analysis suggested a four-factor structure that was extracted after six iterations, explaining about 59.62% of the total variance of the construct (see **Table 1**). A four-factor solution was corroborated by this analysis (four factors emerged with an eigenvalue above 1), which was a manifestation of the multidimensionality of the construct.

The four latent factors comprising of 16 items (**Appendix 2**) were labeled as, *"Attention Impulsiveness,"* "*Emotion Regulation,*" *"Online Vigilance,"* and *"Multitasking*." Furthermore, the first factor (*Attention Impulsiveness*) measures distraction from notifications and smartphone applications as well as the device itself and explained 32.42% of variance. The second factor (*Emotion Regulation*) measures distraction as a coping mechanism for poor mood or distraction as an avoidance mechanism to relieve tension, stress, and anxiety and explained 10.19% of variance. The third factor (*Online Vigilance*) measures distraction due to checking content or preoccupation about checking or if personal online content has been validated, and explained 9.28% of variance. The final factor (*Multitasking*) measures using several smartphone applications while working or walking and using the phone at the same time, and explained 7.72% of variance. Further assessment of the suitability of each item was done by checking the cross-loadings and it was found that the factor loadings were high on their respective constructs.

Confirmatory Factor Analysis

The CFA was used to determine how the data from Sample 2 conformed to the factor structure found in Sample 1. Model fit indices indicated adequate fit for the four-factor model [$\chi^2 = 233.56$, df = 98; $p < 0.001$; $\chi^2/df = 2.38$; RMSEA = 0.053; 90% CI (0.044, 0.061), CFI = 0.940; TLI = 0.927, SRMR = 0.044]. All factor loadings of the SDS were statistically significant ($p < 0.001$) and items related to the latent factor (**Table 2**) (216, 217). Due to high intercorrelations among the four latent factors (**Figure 2**), an alternative model, a second-order (hierarchical) factor model, was examined to ascertain whether it fitted the data better than the four-factor model. This model examined four latent variables as a function of one general higher-order factor. The results from the analysis showed the following statistics: $\chi^2 = 238.28$, df = 100, $p < 0.001$; RMSEA = 0.053; 90% CI. (0.044–0.061), CFI = 0.939; TLI = 0.927; SRMR = 0.045. As can be seen, all fit indices suggest that the second-order factor model also fits the data adequately.

To decide which of the compared models best approximate the data, we used two well-known criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), since the two models were not nested. Typically, the model with the smallest AIC and BIC values is the "best" model. However, if we want to assess the strength of evidence for each candidate model, we could use the ΔAIC and ΔBIC indices (218). ΔAIC and ΔBIC is simply the difference between a model's AIC and BIC (named candidate model and denoted as AICm and BICm) and the model with the smallest AIC and BIC among the compared models (denoted as AIC* and BIC*). Both, ΔAIC and ΔBIC can be used as evidence against a candidate model being the best model. According to Fabozzi and colleagues (218) if a ΔAIC and ΔBIC is <2, it is not worth more than a bare mention. In our case, the ΔAIC is 1.657 and ΔBIC is 6.772.

As can be seen, in terms of the AIC index the four-factor model appears to fit the data better than the competing model (second-order). In terms of the BIC index, the ΔBIC value suggests that the difference between the two models is also small (i.e., 6.772), although no clear decision can be made about which model fits the data better. However, based on the principle of parsimony (219), we concluded that the four-factor model fitted the data better than the second-order factor model.

TABLE 2 | Summary of Confirmatory Factor Analysis results obtained from the 16 items of the Smartphone Distraction Scale (SDS) on Sample 2 ($n = 500$).

Factors/Items	Factor Loadings
ATTENTION IMPULSIVENESS	
I get distracted by my phone notifications.	0.727
I get distracted by my phone apps.	0.731
I get distracted by just having my phone next to me.	0.754
I get distracted by my phone even when my full attention is required on other tasks	0.736
ONLINE VIGILANCE	
I get anxious if I don't check messages immediately on my phone	0.573
I think a lot about checking my phone when I can't access it	0.746
I get distracted with what I could post while doing other tasks	0.634
I get distracted thinking how many likes and comments I will get while doing other tasks	0.595
MULTITASKING	
I use several applications on my phone while working	0.699
I can easily follow conversations while using my phone	0.409
I often walk and use my phone at the same time	0.567
I often talk to others while checking what's on my phone	0.637
EMOTION REGULATION	
Using my phone distracts me from doing unpleasant things	0.675
Using my phone distracts me from negative or unpleasant thoughts	0.660
Using my phone distracts me from tasks that are tedious or difficult	0.798
Using my phone distracts me when I'm under pressure	0.757
Instructions: "Below is a collection of statements about your everyday experience with your smartphone. Using the 1–5 scale below, please indicate how often you currently have each experience. Please answer according to what best reflects your everyday experience."	
All factor loadings were statistically significant ($p < 0.001$)	

Criterion-Related, Convergent, and Divergent Validity

The criterion-related validity of the SDS was assessed by examining participants' test scores on the SDS in relation to daily smartphone use and social media use. As expected, a small positive association between SDS and daily social media use and smartphone use was observed. Convergent validity [the assessment of the level of correlation with a conceptually similar measure (220)] was met with partial correlations with the ACS, MAAS, and MGQ. As shown in **Table 3**, the SDS showed

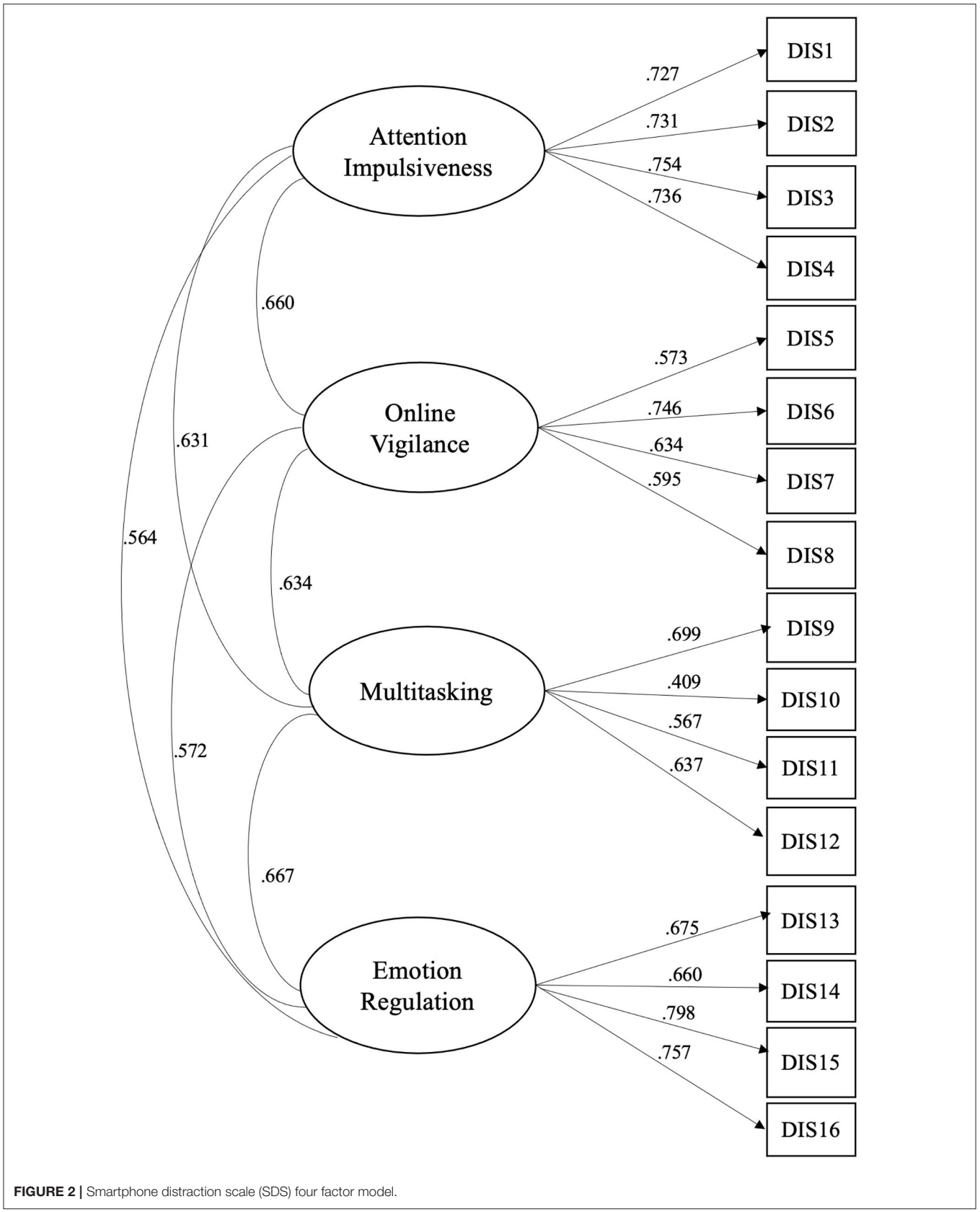

FIGURE 2 | Smartphone distraction scale (SDS) four factor model.

TABLE 3 | Correlations of the Smartphone Distraction Scale (SDS) With Other Scales: Criterion-related Validity, Convergent, and Discriminant Validity ($n = 500$).

Scale	Correlations	Cronbach's α
Daily recreational social media use	0.171**	-
Daily recreational smartphone use	0.148**	-
Attentional control	−0.365**	0.80
Mindful attention and awareness	−0.514**	0.90
Meta-cognition (positive)	0.300**	0.90
Meta-cognition (negative)	0.376**	0.89
Social media addiction	0.595**	0.84
Impulsivity	0.207**	0.77
Deficient self-regulation	0.470**	0.89
Stress	0.271**	0.68
Self-efficacy	0.002	0.86

**$p < 0.001$.

significant negative moderate correlations with the ACS ($r[500] = -0.365$, $p < 0.001$) and the MAAS ($r[500] = -0.514$, $p < 0.001$). Correlations of the SDS with the BIS-8, DSR, and BSMAS were assessed. The highest correlation was observed with BSMAS ($r[500] = 0.595, p < 0.001$), followed by DSR ($r[500] = 0.470, p < 0.001$). Moreover, moderate correlations were observed between the SDS and negative metacognitions ($r\ [500] = 0.376, p < 0.001$) and positive metacognitions ($r[500] = 0.300$, $p < 0.001$) and PSS ($r[500] = 0.271, p < 0.001$). Divergent validity was assessed by examining the correlation with the GSE ($r[500] = 0.002$, $p = 0.675$).

Reliability

Cronbach's alpha (α) was calculated for each of the subscales in order to assess internal consistency (162, 163), with a high alpha value indicating that items in the scale assess the same latent factor. Given the multidimensionality of the construct (221) and the limitations of the Cronbach's alpha [see (222)], an alternative internal consistency reliability coefficient was calculated for each subscale, the McDonald's Omega (ω) (223), which according to some scholars provides more accurate reliability findings for applied research (222, 224, 225). Cronbach's alpha coefficients with values of $\alpha \geq 0.70$ were considered to reflect adequate reliability with an item-total correlation between 0.25 and 0.75 (226). For McDonald's Omega, threshold values of $\omega \geq 0.70$ to 0.90 were considered adequate (221). The response form is a 5-point Likert scale ranging from "*almost never*" to "*almost always,*" where high scores represent higher levels of SD. Cronbach's α for the overall SDS ($\alpha = 0.87$) suggested a high level of internal consistency and therefore these four factors are strong indicators of the construct. The four subscales presented acceptable to good reliability: Cronbach's alpha for Attention Impulsiveness ($\alpha = 0.84$), was followed by Emotion Regulation ($\alpha = 0.80$), Multitasking ($\alpha = 0.75$), and Online Vigilance ($\alpha = 0.74$). More specifically, for Sample 1 ($n = 501$) the Cronbach's alpha was $\alpha = 0.87$, whereas for Sample 2 ($n = 500$) was $\alpha = 0.86$. McDonald's Omega was highest for Online Vigilance ($\omega = 0.83$), followed by Attention Impulsiveness ($\omega = 0.78$), Emotion Regulation ($\omega = 0.74$), and Multitasking ($\omega = 0.63$).

Testing for Measurement Invariance Across Gender

Configural Invariance

Configural invariance tests whether the same number of factors are prevalent in both genders (i.e., a four-factor model) and whether the same items load to each factor (i.e., same pattern of fixed and free loadings) across groups. Measurement invariance of the model for gender was tested through estimating the SDS model separately for male and female young adults by constraining the basic latent structure to equality across groups (227). The fit indices of the unconstrained models (see **Table 4**) demonstrated configural invariance across gender ($\chi^2\ [196] = 340.014$, $p < 0.001$, CFI = 0.935, TLI = 0.921, RMSEA = 0.054 [0.044–0.064], SRMR = 0.051) and therefore an adequate fit for both gender groups. This suggested that both genders had the same basic conceptualization of SD and interpreted the items of each factor similarly.

Metric Invariance

Following configural invariance, metric invariance was evaluated to determine if the strength of the factor loadings of the respective items were equivalent in both groups. A lack of metric invariance could signal a different attribution of importance of certain items or that there is a different understanding of certain items amongst the two groups (228). To assess metric invariance factor loadings are further constrained across groups by choosing an item to serve as a referent metric for each factor with subsequent steps to ensure that the referent item itself is invariant across the two samples. To achieve this all other items on the subscale serve as temporary references against the target item (210). Metric invariance is established if the change in model fit from the configurally invariant model to the metric model does not exceed the following statistical cut-offs:, $\text{CFI} \geq -0.010$ and $\text{RMSEA} \geq 0.015$, or $\text{SRMR} \geq 0.030$ (213). Therefore, a model was tested in which the unstandardized relationships between the items and factors of the SDS were constrained to be equal across the two genders. This constraining to equality did not lead to a significant reduction in model fit ($\Delta\text{CFI} = 0.002$, $\Delta\text{RMSEA} = 0.002$, $\Delta\text{SRMR} = 0.002$), thus supporting metric invariance implying equal salience of factors for both male and female students (**Table 4**) (228).

Scalar Invariance

Since metric invariance was supported, the third step of measurement was scalar invariance establishing whether mean responses for corresponding items were similar across groups. Scalar invariance tests the equality of intercept terms and is achieved by constraining item intercepts to equality and assessing whether the item loadings and the item intercepts are equivalent. It is established if the change in model fit from the metric invariant model does not exceed $\text{CFI} \geq -0.010$ and $\text{RMSEA} \geq 0.015$ or $\text{SRMR} \geq 0.030$ (213). Scalar invariance is considered valid when comparing latent factor means across groups (229, 230), confirming that both genders respond to the scale similarly (231). Therefore, unless scalar invariance is supported, no valid cross-group comparisons can be attempted. Scalar invariance is also a prerequisite to assessing mean differences between the groups (230, 232). Therefore, to test for scalar invariance all

TABLE 4 | Fit indices for multi-group confirmatory factor analysis evaluating measurement invariance of the four factor structure of the SDS ($n = 500$).

Models Males vs. Females	χ^2	df	CFI	TLI	RMSEA	90% CI	SRMR	Model	ΔCFI	ΔRMSEA	ΔSRMR
Configural invariance	340.014*	196	0.935	0.921	0.054	[0.044–0.064]	0.051	-	-	-	-
Metric invariance	347.700*	208	0.937	0.927	0.052	[0.042–0.061]	0.053	2 vs. 1	0.002	0.002	0.002
Scalar invariance	367.237*	220	0.934	0.928	0.052	[0.042–0.061]	0.054	3 vs. 2	0.003	0.000	0.001

*Each model compared with the previous model *p < 0.001.*

n, sample size; χ^2, chi-square; df, degrees of freedom; CFI, Comparative Fit Index; RMSEA, The Root Mean Square error of Approximation; SRMR, Standardized Root Mean Square Residual.

the item intercepts were constrained across groups and results demonstrated that scalar invariance across gender groups was confirmed (ΔCFI = 0.003, ΔRMSEA = 0.000, ΔSRMR = 0.001) (**Table 4**).

Testing for Latent Mean Differences

Since the observed item intercepts and the factor loadings of the items were invariant across genders (211), analysis of potential latent means differences were examined (233). A latent mean analysis was therefore performed for SDS among male and female groups by constraining the latent means of the male group (serving as the reference group) to zero, while the mean of the other group was freely estimated (the decision on which group to constrain is arbitrary with no influence on the final estimated mean values) (234). In the case of the SDS, latent means analysis identified statistically significant gender differences between males and females. Positive values suggest that the comparison group (females) have significantly higher scores than the reference group (males) across all latent factors: Emotion regulation (0.405), Attention Impulsiveness (0.507), Online Vigilance (CR = 0.279), and Multitasking (0.348). These results indicate gender differences underlying both cognitive and emotive dimensions of distraction in smartphone use among males and females.

DISCUSSION

Attention is a scarce resource and fragmented attention appears to be a frequent outcome of smartphone use related to cognitive interference and interruptions (48, 235, 236). Distraction is one expression of attentional loss associated with smartphone use. The present study explored a newly conceptualized, theory-guided, multidimensional measure of SD based on the need to understand and develop a psychometric assessment framework for SD. To achieve this goal, the perceptual control theory (58) and the control model of engagement for social media and smartphone use (52) among young adults were adopted to explain the tendency for distraction in order to control self-presentation, content and relationships online. The present study had the following aims: (i) identify the latent dimensions of SD and develop a respective pool of items, (ii) evaluate the scale's validity and reliability, (iii) investigate the criterion-related, convergent, and divergent validity with existing measures from the smartphone literature, and (iv) establish gender invariance (at the configural, metric, and scalar levels), and test latent mean differences across males and females. The SDS appeared to be a valid and reliable measure for the assessment of SD with sound psychometric properties and invariance across gender among young adults. Results from the measurement invariance analysis supported the configural, scalar, and metric invariance for the four-factor structure, suggesting that the SDS is comparable across the two groups. Furthermore, latent mean differences indicated that females were more susceptible to SD than males, consistent with the smartphone literature (148, 154, 208).

The analyses conducted provided evidence of the validity of a four-factor structure comprising of attention impulsiveness, emotion regulation, online vigilance, and multitasking and confirming that SD entails a cognitive, emotive, and behavioral component, consistent with the evidence reported in the literature (8, 27, 56, 60, 120, 237, 238). Statistically, the four-factor model was followed with a marginal difference in terms of fit by a hierarchical model, providing further evidence of the multidimensional and multifaceted nature of SD rendering a second-order model (239). However, the more parsimonious solution was chosen as suggested by scholars (240). In the four factor model, as hypothesized, the first factor (*Emotion Regulation)* was the strongest factor referring to strategies individuals use to modulate the emotional state they are in, the timing of the emotion and its expression (241), suggesting that SD has a strong regulating function consistent with literature (242–246). Emotion regulation has been found to be associated with self-control and can be dependent on intrinsic (i.e., temperamental) or extrinsic (i.e., attachment) factors (247) and may be regulated through avoidance, suppression, or enforced expression or reappraisal (241). Within smartphone use, distraction appears to serve a protective function by re-directing attention to a situation of less valence avoiding negative emotional states, consistent with evidence of general distraction and interference in anxiety (248, 249). However, overreliance may be associated with problematic smartphone and social media use (83).

The second factor (*Attention Impulsiveness*) referred to difficulties in the regulation of attention and engagement in impulsive behavior. Impulsivity has been linked to temporal discounting of rewards driven by emotion regulation and presenting as reaction to emotional arousal (250). Distraction frequency has been associated with attention impulsiveness, which is triggered by anxiety and takes the form of attentional bias (23), as has been supported in the smartphone and social media use literature (101, 249, 251). Attention impulsiveness has also been associated with habitual checking (121), chronic media multitasking and attention decrements (12) as well as with

impaired disengagement in Internet Gaming Disorder (IGD) (252). In conditions where learning is of low interest, attentional impulsivity is associated with increased interruptions, reduced lecture comprehension, low motivation, and fluid intelligence (35, 36), to the detriment of academic performance and tasks requiring sustained attention (37).

The third Factor (*Online Vigilance*) related to cognitive preoccupation and orientation toward social media content with items reflecting salience (i.e., thinking intensively online spaces), reactivity (i.e., readiness to react to smartphone cues even if it involves interruption of activities), and monitoring (i.e., tendency to actively observe online engagement parallel to other activities) (91). The findings supported a strong relationship between distraction and online preoccupation and vigilance, and may predispose an individual to distract frequently and check digital devices excessively for reassurance (92) and use smartphones more than intended or in a compulsive way (52, 91, 253). Online vigilance therefore, appears potentially fueled by FOMO and associated with disruptions to attend to smartphone content, further corroborating previous findings from the literature reporting regulation deficits in IGD and Problematic Internet Use (PIU) (118, 186, 254, 255). Strong habitual checking behaviors, reinforced by the immediate smartphone access to social media and the disruption of notifications, appear to be leading to self-control failures (125).

The fourth Factor (*Multitasking*) represented general multitasking behavior taking place while using smartphones, which may be associated with a distractive state (237). Task switching requires time investment and mental resources to re-orient to the task at hand with responses being slower and more error-prone (256). Multitasking has been considered as functionally equivalent to distraction (237). However, multitasking may mask the perception of distraction (257). There are reasons to expect a high degree of overlap among the four dimensions, reflected in the high co-variances amongst the factors as well as in the error terms of specific items. All dimensions measured distraction within smartphone use and had an implicit or explicit focus on cognitive preoccupation with smartphone content (primarily social media content, for emotion regulation and resulting attention loss, potentially leading to checking and multitasking), in accordance with evidence (12, 23, 24, 237, 258–260). Therefore, the overlap and the high inter-correlation amongst the factors was expected. However, recent evidence on highly prevalent non-social smartphone and process use (e.g., watching videos, browsing online) (73) has been associated with problematic smartphone use (92, 94) and should therefore be taken into account in future studies by including items related to the diverse content that a smartphone provides access to.

To establish the convergent and discriminant validity of the SDS, the study investigated the association between various cognitive, emotional, and behavioral variables and the SDS factors. Criterion-related and convergent validity was demonstrated through associations with daily smartphone and social media use, attentional control and mindful attention and awareness. Significant correlations were also observed between the four factors of the SDS and corresponding psychological constructs, such as deficits in emotion regulation, problematic social media use, and poor metacognition, thus providing further evidence for the test's convergent validity and bridging research on IGD and PIU with social media and smartphone use in identifying common risk factors and potential outcomes (118, 186, 254, 255, 261, 262). Therefore, the SDS appears to demonstrate acceptable validity and reliability.

Additionally, the present study aimed to assess measurement invariance of the SDS across gender. The findings obtained suggested that the SDS factor structure is the same across gender with equally robust associations between the underlying constructs and the observed indicators across genders, thus providing additional support for the four-factor structure of the SDS. In addition, the SDS achieved both metric and scalar invariance, suggesting equal salience of the indicators across the two groups, providing additional evidence of construct validity for cross-group comparisons for the SDS. As suggested in previous literature, measurement invariance needs to be supported before any cross-cultural investigations of the scale are attempted (231). Although the SDS demonstrated measurement invariance, findings suggested that the latent means for the SDS subscales differed across gender groups. Latent mean differences were assessed by using a latent modeling approach which is considered a more robust approach (when compared to testing mean differences with *t*-tests), providing strong empirical support for gender differences (212). The results from this analysis found that students of both genders were not similar in their endorsement of the SDS subscales, with females exhibiting higher scores than males across all subfactors, contributing to the emerging body of smartphone literature on gender (146, 147, 154).

These results are also in line with findings from previous studies in which females appear to demonstrate higher multitasking and emotion regulation needs, and to manage their emotions more poorly than males and present with higher problematic smartphone use (146, 152, 263–266). Evidence regarding gender differences in multitasking is inconclusive due to conflicting findings, with some evidence suggesting that women are not better than men at multitasking, while other literature suggests that women present with better multitasking skills (151, 267). To explain these differences, the *hunter-gatherer hypothesis* (claiming a cognitive adaptation to different division of labor roles across the sexes) (268) has been proposed to explain findings of females being less affected by task-irrelevant interruptions in experimentally-generated multitasking conditions, suggesting that females are better at multitasking. However, media multitasking is considered the new norm, and inadvertently leads to fragmented attention and frequent micro-disengagements due to interruptions (39), linking multitasking with distraction (269). Still, no direct conclusions may be drawn given the relative absence of research on SD to date. Previous studies examining differences between genders in smartphone use have indicated that females report higher smartphone use and present with greater prevalence of problematic smartphone use (147, 148, 270), which clearly indicates cross-gender differences (271).

To the best of the authors' knowledge, the present study is the first to develop and investigate the psychometric properties

of a newly developed measure on SD, as well as to provide evidence regarding measurement invariance across gender. The findings of this study suggest that the SDS functions well and is invariant across genders among young people, providing new insights in the smartphone literature by suggesting cognitive and emotive effects in terms of attentional loss from smartphone use across genders. The SDS presents with a strong theoretical foundation, good psychometric properties, short length, and easy applicability. The findings obtained suggest that the instrument may be used and further tested in the general population when assessing the construct of SD.

The SDS requires further investigation with ethnically diverse samples and different age groups and settings, establishing its test-retest stability, invariance across different cultures, and its predictive validity, by exploring its relationship with other relevant psychological constructs, such as anxiety and mood disorders or attention deficit hyperactivity disorder (ADHD) (272), especially in clinical samples by identifying how the frequency and compulsiveness of smartphone use and the impact of this cognitive-emotive construct may contribute to the deterioration or alleviation of symptoms of various disorders (273). Additionally, the role of SD should be examined in terms of risky behaviors, physical injuries (17, 274), work performance so that greater knowledge about SD may be generated within distinct subgroups and environments. Associations of SD with metacognition for problematic smartphone use should be further explored with the use of validated instruments (116), as no relevant measure was available during data collection of the present study. Therefore, further validation of the construct is required and to encourage research investigating distraction in other contexts.

Potential limitations in the present study include the lack of specific aspects of internal consistency of the scale such as test-retest reliability and its limited generalizability to the broader population, having relied on a convenience self-selected sample of university students, which may not necessarily be representative of all smartphone users. It is unclear how culturally distinct or age different samples (e.g., young children) might respond to this scale. Additionally, the content of the items may warrant further refinement (i.e., the driving item was not relevant among emergent adults). However, SD has been suggested as a common behavior of concurrent smartphone use among older adults (17). Another important potential limitation constitutes the use of self-report questionnaires and potential biases associated with self-report methods (e.g., social desirability, memory recall). Combined with behavioral and biometric data, psychometric measures of SD as both an adaptive but also as a maladaptive digital experience could provide strong evidence of face validity. Additionally, the construct of SD does not encompass other experiences of distraction on other digital devices or media multitasking or process smartphone use. Smartphones were chosen because they are the most ubiquitous and pervasive devices. Such insight would make it possible to discern whether the nature of distraction similarly to online addiction varies between platforms, digital devices, and content types (275). Future studies may consider including items related to media multitasking and overall digital distraction arising from using multiple devices may provide a more inclusive account of the digital experience. The present study and its findings support the use of the SDS four factor model. However, the present study did not test equivalence for the hierarchical model. Still, the adequate fit of the hierarchical model, which was marginally inferior to the first order, suggests a strong general factor representing the construct of smartphone distraction. Thus, when calculating scores, authors are advised to work with subscale scores or use a total score. However, given that the the hierarchical model was not tested for invariance in this preliminary investigation, which focused primarily on the development and initial validation of the scale, invariance testing of the second order model and latent mean differences is strongly recommended to be tested in a future study to support equivalence across genders and assess gender differences in the hierarchical model. The first step of invariance in the four factor model, which is a prerequisite to testing invariance of the hierarchical model has been satisfied in the present investigation.

The findings obtained suggest that the SDS is a psychometrically sound scale assessing SD guided by two theoretical frameworks according to which cognitive preoccupation and need to control content, relationships, and self-presentation appear to be key drivers for distraction via smartphone use. The SDS was designed to be applicable to young adult smartphone users irrespective of level of smartphone use, whether excessive or judicious. The SDS may be utilized as a screening tool in interventions to reduce the risk of problematic smartphone use in student populations (276). Given that smartphones are ubiquitous, SD is a common behavior, impacting productivity and areas of executive function (277), and therefore reducing distraction may be of particular importance to aid and enhance performance, emotion regulation, and overall psychological well-being.

CONCLUSION

Attention management may be one of the most critical skills of this century where information is abundant. Attention is a scarce resource and its control may be impaired by the online environment and digital devices available. Distraction is invariably part of an individuals' online and offline experiences. The present study sought to devise the first SDS and further investigate its psychometric properties, given the absence of a similar construct in the smartphone literature. The SDS is best conceptualized within a four-factor solution. Additionally, the SDS was found to present with gender measurement invariance at the configural, metric, and scalar levels, suggesting that the scale functions equivalently across the two gender groups. Moreover, latent mean analysis indicated gender differences underlying both cognitive and emotive dimensions of distraction in smartphone use. The SDS is a theory-guided scale, with sound psychometric properties assessing a complex psychosocial construct defined by cognitive-emotive dimensions with positive and negative valence related to attention impulsiveness, emotion regulation, online vigilance, and multitasking. Within the smartphone literature, SD is an emergent issue interfering with

everyday functioning and productivity and potentially implicated in problematic smartphone and social media use.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Nottingham Trent University College of Business, Law and Social Sciences. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MT: principal investigator, main author, study design, data collection, and statistical processing of the data. HP and IT: statistical and methodological supervision. MG, MR, DK, and HP: supporting the study design and supervision of the study. MT, HP, IT, MG, MR, and DK: editing the manuscript. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.642634/full#supplementary-material

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ICD-11-Based Assessment of Social Media Use Disorder in Adolescents: Development and Validation of the Social Media Use Disorder Scale for Adolescents

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Background: A problematic social media use (PSMU) in adolescents is a rising phenomenon often associated with higher perception of psychological stress and comorbid psychiatric disorders like depression. Since the ICD-11 introduced the very first internet-use related disorders, criteria for gaming (and online gambling) disorder can now be transferred to assess social media use disorder (SMUD). Therefore, the development and validation of a self-rating screening instrument for SMUD is of value to researchers and clinicians.

Method: The previously validated ICD-11-based Gaming Disorder Scale for Adolescents (GADIS-A) was adapted to measure SMUD (Social Media Use Disorder Scale for Adolescents, SOMEDIS-A). A representative sample of 931 adolescents aged 10 to 17 years and a respective parent participated in an online study. Item structure was evaluated by factorial analyses. Validated DSM-5-based instruments to assess PSMU by self- and parental ratings (SMDS, SMDS-P), adolescent depressive symptoms (PHQ-9), and stress perception (PSS-10) as well as single items on time spent with social media (SM, frequency and duration) were applied to assess criterion validity. Discrimination between pathological and non-pathological users was examined based on ROC analyses retrieved cut-off values and the results of a latent profile analysis.

Results: The new scale is best described by two factors reflecting cognitive-behavioral symptoms and associated negative consequences. The internal consistency was good to excellent. The SOMEDIS-A-sum score was positively correlated with PSMU, depression, and stress scores as well as the time spent with SM in a moderately to highly significant manner. Thus, good to excellent criterion validity is suggested.

Conclusions: SOMEDIS-A is the first successfully validated instrument to assess SMUD in adolescents based on the ICD-11 criteria of GD. Thus, it can support early

detection in order to prevent symptom aggravation, chronification, and secondary comorbidities. It can contribute to the development of a standardized conceptualization and its two-factorial structure offers promising new insights into the evaluation of SM usage patterns. Further examination including clinical validation is desirable.

Keywords: problematic social media use, behavioral addictions, ICD-11, adolescents, validation, questionnaire, social media use disorder

INTRODUCTION

With access to fast and reliable internet increasingly available, social media (SM) applications are becoming an integral part of people's lives worldwide. According to a representative survey on German families, 93% of the 12- to 19 year-olds in Germany own a smartphone and rate SM apps (especially WhatsApp, Instagram, and YouTube) as their favorite internet services (1). Over 80% of these adolescents reported unrestricted internet access, allowing them almost unlimited SM usage. During the last years and especially since the beginning of the COVID-19 pandemic, adolescent smartphone usage has significantly increased (2). SM has become very important for staying in touch during a period of restrictive social interaction. This is supported by a representative study on 10- to 17-year-old adolescents who mainly used SM to fight boredom (86%), stay in contact with others (89%), and get information on the pandemic (37%) (3). Almost one third of these adolescents reported using SM to forget sorrows (38%), reduce stress (36%), and escape reality (36%). Interestingly, in a recent study on motivations for using social networking sites from late adolescence to early adulthood, Stockdale et al. identified the motives to socially connect and to fight boredom as risk factors for problematic SM use, in contrast to the motive information seeking (4).

There is an ongoing debate whether SM use can take on at-risk or even pathological dimensions, and consequently be described by the criteria for addictive disorders, since longitudinal studies for comparison with other addictions are missing (5–7). However, it has been repeatedly suggested to describe problematic usage patterns by the same set of diagnostic criteria as other addictive disorders (8, 9), including pathological gaming (10), due to similarities between the phenomena (5). In line with this, the aforementioned motives for using SM– *forgetting sorrows*, *reducing stress*, and *escaping reality* – are reminiscent of the *escape* criterion described in the context of internet gaming disorder (IGD) – the first digital media addiction included in a diagnostic manual (DSM-5) as a condition warranting more research (11). Accordingly, if five out of nine criteria have been met for the past 12 months, an IGD can be assumed. These criteria include *preoccupation*, *withdrawal* (when not using), *tolerance*, *persistence* (unsuccessful attempts to reduce or stop usage), *continuation* (of usage despite problems), *deception* (deceiving or covering up usage), *escape* (usage to avoid or reduce adverse moods), *displacement* (giving up other activities), and *conflict* (risking or losing relationships or career opportunities due to excessive usage). Furthermore, as the first official digital media-associated diagnoses, the gaming disorder (GD) and the (online) gambling disorder will be included in the 11th revision of the International Classification of Diseases (ICD-11), under the parent *Disorders due to substance use or addictive behaviors* (12). Both addictive behaviors are described by the following criteria concerning a continuous or episodical on-/off-line usage pattern that is generally present over a period of at least 12 months: (A) impaired control, (B) increasing priority over other activities, (C) continuation or escalation despite the occurrence of negative consequences and (D) the behavior results in clinically significant distress or impairment of personal, social, educational, work-related, and financial functions. Hence, in contrast to the DSM-5 criteria, both symptoms and significant impairments arising from these symptoms must be evident for the diagnoses to be met. In addition, the terms hazardous gaming (HG) and hazardous gambling (and betting) were introduced by the ICD-11, to describe distinct persistent behavioral patterns with awareness of increased risk of physical or psychological harm to self or others due to frequency and duration of use, neglect of alternative activities, risky usage-associated behaviors, and/or negative consequences (12). The results of studies comparing DSM-5- with ICD-11 criteria for pathological gaming suggest that DSM-5 criteria indicate a lower diagnostic threshold (13, 14), thus comprising at-risk and pathological behavior.

To date, no consensus has been found on nomenclature and definitions of concepts regarding problems associated with social media use. Terms include, e.g., *social media addiction* (15), *excessive social media use* (16), *social media dependence* (17), *social media disorder* (10), and *problematic social media use* (18, 19). Accordingly, there has been no agreement on the measurement, leading to conceptual and empirical ambiguity (5).

Most available scales were based on general criteria of addictive disorders (cf. six core components of addiction model by Griffith) (20) or the DSM-5 criteria for IGD [e.g., (10, 21–23)]. According to Billieux et al., the problematic use of SM may depend on a constellation of factors that are unique to this activity and not necessarily relevant when considering other types of internet addiction (24). Other available scales were therefore conceptualized based on literature review and/or expert interviews (25, 26). Interestingly, these show large content overlap with scales developed based on general addictive and IGD concepts (10, 15), thereby debunking assumptions of unrelated entities (27). To date, no scales have been developed based on the ICD-11 framework. We could identify only a few instruments that have explicitly assessed problematic use of SM and have been validated in samples of adolescents (10, 15, 25, 26). The 9-item Social Media Disorder Scale (SMDS) by van den Eijnden et al. (10) was developed based on the IGD criteria. It was validated in samples of adolescents in Europe and China (10, 22, 28, 29),

thus making it one of the most widely used scales to assess a problematic use of SM in this age group.

Recently, the SMDS was used with 10- to 17-year old adolescents from 29 European countries to estimate prevalence rates for problematic SM use (23). The average prevalence was 7.38%, with country-specific values ranging from 3.22% (Netherlands) to 14.17% (Spain). Adolescents seem to be especially vulnerable for developing digital-media associated behavioral addictions (30). On the one hand, they are attracted by the structure and the design of digital apps that built upon psychological mechanisms to achieve strong attachment and increase the time spent with them (31). On the other hand, adolescents' cognitive control abilities contrast with fully developed reward systems leading to an increased sensitivity to motivational cues [cf. neurobiological imbalance model of adolescence, (32)].

Problematic SM use positively correlates with the time spent with SM (8, 33, 34). It is often associated with symptoms of psychiatric disorders like depression, anxiety disorders, attention deficit hyperactivity disorder, obsessive compulsive disorder, and eating disorders (35–37). Moreover, affected adolescents report sleep deprivation with negative effects on daily functioning and mood, lower emotional well-being, higher general stress, as well as stress related to peer neglect (35, 38, 39). As a result, problematic SM use has become a concern for healthcare professionals in recent years. It is currently unclear whether the observed increased time spent with SM use during the COVID-19 pandemic will result in a higher prevalence of problematic use in adolescents over time. Given the increased use and the fact that SM have become part of everyday life, it is particularly important not to exaggerate or globally pathologize intensive patterns of use (24, 40), but rather to detect individual behaviors that might need intervention. Since the ICD-11 criteria require both specific symptoms and significant impairments arising from these symptoms to be present for a potential diagnosis, a higher specificity to detect pathological users can be assumed. As the first ICD-11 GD screening tool for adolescents, the two-factorial Gaming Disorder Scale for Adolescents (GADIS-A) was published by the authors in 2020 (41). It had revealed good to excellent internal consistency, validity, and discriminatory power. The items covered the factors cognitive-behavioral GD symptoms and negative consequences as well as a time criterion. This makes it an interesting candidate for modifying the ICD-11 framework to assess pathological SM use in adolescents.

We will use the term *problematic social media use* (PSMU) in this manuscript to refer to at-risk and pathological SM use based on the DSM-5 criteria for IGD. In addition, analog to the term GD to describe pathological gaming according to the ICD-11 framework, we will use the term *social media use disorder* (SMUD) to describe pathological SM use that potentially requires therapeutic treatment. SMUD is thereby delimited from the term PSMU by its higher specificity.

To the best of our knowledge, despite the potential value to clinicians and researchers working with minors, no validated ICD-11-based screening instrument for SMUD in adolescents is available at this point. Therefore, the aims of this study were (1) the development of a SMUD screening instrument for adolescents (Social Media Use Disorder Scale for Adolescents, SOMEDIS-A) by adapting GADIS-A, (2) the exploration of the psychometric properties of the newly developed scale, and (3) in line with the validation of the original scale, its validation in a representative sample of 10- to 17-year-old frequent (SM) users and a respective parent.

METHOD

Participants and Procedures

14,472 randomly selected German households with adults aged 28 to 75 years were invited by email to participate in an online survey on family media use between November 10 and December 01, 2020. The invited households belong to a continuously growing panel of currently ∼75,000 randomly selected adults and adolescents aged 14 years and above (42). Of 6,764 respondents, 726 reported having children between the ages of 10 and 17 years. Of these, 557 parents and one child each provided necessary information and gave their informed consent to participate in the survey. Additionally, 1,221 representative households that had participated in a previous representative survey were contacted in the same period. Of these, 585 had a child in the age of interest and agreed to take part. This led to a total number of $N = 1{,}142$ participating parent-child dyads. Representativity was ensured regarding region of residence, age, and gender of the participants by the established German market research and opinion polling company forsa based on a random sampling method (42) [for details on the recruitment and sampling method see Paschke et al. (43)]. Parents and adolescents were asked to complete the questionnaires independently after one another.

The study was conducted in accordance with the relevant national and institutional committees on human experimentation, complied with the Declaration of Helsinki, and was approved by the Local Psychological Ethics Commission at the Center for Psychosocial Medicine (LPEK) of the University Medical Center Hamburg-Eppendorf (UKE). Participants could withdraw from the study at any time, for any reason.

1,041 out of 1,142 adolescents [92.0%, 530 boys (50.9%) and 511 girls (49.1%)] reported a SM use of at least once a week and were, together with the corresponding parent, considered for further statistical processing. Of these, 110 had to be excluded due to missing data of more than one third per scale, resulting in a final sample of $N = 931$ parent-child dyads.

Measures

Social Media Usage Patterns

In the online survey, SM were defined as all digital services on which texts, photos, animations, or videos can be shared, commented on or liked (e.g., Instagram, TikTok, YouTube). SMUD was assessed based on the ICD-11 criteria of Gaming Disorder by the newly developed Social Media Use Disorder Scale for Adolescence (SOMEDIS-A). SOMEDIS-A was adapted from the validated ICD-11 based Gaming Disorder Scale for Adolescents (GADIS-A) (41) by clinical experts and scientists in the field of behavioral addictions in adolescence. Thinking of the last 12 months, the adolescents were asked to state their agreement with nine statements choosing one out of five

(Likert-scale) response options (strongly disagree−0, somewhat disagree−1, partially agree/ partially disagree−2, somewhat agree−3, strongly agree−4). These could be summed up to a maximum score of 36. The frequency and duration of problems, conflicts, or difficulties due to SM use was assessed by an additional question with four response options (not at all—, only on single days−1, for longer periods−2, nearly daily−3). A score of 2 and above was considered significant regarding the ICD-11-time criterion. The GD adapted ICD-11 symptoms and their corresponding DSM-5 criteria are displayed in **Table 1** together with the English version of the SOMEDIS-A items. Symptoms A to C were covered by two items each. Impairment (D) was addressed by three items on personal, social and educational/working difficulties caused by SM use. The complete questionnaire can be found in the **Appendix**.

To compare the results of the new scale with validated DSM-5 based scales, PSMU was assessed by the Social Media Disorder Scale in its self- (SMDS) (8) and parental-judgement version (SMDS-P) (44). The SMDS was developed based on the DSM-5 criteria for IGD and the Internet Gaming Disorder Scale (IGDS) (45). A higher total score of the one-factorial polythetic questionnaire including nine items with a dichotomous response format (no—0/yes—1) indicated a higher risk for PSMU. The SMDS had been repeatedly applied to adolescent samples and showed adequate to good psychometric properties (8–10). Its parental version was validated in a representative sample of German adolescents and their parents to add external views and revealed good psychometric properties (44). In the sample of the current study both scales showed a good internal consistency (SMDS: Cronbach's $\alpha = 0.81$; SMDS-P: Cronbach's $\alpha = 0.85$). Analog to the procedure of Ko et al. (13) and Jo et al. (14) for IGD, SMDS items reflecting the DSM-5 criteria that correspond to the ICD-11 (*persistence, displacement, problem, conflict*) were considered separately.

PSMU has been found to positively correlate with the time spent with SM (8, 33, 34). The temporal pattern of SM use was measured by querying the average number of usage days per week (frequency) as well as the average usage duration on week (school) days and on weekend (leisure) days. Out of the two measures a mean daily usage time was calculated.

Psychological Stress Perception and Depressive Symptoms

Psychological stress and depressive symptoms were shown to be associated with PSMU (35, 36, 39). Therefore, these constructs were included to assess additional criteria validity. The level of psychological stress was determined by the Perceived Stress Scale (PSS-10) (46) — a 10-item self-report scale that has been validated in adolescents (47). They were asked to rate the frequency of statement contents within the past month on a five-point Likert scale (never—1 to always—5 for negatively, and inversed for positively phrased items). Higher scores indicated higher stress perception. The internal consistency of the scale in the current sample was good (Cronbach's $\alpha = 0.82$). The 9-item Patient Health Questionnaire (PHQ-9) was used to assess depressive symptoms on a 4-point Likert scale in the adolescents (agreement to given statements: not at all—0 to nearly every day—3). It was originally described by Kroenke, Spitzer, and Williams (48) based on the DSM-IV and has been modified for adolescent samples (49, 50). The word "dead" in the last item ("thoughts that you would be better off dead, or of hurting yourself in some way") was exchanged by "gone" to be more suitable for the anonymous online survey assessment that does not enable personal contact with the interviewee. The internal consistency of the scale in this study was also good (Cronbach's $\alpha = 0.88$).

Statistical Analyses

Data Management

Missing values of the final sample were replaced by performing multiple imputations in the statistical program R using the package mice (51, 52). This led to a total replacement of 0.18% (SOMEDIS-A), 1.31% (SMDS), 2.92% (SMDS-P), 0.55% (PHQ-9), and 1.45% (PSS-10) per instrument. The data was revised for normality distribution if appropriate. Absolute values of skewness >2.0 and kurtosis >7.0 served as reference values to determine substantial univariate non-normality (53). Of all scale variables, this was the case for the individual SOMEDIS-A item 8 (skewness = 2.3, kurtosis = 5.63) and item 9 (skewness = 2.02, kurtosis = 4.16). Multivariate normality was investigated by Mardia's test using the R package QuantPsyc (54).

Factor Analyses

A split-half validation method was applied before conducting an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA) with diagonally weighted least squares (DWLS) to account for the ordinal variable structure and multivariate non-normality using the R packages psych and lavaan (55, 56). For this purpose, the sample was randomly divided into two (nearly) equal proportions by the R package rsample ($n_1 = 466$ dyads; $n_2 = 465$ dyads) (57). The Kaiser-Meyer-Olkin (KMO) criterion and Bartlett's test of sphericity were calculated to affirm the suitability of the data for factor analysis. The visual scree test, parallel analysis, and the Wayne Velicer's Minimum Average Partial (MAP) criterion were applied to reveal the appropriate number of factors following the recommendation of Velicer et al. (58). The authors state that for sample sizes ≥ 300 a minimum ratio of 4:1 variables per factor leads to an accurate determination of factors (58). CFA model goodness of fit was assumed according to the following criteria: χ^2/df ratio < 5, root mean square error of approximation (RMSEA) < 0.08, standardized root mean squared residual (SRMR) < 0.08, Tucker-Lewis Index (TLI) ≥ 0.95, comparative fit index (CFI) ≥ 0.95 (59). The Satorra-Bentler mean adjusted χ^2-difference statistic was used to compare model fits (60).

Internal Consistency

The coefficients Cronbach's α and McDonald's ω were calculated to determine internal consistency with the following interpretation: ≥0.9–excellent, ≥0.8–good, ≥0.7–acceptable, ≥0.6–questionable, ≥0.5–poor, and <0.5–unacceptable (61, 62).

Criterion Validity

Depending on the item/scale distribution, Pearson and Spearman rank correlations between the SOMEDIS-A sum score and the

TABLE 1 | SOMEDIS-A items with corresponding ICD-11 and DSM-5 criteria.

ICD-11 criteria[a] and corresponding *DSM-5* item	**SOMEDIS-A items** **Thinking of the last 12 months, how strongly do you agree with the following statements?**
A) Impaired control over SM use (e.g., onset, frequency, intensity, duration, termination, context)	1. I often use social media more frequently and longer than I planned to or agreed upon with my parents[b]
Persistence	2. I often cannot stop using social media even though it would be sensible to do so or for example my parents have told me to stop
B) Increasing priority given to SM use to the extent that it takes precedence over other life interests and daily activities	3. I often do not pursue interests outside the digital world (e.g., meeting friends or partner in real life, attending sports club/societies, reading books, making music) because I prefer using social media
Displacement	4. I neglect daily duties (e.g., grocery shopping, cleaning, tidying up after myself, tidying my room, obligations for school/apprenticeship/job) because I prefer using social media
C) Continuation or escalation of SM use despite the occurrence of negative consequences	5. I often continue using social media even though it causes me stress with others (e.g., my parents, siblings, friends, partner, teachers)
Continuation	6. I continue using social media although it harms my performance at school/apprenticeship/job (e.g., by being late, not participating in class, neglecting homework, worse grades)
D) The behavioral pattern is of sufficient severity to result in significant impairment in personal, family, social, educational, occupational, or other important areas of functioning *Conflict*	7. Due to my social media use, I neglect my appearance, my personal hygiene, and/or my health (e.g., sleep, nutrition, exercise) 8. Due to my social media use, I risk losing important relationships (friends, family, partner) or have lost them already 9. Due to my social media use, I have disadvantages at school/apprenticeship/job [e.g., bad (final) grades, inability to continue to the next grade/no graduation, no apprenticeship or university spot, poor reference, warning/dismissal]
E) The pattern of SM use may be continuous or episodic and recurrent and normally evident over a period of at least 12 months	10. How often did you experience such problems, conflicts, or difficulties due to social media use during the past year? Did this only occur on single days, during longer periods of several days to weeks or months, or was it almost daily?[c]

SOMEDIS-A, Social Media Disorder Scale for Adolescents; ICD-11, 11th revision of the International Classification of Diseases; DSM-5, 5th revision of the Diagnostic and Statistical Manual of Mental Disorders; SM, social media; [a]ICD-11 Gaming Disorder criteria adapted to social media usage; [b]response options for item 1-9: 5-point Likert-Scale: "strongly disagree"-"strongly agree"; [c]response options: "not at all," "only on single days," "during longer periods," "almost daily."

total scores of the questionnaires SMDS, SMDS-P, PHQ, and PSS-10 as well as the mean time spent with SM per day (in minutes) and the usage days per week were computed to obtain criterion validity based on the following interpretation: $0.00 \leq$ Pearson's $r \leq 0.10$ zero or negligible relationship; $0.10 < r \leq 0.30$ weak relationship; $0.30 < r \leq 0.50$ moderate relationship; $r > 0.5$ strong relationship (63); $0 \leq$ Spearman's $\varrho \leq 0.10$ zero or negligible relationship; $0.1 < \varrho \leq 0.40$ weak relationship; $0.40 < \varrho \leq 0.70$ moderate relationship; $0.70 < \varrho \leq 0.90$ strong relationship; $\varrho > 0.90$ perfect relationship (64).

Sensitivity and Specificity

Sensitivity and specificity across SOMEDIS-A sum scores were compared by a receiver operating characteristic (ROC) curve analysis to predict SMUD according to the SMDS classification. The analysis was realized using the R package pROC (65). 95% confidence intervals (CI) were estimated based on 999 bootstrapping replications. Youden's criterion was applied to define cut-off points. The area under curve value (AUV) reflected the goodness of differentiation between the two groups (66). Based on the calculated cut-off points, adolescents were classified as pathological or non-pathological SM users. Associated prevalence was estimated using 95% CI. The means and standard error of means (se) of age and SMDS, SMDS-P, PHQ, and PSS-10 sum scores as well as SM usage days per week and mean SM usage hours per day were calculated for each group. The variables were included in a MANOVA with *post-hoc* Scheffé tests to compare both groups. Given the large sample size, the central limit theorem applied and MANOVA test result could be assumed to be robust even though the assumption of multivariate normality was violated (67, 68). The proportion of sex of both groups was computed together with 95% CI and compared via χ^2 test. Corresponding effect sizes were interpreted as follows: Cramer's V (categorial variables) >0.5 strong, >0.3 moderate, >0.1 weak effect (69); Cohen's d (metric variables) >0.8 large, >0.5 medium, >0.2 small effect (70).

Classification

In addition to a cut-off based classification, a latent-profile analysis (LPA) on the SOMEDIS-A factor sum scores and the SOMEDIS-A time criterion was performed to estimate the number of latent subgroups of SM users within the sample using the R package mclust (71). This package uses a model-based approach where each component of a Gaussian finite mixture density is associated with a profile. Scrucca et al. provide a detailed description of the underlying procedure and emphasize an appropriate application on data sets of various disciplines including clinical psychology (71). The adolescents' membership to a profile was inferred. Due to multivariate non-normality, the

robustness of the LPA results was assessed by means of 999 non-parametric bootstrapping operations. Based on the results of the bootstrap likelihood ratio test (BLRT), the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the integrated completed likelihood (ICL), the ideal number of profiles was determined. The BLRT compared the fit between a model of a certain number of profiles and a model with one profile less (72). Bootstrap samples were used to estimate the distribution of the log likelihood difference test statistic. According to the null hypothesis, the smaller model was the best model. If the larger model fitted the data significantly better ($p < 0.001$), the null hypothesis would be rejected. Furthermore, lower BIC, AIC, and ICL values reflected better model solutions (73, 74). All profile groups were described regarding prevalence and sex by frequency estimations with 95% CI, as well as SOMEDIS-A factor 1, factor 2, and time criterion scores, age, SMDS, SMDS-P, PHQ, and PSS-10 sum scores, SM days per week, SM hours per day by means with standard error of means (se). The group proportions of sex were compared by χ^2 test and the group differences regarding the SOMEDIS-A factors by effect-size estimation. The other dependent variables were included in a MANOVA with the latent profile group as independent factor and further evaluated by *post-hoc* Scheffé tests and effect-size estimation. Again, given the multivariate non-normality of the data, model robustness was assumed based on the central limit theorem.

RESULTS

Sample Description

A detailed description of the final sample can be found in **Table 2**.

Factor Structure

Bartlett's test revealed significant correlations between the nine SOMEDIS-A items on the first half of the sample data [$\chi^2(34) = 2{,}402.13$, $p < 0.001$]. KMO criterion was 0.88 overall for the first sub-sample and ranged between 0.83 and 0.95 for individual items. Thus, good suitability of the data for EFA could be demonstrated (75). Visual scree test, parallel analysis, and MAP criterion suggested that two factors should be retained (eigenvalue factor 1 = 5.13 and eigenvalue factor 2 = 1.14; minimum Velicer MAP of 0.05). Communalities of the individual items ranged from 0.50 to 0.76. The cumulative variance explained by the two factors was 0.62 (variance of factor 1 = 0.35). Factor loadings varied between 0.59 and 0.82 for factor 1 and 0.56 and 0.84 for factor 2. A CFA based on a 2-factorial model yielded mixed results: On the one hand, CFI of 0.993 and TLI of 0.990 indicated excellent fit and SRMR of 0.058 as well as χ^2/df ratio of 4.96 [$\chi^2(23) = 129.04$, $p < 0.001$] acceptable fit. On the other hand, RMSEA of 0.092 indicated a poor fit. Yet, a two-factorial model suggested a significantly better fit to the data than a single-factor solution [χ^2_{diff} (1) = 52.29, $p < 0.001$]. All item factor loadings were significantly positive, with standardized coefficients lying between 0.73 and 0.90.

SOMEDIS-A items 7 to 9 (personal, social, and academic/occupational impairments), 6 (continuation despite academic/occupational disadvantages), and 3 (loss of other interests due to gaming) loaded highest on factor 1. This factor reflects impending or manifest consequences due to SM use. SOMEDIS-A items 1 and 2 (loss of control), 5 (continuation despite social stress) and 4 (neglecting daily duties) loaded highest on factor 2 which symbolizes cognitive-behavioral symptoms associated with SM use. **Figure 1** shows EFA-factor loadings and the variance proportion explained by the two factors. All EFA- and CFA- (standardized) factor loadings are presented in **Table 3** together with the EFA communalities. Inter-item correlations and the relative item-response frequencies are depicted in **Tables 4**, **5**. All items showed a moderate correlation with the time criterion ($0.41 \leq r \leq 0.64$).

Internal Consistency

Regarding the total SOMEDIS-A scale, Cronbach's α of 0.91 and McDonald's ω of 0.93 were calculated. For the first factor-associated subscale, Cronbach's α of 0.88 and McDonald's ω of 0.91 were computed. For the second subscale, Cronbach's α was 0.84 and McDonald's ω was 0.86. Thus, the total scale indicates excellent and the two subscales good internal consistency.

Criterion Validity

Strong positive correlations were found between the total sum scores of SOMEDIS-A and SMDS (Pearson's $r = 0.68$, $p < 0.001$) as well as SMDS-P ($r = 0.54$, $p < 0.001$). PSS-10 ($r = 0.43$, $p < 0.001$) and PHQ-9 ($r = 0.48$, $p < 0.001$) sum scores positively correlated with SOMEDIS-A sum score in a moderate manner. Whereas, the correlations between the SOMEDIS-A sum score and the average daily duration of SM usage was also moderately positive ($r = 0.37$, $p < 0.001$), no significant association could be found with the usage days per week (Spearman's $\varrho = 0.05$, $p = 0.10$). All significant coefficients are shown in **Figure 1** (right column).

Sensitivity and Specificity

Adolescents were classified as pathological or non-pathological SM users according to their responses on the ICD-11 related SMDS items. This classification was included into two ROC curve analyses together with the two SOMEDIS-A subscale sum scores (following the two-factorial scale structure). According to Youden's criterion, the optimal cut-off for SOMEDIS-A factor 1 was 6.5 (95% CI 6.5, 7.5) with a specificity of 87.39% (95% CI 87.39, 94.03), a sensitivity of 81.48% (95% CI 66.67, 96.30), an AUC value of 88.4% (95% CI 79.7, 97.0) and an accuracy of 89.47%. An optimal cut-off of 8.5 (95% CI 7.5, 9.5) was calculated for factor 2 with a specificity of 82.96% (95% CI 74.89, 91.04), a sensitivity of 88.89% (95% CI 74.07, 1.00), an AUC value of 88.8% (95% CI 80.1, 97.5) and an accuracy of 84.0%. Considering both factor cut-off values a good differentiation between adolescents with and without SMUD was indicated.

Classification by Cut-Off Values

Applying the cut-off of >6 for factor 1 and >8 for factor 2 as well as considering the ICD-11-time criterion (symptoms at least for longer periods or daily), 3.3% (95% CI 2.2, 4.5) of the adolescent SM users could be classified as pathological (N = 31). Except for age, all ten dependent variables included in a

TABLE 2 | Characteristics of final sample parent-child dyads[a].

Variables/categories	Adolescents *N* [% (95%–CI)]/mean (SD; range)	Parents *N* [% (95%–CI)]/mean (SD; range)
Absolute frequency	931	931
Gender		
Male	468 [50.3 (47.1–53.5)]	466 [49.9 (46.7–53.2)]
Female	463 [49.7 (46.5–52.9)]	465 [50.1 (46.7–53.2)]
Age in years	13.67 (2.19; 10–17)	47.13 (7.62; 28–75)
Relationship status		
Biological child	851 [91.5 (89.7–93.3)]	
Adoptive child	6 [0.7 (0.1–1.2)]	
Stepchild	46 [5.0 (3.6–6.3)]	
Other[b,c]	27 [2.9 (1.8–4.0)]	
Education level[d,e]		
High	291 [60.9 (56.5–65.3)]	285 [30.7 (27.7–33.7)]
Medium	150 [31.4 (27.2–35.5)]	548 [59.1 (55.9–62.2)]
Low	37 [7.7 (5.3–10.1)]	95 [10.2 (8.3–12.2)]
Occupation[f]		
Full-Time employment/ school attendance	415 [86.5 (83.4–89.5)]	570 [61.4 (58.2–64.5)]
Part-Time employment/ apprenticeship	43 [9.0 (6.4–11.5)]	255 [27.5 (24.6–30.3)]
Other[g]	22 [4.5 (0.5–8.7)]	104 [11.4 (8.0–14.4)]
Place of residence		
Urban living[h]	766 [17.7 (15.3–20.2)]	
Rural living	165 [82.3 (79.8–84.7)]	
Psychological measures		
PSS-10 sum score	15.19 (6.63, 0–39)	–
PHQ-9 sum score	4.50 (4.52, 0–27)	–
SMDS/SMDS-P sm score	1.54 (2.08, 0–9)	1.71 (2.36, 0–9)

N, absolute frequency; CI, confidence interval; SD, standard deviation; PSS-10, Perceived Stress Scale; PHQ, Patient Health Questionnaire; SMDS-(P), Social Media Disorder Scale (Parental Version); [a]dyads with frequently social media using adolescents, i.e., adolescents use social media at least once a week; [b]foster child/not specified; [c]no response n = 1; [d]for parents: highest level achieved–high = bachelor/master's degree to doctorate (Ph.D), medium = secondary school-leaving certificate (Realschulabschluss)/university entry qualification (Abitur)/completed apprenticeship, low = no or lower school-leaving certificate (Hauptschulabschluss); for adolescents: (prospective) school leaving certificate (based on the current school performance)–high = university entry qualification (Abitur), medium = secondary school certificate (Realschulabschluss), low = no/special-school (Förderschulabschluss)/lower school certificate (Hauptschulabschluss); [e]no response adolescents n = 453, no response parents n = 3; no response/item not presented to adolescents younger than 14 years; [f]no response adolescents n = 451, no response parents n = 2; no response adolescents/item not presented to adolescents younger than 14 years; [g]for adolescents: university students, in voluntary service, military service, other occupation, or unemployed; for parents: job-seeking, welfare recipient, pensioners, disabled, trainee, student, no specification; [h]areas with ≥ 5,000 residents.

MANOVA reached significance regarding adolescents with and without SMUD [Pillai score (1, 905) = 0.38, F (10, 896) = 55.14, $p < 0.001$]. **Table 6** shows the MANOVA results and the comparison of affected and non-affected adolescents regarding sex as well as the variables included in the *post-hoc* MANOVA tests. No differences were found between the proportion of sex, age and number of usage days in either group. Pathological SM users showed (per definition) higher SOMEDIS-A subscale and time criterion scores, but also higher SMDS and SMDS-P as well as higher PHQ-9 and PSS-10 sum scores with a large effect sizes compared to uncritical SM users.

Classification by LPA

A latent profile analysis (LPA) on the two SOMEDIS-A subscale and the time criterion score with an ellipsoidal, equal volume and shape model describing three profiles showed the best fit based on smallest AIC, absolute BIC, and ICL values (see **Table 7**). The log likelihood value was significantly smaller for a three-profile compared to a four-profile solution. Thus, including more profiles in the model did not suggest any benefit according to the likelihood ratio test (LRT). Robustness of this three-profile model could be shown by the bootstrapping procedure. Accordingly, the current sample could be divided into three mutually exclusive and exhaustive latent profiles that mirror SM usage patterns (based on the three SOMEDIS-A scores) as unobserved categorical variable.

More than half of the frequent SM users was classified in profile 2 based on the LPA results ($N_{profile2} = 543$; 58.3%), about one third in profile 3 ($N_{profile3} = 329$; 35.3%), and a small proportion of 6.3% in profile 1 ($N_{profile1} = 59$).

The three profiles were investigated based on the patterns of the three SOMEDIS-A score means (two factors and time criterion, **Table 8**). Moreover, a comparison of sex and a MANOVA with seven dependent variables were applied to further characterize differences between the three profiles. The MANOVA revealed a significant result [Pillai score (1, 905) = 0.32, F_{approx} (7,899) = 60.433, $p < 0.001$)]. The comparison of the three user profiles regarding sex, the SOMEDIS-A scores, the MANOVA results, as well as the variables included in the *post-hoc* MANOVA tests are presented in **Table 8**. Again, on the one hand, no significant differences were found regarding sex proportions, age, and the number of usage days based on the classification. On the other hand, significant differences were computed between the three profile groups with higher SMDS(-P) sum scores. The effect sizes were large for both comparisons and the differences between the SOMEDIS-A factors and time-criterion scores. The mean SOMEDIS-A, SMDS, and SMDS-P scores exceeded the cut-off values in the first profile (8). The third profile reported no prolonged problems at all (100%; 95% CI 100; 100) and the second profile consistently stated problems on single days only during the last year (100%; 95% CI 100; 100). In contrast, the first profile reported problems for longer periods (64.41%; 95% CI 52.19, 76.62) or even daily (35.59%; 95% CI 23.38, 47.81). Longer daily usage times were calculated for profile 1 than for the other groups, again with large effect sizes. The second profile users reported daily usage times to be about 50 min longer than those of the third profile users in a significant manner with a small, almost medium, effect size (0.44). Furthermore, PHQ-9 and PSS-10 sum scores were also significantly higher in profile 1 compared to the other profiles with large effect sizes. Profiles 2 and 3 also differed regarding PHQ-9 and PSS-10 scores with significantly higher values found for profile 2 and small, almost medium, effect sizes (0.46/0.49).

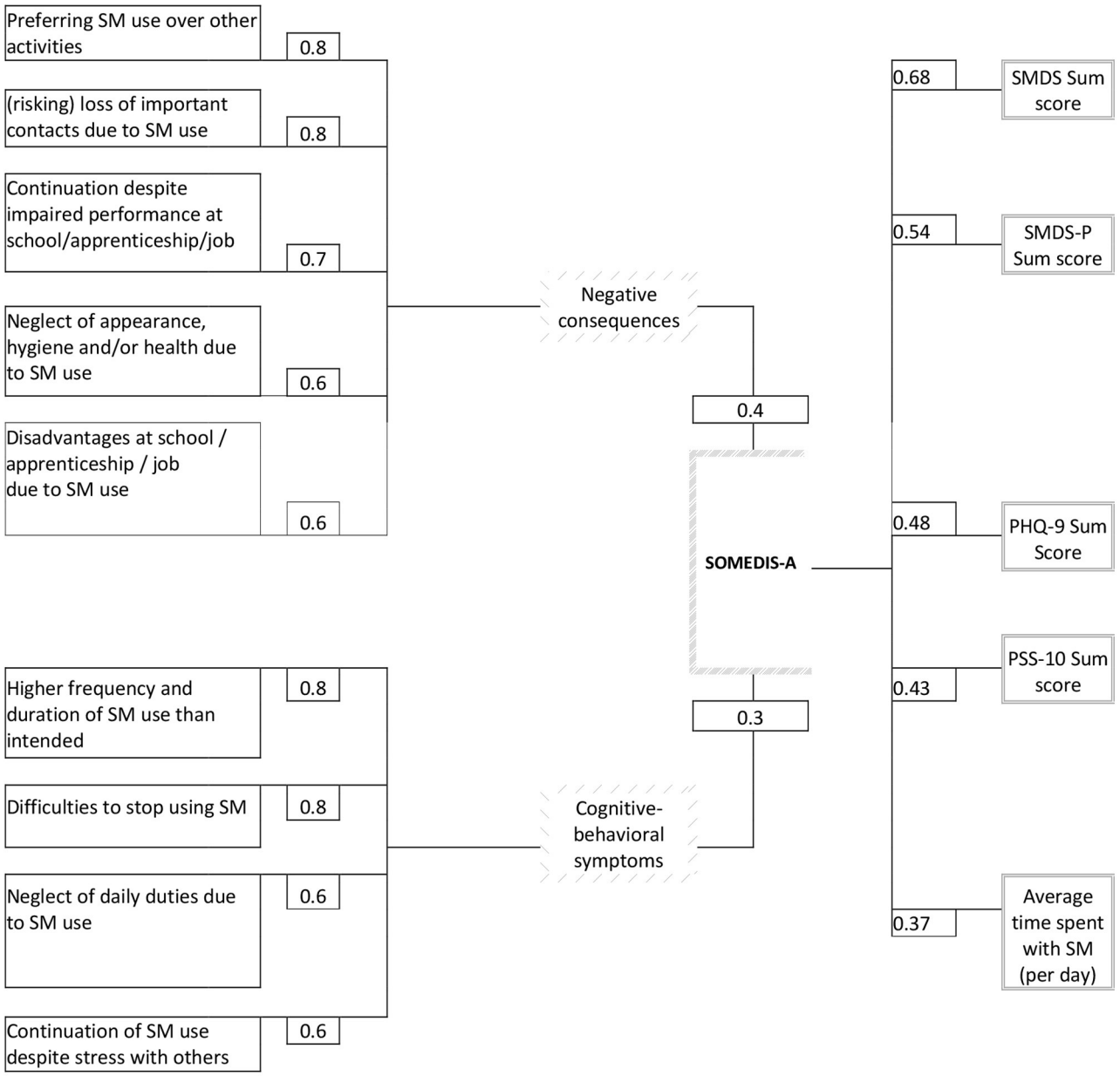

FIGURE 1 | EFA factor loadings on the latent SOMEDIS-A factor 1 (negative consequences) and SOMEDIS-A factor 2 (cognitive-behavioral SM use symptoms) are shown on the left [next to the individual scale item (manifest variable)] together with the proportion of explained variance (given above and below the SOMEDIS-A box). Correlation coefficients of the SOMEDIS-A sum score with criteria are presented on the right side (next to the criteria variables). All factor loadings and correlations were significant with $p < 0.001$. The usage days per week did not significantly correlate with the SOMEDIS sum score and are, thus, not depicted. SOMEDIS-A, Social Media Disorder Scale for Adolescents; SMDS(-P), Social Media Disorder Scale (Parental Version); SM, social media; PHQ, Patient Health Questionnaire; PSS, Perceived Stress Scale.

DISCUSSION

To our knowledge, this study is the first to introduce a screening instrument for assessing SMUD in adolescents according to the ICD-11 criteria for GD. SOMEDIS-A was successfully validated in a representative sample of adolescent frequent SM users and their respective parents as an instrument with good to excellent internal consistency and criterion validity as well as good to excellent discriminatory power. The instrument includes nine SMUD symptom items and one item to assess frequency and duration according to the ICD-11-time criterion. Thus, besides showing psychometrically robust properties, it is also very economical and easy to administer.

SOMEDIS-A was modified from the adolescent self-assessment instrument GADIS-A (41). The two-factorial structure of the GADIS-A was replicated for the SOMEDIS-A by an exploratory and a confirmatory factor analysis. The two factors best reflect cognitive-behavioral symptoms (such as increased SM use frequency and duration, inability to stop SM use or neglect of daily duties) and negative consequences due to SM usage behavior (such as loss of important contacts, withdrawal, poor health, or lower academic performance). The endorsed two-factor solution is at odds with approaches in which symptoms and impairments are not weighted equally, as is the case in the DSM-5 IGD definition and questionnaires derived from them, such as the SMDS (10, 11). Accordingly, functional impairment is considered by two out of nine criteria. If five of the nine criteria are met, an IGD, resp. a PSMU, can be assumed without the mandatory presence of an impairment symptom. Consequently, a differentiation between pathological and at-risk usage might not be clearly possible (76). In addition, the four-item GDT (Gaming Disorder Test) by Pontes et al. to assess ICD-11 GD favors a one-factorial solution (77). However, the equal consideration of both the behavioral SM usage pattern and the resulting negative consequences that lead to significant impairment is consistent with the biaxial model of addiction and the ICD-11 novelties (78–80). Analog to this model, impairments must be present in addition to specific symptoms to define SM use as disordered. Without meeting the impairment criterion, but with significant presence of the cognitive-behavioral symptoms, SM use could be considered hazardous (6, 7).

TABLE 3 | Factorial analyses of SOMEDIS-A items.

SOMEDIS-A item[a]	Factor 1[b]	Factor 2[b]	Communalities
Item 1 EFA	0.17	0.75	0.60
CFA	–	0.73	–
Item 2 EFA	0.26	0.84	0.77
CFA	–	0.86	–
Item 3 EFA	0.59	0.43	0.54
CFA	0.84	–	–
Item 4 EFA	0.50	0.57	0.58
CFA	–	0.82	–
Item 5 EFA	0.53	0.56	0.59
CFA	–	0.83	–
Item 6 EFA	0.70	0.38	0.63
CFA	0.90	–	–
Item 7 EFA	0.64	0.30	0.50
CFA	0.74	–	–
Item 8 EFA	0.78	0.18	0.63
CFA	0.86	–	–
Item 9 EFA	0.82	0.19	0.71
CFA	0.90	–	–

*SOMEDIS-A, Social Media Disorder Scale for Adolescents; EFA, Explanatory Factor Analysis (based on split-half sub-sample of n1 = 466 dyads); CFA, Confirmatory Factor Analysis (based on split-half sub-sample of n2 = 465 dyads), SOMEDIS-A factor 1 = negative consequences, SOMEDIS-A factor 2 = cognitive-behavioral symptoms; [a]for the description of the items, refer to **Table 1**. [b](standardized) factor loadings are depicted.*

The internal consistency for the whole scale and the two subscales is comparable to the original GADIS-A scale with good to excellent Cronbach's α values of 0.84 to 0.91 and McDonald's ω of 0.86 to 0.93. The SOMEDIS-A sum scores positively correlated with the SMDS sum score of the DSM-5 based adolescents' self- (SMDS) and parental ratings (SMDS-P) in a strong manner. Besides good criterion reliability, excellent criterion validity is therefore indicated.

The time spent with SM (per day) positively correlated with the SOMEDIS-A sum score in a moderate manner. Hence, no significant correlation could be found with the number of SM usage days per week. Previous studies reported weak positive correlations between PSMU and usage frequencies and durations in adolescents (8, 44). In contrast, Guo et al. (81) found strong associations between PSMU and self-reported usage duration in young adults. In comparison to the cited studies, our data were acquired during the COVID-19 pandemic. A recent longitudinal study described a significant increase in the proportion of daily SM users and time spent with SM per day in German adolescents from before to during the pandemic (82). Accordingly, irrespective of the usage pattern, the majority of adolescents (75%) used SM daily during the pandemic (compared

TABLE 4 | Inter-item correlation of SOMEDIS-A items[a].

Items[b]	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Timing item
Item 1	1.00									
Item 2	0.69	1.00								
Item 3	0.40	0.52	1.00							
Item 4	0.48	0.58	0.55	1.00						
Item 5	0.50	0.60	0.57	0.55	1.00					
Item 6	0.39	0.49	0.57	0.61	0.57	1.00				
Item 7	0.35	0.42	0.51	0.50	0.47	0.53	1.00			
Item 8	0.29	0.39	0.64	0.46	0.54	0.56	0.57	1.00		
Item 9	0.32	0.43	0.54	0.52	0.52	0.74	0.58	0.66	1.00	
Timing item	0.64	0.61	0.46	0.51	0.50	0.49	0.45	0.41	0.46	1.00

*SOMEDIS-A, Social Media Disorder Scale for Adolescents; [a]based on total sample of N = 931 adolescents; [b]for the description of items, refer to **Table 1**. The items of factor 2 are highlighted in gray.*

TABLE 5 | Relative item-response frequency of SOMEDIS-A items (in %)[a].

SOMEDIS-A items[b]	Response options				
	Strongly disagree	**Somewhat disagree**	**Partially agree/partially disagree**	**Somewhat agree**	**Strongly agree**
Item 1	18.4	23.6	31.6	19.3	7.1
Item 2	28.9	28.6	23.6	13.5	5.0
Item 3	61.0	23.2	9.9	4.3	1.6
Item 4	40.4	28.2	19.4	7.6	4.3
Item 5	48.4	26.7	15.8	6.4	2.6
Item 6	59.4	23.1	11.1	4.3	2.1
Item 7	61.5	23.3	9.9	3.3	1.9
Item 8	72.4	18.6	5.8	1.9	1.3
Item 9	68.1	20.9	7.3	2.3	1.4
	Not at all	**Only on single days**	**For longer periods**	**Nearly daily**	
timing item	35.3	58.3	4.1	2.3	

*SOMEDIS-A, Social Media Disorder Scale for Adolescents; [a]based on the total sample of N = 931 adolescents; [b]for the description of items, refer to **Table 1**. The items of factor 2 are highlighted in gray.*

TABLE 6 | MANOVA and *post-hoc* test results on adolescents ROC-classified with/without SMUD.

Variables	SMUD	No SMUD	*F*-value	χ^2/*post-hoc* Scheffé tests	Cramer's V/Cohen's d
Absolute frequency	31	900	–	–	–
Relative frequency in % (95%–CI)	3.33 (2.18, 4.48)	96.67 (95.52, 97.82)	–	–	–
Female sex in % (95%–CI)	58.06 (40.69, 75.44)	49.44 (46.18, 52.71)	–	0.01 NS ($p = 0.93$)	–
Mean age (SE)	13.71 (0.29)	13.67 (0.07)	0.01 NS ($p = 0.94$)	–	–
Mean SOMEDIS-A factor 1 score (SE)	13.13 (0.88)	2.43 (0.1)	357.52***	10.7***	3.42
Mean SOMEDIS-A factor 2 score (SE)	12.45 (0.49)	4.81 (0.12)	146.06***	7.64***	2.19
Mean SOMEDIS-A time criterion score (SE)	2.42 (0.09)	0.67 (0.02)	294.82***	1.74***	3.11
Mean SMDS sum score (SE)	6.29 (0.44)	1.38 (0.06)	200.38***	4.91***	2.6
Mean SMDS-P sum score (SE)	5.71 (0.57)	1.58 (0.07)	104.14***	4.13***	1.84
Mean usage days per week (SE)	6.39 (0.29)	6.33 (0.05)	0.02 NS ($p = 0.88$)	–	–
Mean time spent with SM per day [in minutes] (SE)	337.77 (48.7)	159.46 (21.64)	57.79***	187.32***	1.39
PHQ sum score	12.71 (0.25)	4.21 (0.14)	118.9***	8.5***	2
PSS sum score	23.39 (0.18)	14.91 (0.22)	51.08***	8.5***	1.31

$^{***}p \leq 0.001$, NS, not significant; MANOVA, Multivariate Analysis of Variance; ROC, receiver operating characteristic; SMUD, social media use disorder; χ^2, chi-square; Cramér's V/Cohen's d, effect sizes; (95%–CI), 95% confidence interval; SE, standard error of the mean; SOMEDIS-A, ICD-11 Social Media Disorder Scale for Adolescents; SMDS(-P), DSM-5 Social Media Disorder Scale (parental version); SOMEDIS-A factor 1, negative consequences; SOMEDIS-A factor 2, cognitive-behavioral symptoms; SM, social media; PHQ, Patient Health Questionnaire; PSS, Perceived Stress Scale.

TABLE 7 | Comparison of number of latent classes according to latent profile analysis (LPA).

Latent classes	Log likelihood	AIC	BIC	ICL	LRTS
1	−3,342.78	6,703.56	−6,747.09	−6,747.09	0.00***
2	−3,243.62	6,519.23	−6,596.61	−6,600.03	198.33***
3	−2,293.1	4,632.2	−4,743.43	−4,743.44	1,901.04***
4	−2,293.16	4,646.33	−4,791.41	−5,005.09	−0.13

$^{***}p \leq 0.001$; LPA, Latent Profile Analysis; AIC, Akaike information criterion; BIC, Bayesian information criterion; ICL, Integrated Completed Likelihood; LRTS, likelihood ratio test score based on bootstrapping with 999 replications.

to 66% before the pandemic). The time spent with SM per day increased by about 1 h. Thus, while the usage days per week might have reached ceiling effects, the time spent with SM per day appears to be a differential measure in reference to usage patterns in a time of reduced alternative activities and contact restrictions.

TABLE 8 | Comparison of the three SM user profiles based on LPA.

Variables	Problematic SM users (PSMU)	Intensive SM users (ISMU)	Light SM users (LSMU)	*F*-value	χ^2/*post-hoc* Scheffé tests[a]	Cramer's V/Cohen's d
Absolute frequency	59	543	329	–	–	–
Relative frequency in % (95%–CI)	6.34 (4.77, 7.9)	58.32 (55.16, 61.49)	35.34 (32.27, 38.41)	–	–	–
					–	–
					–	–
Female sex in % (95%–CI)	49.15 (36.4, 61.91)	50.83 (46.62, 55.03)	48.02 (42.63, 53.42)	–	0.01 NS ($p = 0.91$)	0.01
					0.00 NS ($p = 0.99$)	0.01
					0.54 NS ($p = 0.46$)	0.03
Mean SOMEDIS-A factor 1 score (SE)	9.83 (0.73)	3.15 (0.14)	0.94 (0.1)	–	–	1.91
					–	3.27
					–	0.81
Mean SOMEDIS-A factor 2 score (SE)	10.31 (0.45)	6.53 (0.13)	1.7 (0.1)	–	–	1.25
					–	4.04
					–	1.87
Mean SOMEDIS-A time criterion score (SE)	2.36 (0.06)	1 (0)	0 (0)	–	–	9.03
					–	12.59
					–	Inf
MANOVA and *post-hoc* tests Mean age (SE)	13.86 (0.24)	13.57 (0.09)	13.81 (0.13)	0.64 NS ($p = 0.42$)	–	–
Mean SMDS sum score (SE)	4.88 (0.38)	1.85 (0.08)	0.42 (0.06)	321.06***	−3.03***	1.49
					−4.46***	2.88
					−1.43***	0.86
Mean SMDS-P sum score (SE)	4.75 (0.4)	2.02 (0.1)	0.66 (0.08)	187.66***	−2.73***	1.12
					−4.09***	2.3
					−1.36***	0.66
Mean usage days per week (SE)	6.34 (0.2)	6.45 (0.06)	6.14 (0.09)	5.41*	0.11 NS ($p = 0.86$)	0.08
					−0.2 NS ($p = 0.63$)	0.13
					−0.2*	0.21
Mean time spent with SM per day [in minutes] (SE)	291.88 (30.42)	176.72 (5.44)	125.27 (5.28)	82.34***	−115.16***	0.82
					−166.61***	1.32
					−51.45***	0.44
Mean PHQ-9 sum score (SE)	10.71 (0.87)	4.76 (0.18)	2.95 (0.19)	143.65***	−5.95***	1.34
					−7.76***	1.87
					−1.81***	0.46
Mean PSS-10 sum score (SE)	21.93 (0.67)	15.91 (0.27)	12.8 (0.36)	117.53***	−6.02***	0.99
					−9.13***	1.46
					−3.11***	0.49

****$p \leq 0.001$, *$p \leq 0.05$, NS, not significant; [a]post-hoc tests reported in the following sequence: PSMU–ISMU, PSMU–LSMU, ISMU–LSMU. MANOVA, Multivariate Analysis of Variance; LPA, Latent Profile Analysis; SM, social media; χ^2, chi-square; Cramér's V/Cohen's d, effect sizes; (95%–CI), 95% confidence interval; SE, standard error of the mean; SOMEDIS-A, ICD-11 Social Media Disorder Scale for Adolescents; Inf, infinite number; SMDS(-P), DSM-5 Social Media Disorder Scale (parental version); SOMEDIS-A factor 1, negative consequences; SOMEDIS-A factor 2, cognitive-behavioral symptoms; PHQ, Patient Health Questionnaire; PSS, Perceived Stress Scale.*

Moderate positive correlations were also found between the SOMEDIS-A and the PHQ-9 sum score. These results are in line with the findings of recent systematic reviews reporting positive associations between PSMU and depression in high school students (83) and adults (35). Moreover, SOMEDIS-A as well as the PSS-10 sum scores significantly correlated in a moderate manner. Correspondingly, the meta-analytic review of Vahedi and Saiphoo (84) found small-to-medium associations between smartphone use and stress. The cross-sectional study of Beyens et al. (85) reported higher stress levels associated with SM use in adolescents. Moreover, a recent cross-sectional study on a large representative German sample of 10- to 17-year olds found a positive association between SMDS scores and psychological stress perception (19). Our results support a good criterion validity of the new scale and mirror the clinical significance of SMUD.

For a SMUD to be assumed, the cut-off values of both factors plus the time criterion had to be fulfilled. The cut-off values of the two subscales were determined by a ROC curve analysis based on the four ICD-11 associated items of the SMDS. They were slightly different from those of the GADIS-A: The value for factor 1 (negative consequences) was 6.5, one point higher, while the value for factor 2 (cognitive-behavioral symptoms) was 8.5, one point lower. Both questionnaires showed overlapping confidence intervals for the cut-off values. The confidence intervals regarding sensitivity and specificity for both cut-offs were also overlapping indicating no statistically significant differences. Slightly different cut-off values seem to be reasonable since both instruments are based on the same symptom criteria but most likely refer to separate behavioral addiction entities (86, 87). Based on the cut-offs and the time criterion, pathological SM users could be distinguished from non-pathological users. Accordingly, 3.33% (95% CI 2.18, 4.48) of the frequent SM users fulfilled the criteria of a SMUD. Keeping in mind that 92% of our initial representative adolescent sample were frequent SM users, this prevalence does not differ from the DSM-5 based estimate of 2.6% (95% CI 1.6, 3.6) in a representative sample of 12- to 17-year-old German adolescents from Germany by Wartberg et al. (88).

No differences between normal and disordered SM users were found in terms of gender. In line with our results, Wartberg et al. and Fung could also not find a significant gender influence (22, 88). In contrast, Boer et al. reported a very weak but significant positive association between female gender and PSMU (23), and van den Eijnden et al. found more boys than girls to be engaged in PSMU in one out of their three study samples (8). Diverging findings might be due to different SM definitions. In the present survey, YouTube was mentioned as an explicit example of SM since it includes a comment and like function. Whereas various SM applications seem to attract girls due to typical female usage motives (e.g., affiliation, self-disclosure), YouTube is predominantly consumed by boys (63). With respect to age, adolescents with and without SMUD also did not differ. This is consistent with the findings e.g., by van den Eijnden et al. (8, 10), and Austermann et al. (41) in comparable age groups.

Adolescents with SMUD could be clearly distinguished from other frequent users by the higher number of fulfilled DSM-5 criteria assessed by SMDS and SMDS-P, as well as by more time spent with SM. On average, adolescents classified with SMUD used SM 3 h longer per day than those without SMUD. Both groups did not differ regarding the number of usage days per week (6.39 vs. 6.33 days). In data acquired before the COVID-19 pandemic, adolescents with PSMU used SM slightly more often per week and 1 h longer than unproblematic users (44). Bányai et al. found the daily usage times of adolescents without PSMU to be 1 to 2 h lower than those of adolescents with PSMU (89). About 3 times higher PHQ-9 scores were revealed in users with SMUD compared to users without SMUD indicating more depressive symptoms in affected adolescents. According to the severity categories reported by Richardson et al. (90), the observed value of 12.71 for adolescents with SMUD refers to a moderate depressive symptom expression. With a mean score of 4.21, adolescents without SMUD did not show relevant depressive symptoms. Moreover, almost 60% higher PSS-10 scores were found for adolescents classified with SMUD compared to those without SMUD, indicating higher levels of psychological stress perception. As stress is a major predisposing factor for health problems (91), when taken together with the expression of depressive symptoms, the clinical significance of an accurate SMUD classification, is emphasized.

The results of the cut-off-based classification were supported by the LPA profile characterization. An LPA on the two SOMEDIS-A factors sum scores and the time criterion revealed three distinct profiles. Adolescents of the first profile showed significantly higher SOMEDIS-A sum scores with large effect sizes compared to the other profiles. Their factor 1 and 2 sum scores were two to three points below those of the adolescents classified as SMUD by the cut-off approach. Although it can be assumed that 3.01% of the adolescents classified in this group had a value below the cut-off of at least one factor, their mean scores were clearly above the cut-off values. Thus, they could be referred to as problematic SM users (PSMU) with a prevalence of 6.34% (95% CI 4.77, 7.9). This rate is not different from a prevalence of 5.4% reported by Boer et al. for German adolescents (23). The adolescents with PSMU had significantly higher SMDS and SMDS-P scores, more time spent with SM per day, and had larger PHQ-9 and PSS-10 scores than adolescents of the other two LPA profiles. Their mean PHQ score of 10.71 was associated with moderate depressive symptoms (90). Although subsuming pathological and at-risk SM users, this LPA group therefore features clinically relevant properties. The largest LPA group comprised 58.32% (95% CI 55.16, 61.49) of the frequent SM users. Adolescents in this profile had scores on the SOMEDIS-A, SMDS (-P), PHQ-9, and PSS-10, as well as reported time spent with SM, that were between those of the other two profiles with significant difference. Further, they used SM on average about 50 min longer per day than the third LPA group that included 35.34% (95% CI 32.27, 38.41) of the adolescents but about 115 min shorter than the PSMU group. We referred to them as intensive SM users (ISMU). Their PHQ-9 scores could be categorized as reflecting mild depressive symptoms (90). The last group was very inconspicuous in all variables surveyed suggesting no depressive symptoms and low psychological stress levels. They were referred to as light SM users (LSMU).

Collectively considering the above results, the SOMEDIS-A could be shown to be highly effective in distinguishing potentially clinically relevant from non-relevant SM users. A differentiation between light and intensive users who differ not only regarding usage patterns and durations but also subclinical depressive symptoms and stress perception could also be shown.

Although the SMUD has not yet been included in diagnostic manuals, the current results support the assumption that SMUD deserves its own conceptualization as addictive disorder (6, 9) in the context of ICD-11 behavioral addictions (68). Affected users can be typically described by criteria of established addiction concepts (9). Accordingly, SOMEDIS-A revealed usage patterns that are comparable to other (substance and behavioral) addictions (6) in a small but significant proportion of adolescents. Moreover, adolescents classified with SMUD showed greater mental distress—a common finding in patients

with substance use disorders and behavioral addictions (6). In their review, Pluhar et al. described pathological media use in adolescence as a comorbidity of psychiatric conditions such as attention-deficit/hyperactivity, affective, anxiety, sleep, and autism spectrum disorders (92). However, more evidence is needed to show that SMUD is not a manifestation of another underlying pathology. Given this and the high rate of comorbidities in addiction disorders in general, a valid and reliable assessment in research and clinical settings is crucial for a better understanding of this relatively new phenomenon.

Further research on a standardized conceptualization and assessment including the two-factorial approach in SMUD should be supported to distinguish SMUD from other behavioral addictions and other mental disorders. By considering two factors involving specific symptoms and adverse outcomes, usage patterns could be described in more detail compared to polythetic approaches (80). Respectively, new hypotheses on different etiologies of pathological and hazardous SM use could be derived and tested within samples of overrepresented problematic users. More research is needed on neurobiological features of affected adolescents and the longitudinal course of the symptoms (7). Clinical validation of the SOMEDIS-A in future studies is desirable to evaluate the clinical significance of symptoms and impairments and to allow application in clinical settings.

Complementary to clinical expertise, the SOMEDIS-A could thus contribute to a better conceptualization and the early detection of potentially affected adolescents, in order to increase understanding and provide appropriate treatments and interventions as early as possible. This is urgently required by clinicians and a prerequisite for successful symptom reduction and prevention of secondary impairments, comorbidities, or even chronicity (93).

LIMITATIONS

Although representativeness was ensured in terms of age, sex, and place of residence of the adolescent sample of frequent SM users, it may have been reduced in other respects by the data collection procedure. First, the sample only included households with sufficient knowledge of the German language, thus families with migration background might not have been sufficiently taken into account. Furthermore, about 5% of German households do not have internet access (94) and could not be considered for this study. Online questionnaires are highly valued instruments in large epidemiological surveys for economic reasons but missing data is a common problem, especially when studying parent-child dyads that include young adolescents. 110 parent-child dyads had to be excluded from further analysis, which might have further reduced representativeness. All participants were asked to answer the questionnaire independently but the influence of others cannot be ruled out. The current validation lacks objective markers such as logged usage times. The aspect of re-test reliability could not be addressed since a cross-sectional design was chosen. The present analyses were based on a categorical approach using cut-off values and neglecting behavioral spectrums. However, this approach is in line with current clinical practice, which requires efficient action even in the presence of uncertainty or "binary" yes/no decisions. Moreover, by using the four ICD-11-related items of the SMDS (13, 14) to determine cut-off values, not all relevant aspects could be covered by the criterion (e.g., loss of relationships, negative impacts on school performance or health behavior were not explicitly addressed). Most importantly, no clinical evaluation of the responses including the interpretation of the clinical relevance of the individual symptomatology exists. An external verification of the screening results by an experienced clinician would have been the gold standard for concordant validity. However, given the early stage of SMUD research, the current study supports important steps toward a better understanding of the phenomenon and early detection of affected adolescents by introducing the very first ICD-11 based screening instrument.

CONCLUSION

The SOMDIS-A is the first screening tool to assess SMUD based on the ICD-11 criteria of GD. It showed good to excellent internal consistency reliability and criterion validity in a representative sample of frequent adolescent SM users. A two-factorial structure was supported analog to the original GADIS-A and in line with the biaxial model of addiction as well as the conceptual ICD-11 novelties. Accordingly, cognitive-behavioral symptoms and their negative consequences are equally weighted. The inclusion of a temporal item allows a distinction between occasional and persistent problems of clinical value. The SOMEDIS-A was able to reliably discriminate between adolescents with and without SMUD in terms of usage patterns and time spent with SM, psychological stress perception, and depressive symptoms. It is easy and economical to administer in clinical and research settings thus allowing broad application. The presented findings support the assumption that SMUD deserves its own conceptualization in the context of ICD-11 behavioral addictions and could contribute to the development of a standardized conceptualization leading to more clarity in definitions and assessment. Future clinical validation studies are warranted.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the corresponding author (KP) upon reasonable request after all results of the parent-child survey have been published.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Local Psychological Ethics Commission at the Center for Psychosocial Medicine (LPEK) of the University Medical Center Hamburg-Eppendorf (UKE). Informed consent to participate in this study was provided by the participants themselves and their legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

KP contributed to the conceptualization, methodology, software, validation, investigation, and original draft preparation. MA contributed to the conceptualization, validation, investigation, review, editing, and visualization. RT contributed to the resources, project administration, supervision, and funding acquisition. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.661483/full#supplementary-material

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Psychometric Properties of the Nine-Item Problematic Internet Use Questionnaire in a Brazilian General Population Sample

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Objective: The goal of the study is to adapt and examine the psychometric properties of the Brazilian version of the nine-item Problematic Internet Use Questionnaire (PIUQ-SF-9).

Methods: A convenience sample of Brazilian internet users aged between 18 and 89 years (72.7% female, mean age 38.7 years ± 13.5) was recruited online from September 2018 to July 2019 (test sample = 1,525; retest sample = 237). Participants responded to the adapted version of the PIUQ-SF-9, as well as the Center for Epidemiologic Studies-Depression Scale (CES-D-10) and sociodemographic questions.

Results: A bifactor model with one general factor and three specific dimensions (obsession, neglect and control disorder) yielded the best fit indices [χ^2 = 67.66, df = 15, CFI = 0.99, TLI = 0.99, RMSEA = 0.048 (0.037–0.060), RMSEA *p* close = 0.587 and SRMR = 0.01]. McDonald's hierarchical omega coefficient was 0.76 for the general factor and varied between 0.16 and 0.33 for the specific dimensions. The intraclass correlation coefficient was 0.73 for the general factor and varied between 0.64 and 0.72 for the specific dimensions. The MIMIC model supported the scale's construct validity as the relationship of the predictors (age, time spent online, self-perception of problematic internet use, and depression symptoms) with the PIUQ-SF-9 factors was in line with the assumptions based on the literature.

Conclusion: PIUQ-SF-9 seems to be a brief and culturally validated instrument with sound psychometric properties to be used in future studies on problematic internet use in the Brazilian population.

Keywords: internet addiction, Problematic Internet Use Questionnaire, cultural adaptation, psychometrics, Brazil

INTRODUCTION

The internet has become an integral part of most people's lives, and in some cases, its countless benefits seem to give way to negative consequences from its overuse. Problematic internet use can be defined as excessive and uncontrolled internet use associated with significant impairment in the individual's physical and emotional health, social relationships, and professional life (1, 2). Its occurrence is associated with high rates of psychiatric comorbidities, such as depressive and anxiety disorders (3), and it is more prevalent in adolescents and young adults, who use the internet for longer periods of time than other age groups (4). Problematic internet use is an umbrella term that includes behaviors related to gaming, social network use, and access to pornography, among others (5).

In recent years, Brazil has undergone a major technological revolution, and it is estimated that ∼75% of the Brazilian population has regular access to the internet, which corresponds to more than 150 million individuals (6). Research on the problematic internet use in Brazil is on the rise, as it is in many countries. However, one of the existing difficulties is the paucity of instruments available to study this phenomenon, since only the Internet Addiction Test [IAT; (7, 8)], and the Online Cognition Scale [OCS; (9–11)] have been translated and culturally adapted to Brazilian Portuguese. The IAT, despite being the most widely used, had no psychometric properties other than the internal consistency assessed in our population. The OCS has been assessed for semantic equivalence, reliability, and construct validity among university students, but it has been considerably less investigated, perhaps because it is longer and more time-consuming. The development of measurement tools that are valid, reliable, and validated across cultural settings is essential for screening people in risk of problematic internet use, investigating clinical and etiological aspects of this phenomenon, and evaluating prevention and treatment strategies (2).

The Problematic Internet Use Questionnaire—Short Form-9 (PIUQ-SF-9) is a nine-item comprehensive screening tool assessing three basic aspects of problematic internet use: obsession (i.e., preoccupation and withdrawal symptoms), neglect (i.e., negligence of everyday activities and basic needs), and control disorder (i.e., trouble in controlling internet use) (12). Several studies have examined its psychometric properties, showing high internal consistency, replicable factor structure, and moderate to good test–retest properties. It has also proved to be valid across various methods of data collection (i.e., online as well as paper–pencil) and age groups, being considered suitable for time-limited surveys (12, 13). Cross-cultural psychometric studies found that the PIUQ-SF-9 demonstrated adequate measurement invariance across several European and Asian countries (14–16).

The aim of the present study is to describe the cultural adaptation process of the PIUQ-SF-9 to Brazilian Portuguese and the evaluation of its psychometric properties in a general population sample.

MATERIALS AND METHODS

Cultural Adaptation Process

The original instrument (including instructions, all items and answer possibilities) was independently translated by six bilingual translators whose native language was Brazilian Portuguese, divided into two groups (two psychologists and one psychiatrist in each group). The translated versions were examined by an expert committee to assess semantic discrepancies (including linguistic and conceptual issues), and, by consensus, a synthesized version of the translation was developed. The expert group was composed of 15 members skilled in psychometric research and also in internet use disorders.

It was then back translated into English by two native English speakers who worked independently to produce back-translations. The first back-translator was a psychologist born in the USA, and the second was an English teacher born in England, and both of them have lived in Brazil for many years. None of the translators previously knew the questionnaire being adapted, and they were not informed about the objectives of the study. The back-translated versions were then evaluated by two independent groups, composed of three members each, to verify how much the instructions, each item and the answer possibilities differed from the original instrument in relation to their meaning, rating on a four-point Likert scale from 1 (much altered) to 4 (not altered). At a new meeting of the experts' group, based on the insights from the back-translations' evaluations, all items on the scale were revised and, when necessary, consensually adjusted to maintain the meaning of the original instrument, producing a new synthesized and unified version in Brazilian Portuguese. A synthesized version of the back-translation was also produced and, along with the description of the adaptation process, were forwarded to the PIUQ-SF-9 authors for appraisal.

This version was then sent, in an online format, to a group of 15 people to investigate the face validity of the instrument, that is, whether the items, instructions and response scale were comprehensible to the target population (17). Comments and suggestions regarding clarity and comprehensibility were requested for each item, as well as for the whole questionnaire.

Sample and Procedures

A convenience sample of Brazilian internet users aged between 18 and 89 years was recruited online *via* social media platforms and email, between September 2018 and July 2019. Data collection was carried out anonymously through the online research platform Survey Monkey, and the questionnaire could be accessed and answered *via* smartphone, computer, or tablet. At the end of the questionnaire, participants were offered feedback on their results from the questionnaire on problematic internet use, for which an email address was requested. Those who provided the email address were invited, in August 2019, to answer the PIUQ-SF-9 scale again for the retest validation. The invitation was made in an automated way so that the researchers did not have contact with the participants' email contacts. The time between the test and the retest was at least 4 weeks.

All participants who filled in the sociodemographic data and completed at least 90% of the PIUQ-SF-9 were included. The missings were at random and were excluded from subsequent analyzes. The sample size estimate was 1,000, considered "excellent" for carrying out the confirmatory factor analysis (CFA) and other psychometric testings (18, 19).

This cross-sectional study is part of a multicentric project carried out in 16 countries, whose main objective is to assess cross-cultural aspects of internet and smartphone problematic use. The study was approved by the Research Ethics Committee of the Hospital de Clínicas de Porto Alegre (protocol number 89702318.2.0000.5327), and it was conducted in accordance with the Declaration of Helsinki.

Variables and Measures

Sociodemographic and internet use data: participants were asked about their age, sex, education, working and marital status, as well as number of hours of daily internet use, main device for internet connection, and self-perception of problematic internet use.

PIUQ-SF-9, (12): this questionnaire consists of nine items, which evaluate problematic internet use based on the three-factor structure of the original 18-item instrument (20): obsession, neglect, and control disorder. All questions have five-point Likert-type answers, ranging from 1 "never" to 5 "almost always/always." Total scores range from 9 to 45, and higher scores indicate a higher risk of problematic use. Internal consistency, measured by Cronbach's alpha, varies between 0.91 and 0.93 for the whole instrument and between 0.77 and 0.89 for specific dimensions (12, 21). Test–retest reliability varies between 0.61 and 0.90 for the whole instrument and between 0.53 and 0.90 for the specific factors (20, 21).

Center for Epidemiologic Studies—Depression Scal-10 [CES-D-10; (22–24)]: it is a brief version of the CES-D, which aims to assess depressive symptoms. It consists of 10 items that are evaluated on a Likert-type scale ranging from 0 ("rarely or never") to 3 ("most of the time or all the time"). Scores can range from 0 to 30 and, according to Andresen et al. (22), scores $\geq$ 10 suggest significant depressive symptomatology. In the original study and also in recent validations, Cronbach's alpha is higher than 0.80 in all subgroups (23, 25).

Statistical Analysis

The analyses were performed in R environment (version 3.2.2) implemented by the *lavaan* package (26). In addition, *semTools* package was used to estimate reliability measures (27), and *semPlot* package was used to produce the MIMIC diagram (28). For ordered categorical variables, the Diagonal Weighted Least Squares estimation method and polychoric correlation coefficients were used with robust estimation of the means, variances, and standard errors.

CFA was performed to verify the structural validity of the instrument. In addition to the analysis of the fitted model suggested by the original study (12), other three alternative models were also evaluated as proposed by a recent study that verified the psychometric properties of this questionnaire in nine European countries (14). The model originally proposed is composed of three oblique factors (neglect, obsession, and control disorder). The alternative models presented are: (1) two oblique factors model in which the dimensions neglect and control disorder belong to the same factor; (2) bifactorial model composed of a general factor and three specific dimensions (neglect, obsession, and control disorder); and (3) bifactorial model consisting of the general factor and two specific dimensions, in which neglect and control disorder compose the same dimension. The fit indices considered to compare the model's adequacy were: Comparative Fit Index and Tucker-Lewis Index (CFI and TLI, $\geq$0.95), Root Mean Square Error of Approximation (RMSEA, $\leq$0.06) with associated *p*-value and Standardized Root Mean Residual ($\leq$0.10) (29).

The internal consistency was assessed using McDonald's hierarchical omega coefficient (ωH), considering satisfactory if higher than 0.70 (but in the case of a bifactor model, this parameter is valid only for the general factor, once the specific dimensions scores are controlled for the variance due to the general factor) (30). Cronbach's alpha (α) was also reported for the sake of comparability with previous research. To estimate test–retest reliability, the intraclass correlation coefficient (ICC) and corresponding 95% confidence interval (CI) were calculated, and reliability was considered adequate for values between 0.50 and 0.75, good for values between 0.75 and 0.90, and excellent for values $>$ 0.90 (31).

We also conducted a Multiple Indicators Multiple Causes (MIMIC) model to explore construct validity by estimating simultaneously the influence of possible predictors (age, time spent online, self-perception of problematic use, and depression symptoms) on the PIUQ-SF-9 general and specific factors, *via* standardized partial regression coefficients. The MIMIC is a variety of Structural Equation Modeling, which describes the effects of covariates on latent variables and the inter-relationships of latent variables, thus providing better insight than traditional correlational analysis (32, 33). Based on the literature, it was assumed that age would have a negative effect on the PIUQ-SF-9 factors while time spent online, self-perception of problematic internet use, and depression symptoms would have a positive effect on the PIUQ-SF-9 factors.

Floor and ceiling effects are considered to be present if more than 15% of respondents achieved the lowest or highest possible score, respectively (34). The dataset and the analysis script were uploaded can be accessed from the following link: https://github.com/wagnerLM/PIUQ/blob/main/PIUQ-SF-9_script_data.R.

RESULTS

Cultural Adaptation

The two forward translations achieved very similar results, and only minor adjustments were needed to obtain by consensus, a synthesized version. All back-translation items were considered to be unaltered from the original instrument in relation to their meanings. No adjustment needs were identified by the authors of the original instrument when evaluating the synthesis of the back-translations. On pre-test, all respondents rated the questionnaire as "easy to understand," and there were only a couple of minor suggestions involving word order and replacement of a term by a synonym. The final Brazilian

TABLE 1 | Descriptive statistics of sociodemographic variables.

	Test sample (n = 1,525)	Retest sample (n = 237)
Mean age in years (SD)	38.75 (13.55)	38.08 (13.80)
Gender		
Women (%)	1.106 (72.7%)	177 (74.7%)
Occupation (%)		
Studying only	217 (14.2%)	41 (17.3%)
Studying and working	368 (24.2%)	66 (27.8%)
Working only	817 (53.6%)	105 (44.3%)
Not working, not studying	121 (7.9%)	25 (10.5%)
Educational level (%)		
Elementary School	15 (1.0%)	–
High school, incomplete	17 (1.1%)	–
High school, complete	74 (4.9%)	8 (3.4%)
High school, complete + 1–3 years of study	163 (10.7%)	33 (14.1%)
High school, complete + 4–6 years of study	311 (20.3%)	43 (18.4%)
High school, complete + 7 or more years of study	931 (61.1%)	150 (64.4%)
Marital status (%)		
Single	389 (25.6%)	73 (30.8%)
Dating	191 (12.6%)	34 (14.3%)
Living together	238 (15.6%)	28 (11.9%)
Married	566 (37.2%)	80 (33.8%)
Divorced	118 (7.8%)	18 (7.6%)
Widowed	18 (1.2%)	4 (1.7%)

SD, Standard deviation.

Portuguese version of the PIUQ-SF-9, as well as the original English version, are available in **Appendices A, B**, respectively.

Demographic Data

A total of 1,525 people answered the sociodemographic part, the questions about internet use and the PIUQ-SF-9 (72.7% were female, mean age was 38.7 years ± 13.5). A total of 735 participants informed their email at the end of the questionnaire and were invited to complete the PIUQ-SF-9 retest. Thus, 237 out of the 735 responded to the PIUQ-9 retest (74.7% were female, mean age was 38.1 years ± 13.8), in an average time of 6 months after the original completion. The main sociodemographic data of the test and retest samples are presented in **Table 1**.

Psychometric Properties

We evaluated the factor structure of the PIUQ-SF-9 testing the four models previously proposed by Laconi et al. (14) and the fit indices are reported in **Table 2**. The bifactor model with one general factor and three specific dimensions (obsession, neglect, and control disorder) yielded the best fit to the data [$\chi^2 = 67.661$, df = 15, CFI = 0.99, TLI = 0.99, RMSEA = 0.048 (0.037–0.060), RMSEA p close = 0.587 and SRMR = 0.01]. Factor loadings for this model are presented in **Table 3**. After confirming the factorial structure of the instrument, a normative table was produced, which can be found in **Appendix C**.

Regarding internal consistency of PIUQ-SF-9, ωH was 0.76 for the general factor and varied between 0.16 and 0.33 for the specific dimensions. Cronbach's alpha was 0.91 for the general factor and varied between 0.73 and 0.88 for the specific dimensions. For the test–retest reliability, ICC was 0.73 for the general factor and varied between 0.64 and 0.72 for the specific dimensions (complete results for both internal consistency and test–retest reliability measures are presented in **Table 3**).

The MIMIC model had an excellent fit to the data [$\chi^2(35) = 108.9$, CFI/TLI = 0.99, RMSEA = 0.04 (90% C.I. = 0.03–0.05)]. Predictors explained the variance of the general and specific factors as follows: general factor = 34%, neglect = 25%, obsession = 8%, and control disorder = 35%. According to the model, the age of the respondents had no effect on the general factor, but a small negative effect on all the specific factors. Time spent online had a small positive effect on neglect and obsession, but no effect on the general factor and control disorder. Self-perception of problematic internet use had a large positive effect on general factor and control disorder, a small effect on negligence, and no effect on obsession. Depression symptoms had a small positive effect on the PIUQ-SF-9's general factor and all specific dimensions. A diagram of PIUQ-SF-9's factorial structure and the results of all regressions paths and correlations, as well as a **Supplementary Material** link for the detailed measurement model assessment, are presented in **Figure 1**.

Regarding floor and ceiling effects, 4.2% of the sample answered the minimum value for PIUQ-SF-9, while 0.1% answered the maximum value, which were considered satisfactory.

DISCUSSION

This study aimed at culturally adapting the PIUQ-SF-9 for use in Brazil, as well as examining its psychometric properties. Our findings demonstrated that the questionnaire has shown the best fit in the bifactor model (one general factor and three specific dimensions: neglect, obsession, and control disorder). Therefore, reliability and validity tests were carried out taking into account this factorial structure. The Brazilian Portuguese version of the PIUQ-SF-9 has shown good internal consistency and the test–retest procedures highlighted moderate stability. Construct validity was demonstrated with the MIMIC model, by the means of hypothesis testing, with an excellent fit to the data.

The bifactor model suggests that a general factor (problematic internet use) explains most of the variance in the PIUQ-SF-9 scores, while the three specific dimensions have distinct but smaller participation in the variance. In the original version of the instrument (12, 18) the most appropriate factorial structure was the three-factor model, that would be neglect, obsession, and control disorder. When evaluating the psychometric properties of PIUQ-SF-9 in samples from nine European countries, Laconi et al. (14) observed that the bifactor model with one general factor and two specific dimensions had an acceptable or good fit in eight out of nine subsamples. However, in that same study, the bifactor model with the three specific dimensions showed acceptable fit indices in six out of nine languages (Italian, German, Spanish, Turkish, English, and Greek). All items loaded significantly on the general factor. Item 6 (concealing the time

TABLE 2 | Confirmatory factor analysis of four measurement models of the PIUQ-SF-9.

	χ^2	df	*p*	CFI	TLI	RMSEA (95% CI)	RMSEA *p*-close	SRMR
Three-factor model	528.277	24	<0.001	0.97	0.96	0.117 (0.109–0.126)	0.000	0.05
Two-factor model	668.107	26	<0.001	0.97	0.95	0.127 (0.119–0.136)	0.000	0.06
Bifactor model with three specific dimensions	67.661	15	<0.001	0.99	0.99	0.048 (0.037–0.060)	0.587	0.01
Bifactor model with two specific dimensions	218.172	17	<0.001	0.99	0.98	0.088 (0.078–0.099)	0.000	0.03

PIUQ-SF-9, Problematic Internet Use Questionnaire–Short Form–9 items; χ^2, chi-square; df, degrees of freedom; CFI, comparative fit index; TLI, Tucker-Lewis Index; RMSEA, root-mean-square error of approximation with 95% confidence interval; SRMR, standardized root mean residual.

TABLE 3 | Standardized factor loadings and reliability indicators of the bifactor model with three specific dimensions of the PIUQ-SF-9.

	General factor	Specific dimensions		
		Neglect	Obsession	Control disorder
Item 1	0.64	0.47		
Item 3	0.57	0.49		
Item 9	0.70	−0.01		
Item 5	0.72		0.48	
Item 7	0.56		0.63	
Item 8	0.69		0.52	
Item 2	0.72			0.53
Item 4	0.75			0.56
Item 6	0.87			−0.08
ωH	0.76	0.16	0.33	0.18
α	0.91	0.73	0.88	0.86
ICC	0.73	0.72	0.68	0.64
ICC 95% CI	0.67–0.79	0.66–0.78	0.61–0.75	0.56–0.71

PIUQ-SF-9, Problematic Internet Use Questionnaire – Short Form – 9; ωH, McDonald hierarchical omega coefficient; α, Cronbach's alpha; ICC, Intraclass correlation coefficient; ICC 95% CI, 95% confidence interval.
The significance test showed $p < 0.001$ for all intraclass correlation coefficients.

spent online) showed the highest load in the general factor (0.87), although there was non-significant loading on the control disorder specific dimension. Item 9 (people complaining about too much time online) also loaded only in the general factor (0.70), but not on the neglect specific dimension. This was also observed in the nine subsamples evaluated in the study by Laconi et al. (14), and we may hypothesize that these behaviors are more frequent when a pattern of problematic use is already established, and when one's perception of problematic use is higher.

The internal consistency of the Brazilian version of PIUQ-SF-9 demonstrated good levels of homogeneity, as demonstrated by the analysis of both the α and the ωH indices, which is in line with previous international validating studies of the questionnaire (14, 35). It is worth mentioning that, in bifactor models, the ωH for the specific dimensions represent the reliability of a subscale score after controlling for the variance due to the general factor, explaining why these values are much smaller than the ωH value for the general factor (30).

Test–retest reliability was considered to be moderate, not differing much from other recent validation studies (21). It is possible that methodological aspects may have influenced the stability of the measure, like the time interval between the test and the retest, and also the possible different contexts in which participants responded to the instrument for the first time (during the academic year or during holidays, for example). On the other hand, we can also raise the hypothesis that problematic internet use may present variations in its natural course, either in the intensity of symptoms or in its recovery, as a chronic disorder with spontaneous remission and recurrences (20). It is also worth mentioning that both the test and the retest were carried out before the COVID-19 pandemic, which greatly interfered with the use of the internet.

Although there are dozens of instruments developed to assess problematic internet use (36), none of them is considered to be the gold standard, which makes it difficult to assess the PIUQ-SF-9's criterion validity. MIMIC analyses used to assess the construct validity was based on findings in the literature showing that problematic use is related to more time spent on the internet (not for studies or work), is more prevalent in young adults than in older age groups, and it is also often associated with psychiatric comorbidities (especially depression). All the associations and their degrees were consistent with previous studies (13, 37, 38). The greatest magnitudes were found in the positive effect of self-perception of problematic internet use on the PIUQ-SF-9's general factor (0.48) and control disorder (0.51). Interestingly, self-perception of problematic use showed a non-significant effect on the obsession dimension, perhaps because it is the most subjective dimension of the scale. Taken together, these results also reinforce the usefulness of a bifactor model.

The validation process of an instrument needs to be understood within the context in which it was used and, in this sense, it may have some limitations about the findings of this study. The first is that the cross-sectional design of the study doesn't permit to make causal inferences, and the terms "predictors" and "effect" related to the MIMIC model are only statistical predictors and effects, not real causal prediction. The second is that the study sample was selected in a non-probabilistic way, which may limit the external validity of our findings. In a continental and culturally diverse country as Brazil, it is possible that not all regions of the country have been equally represented in the study population, despite the efforts of researchers to seek this representation when recruiting the sample. We observed that both test and retest participants had a high level of education, considerably higher than the average Brazilian population (39). Although internet use in Brazil has been shown to be associated

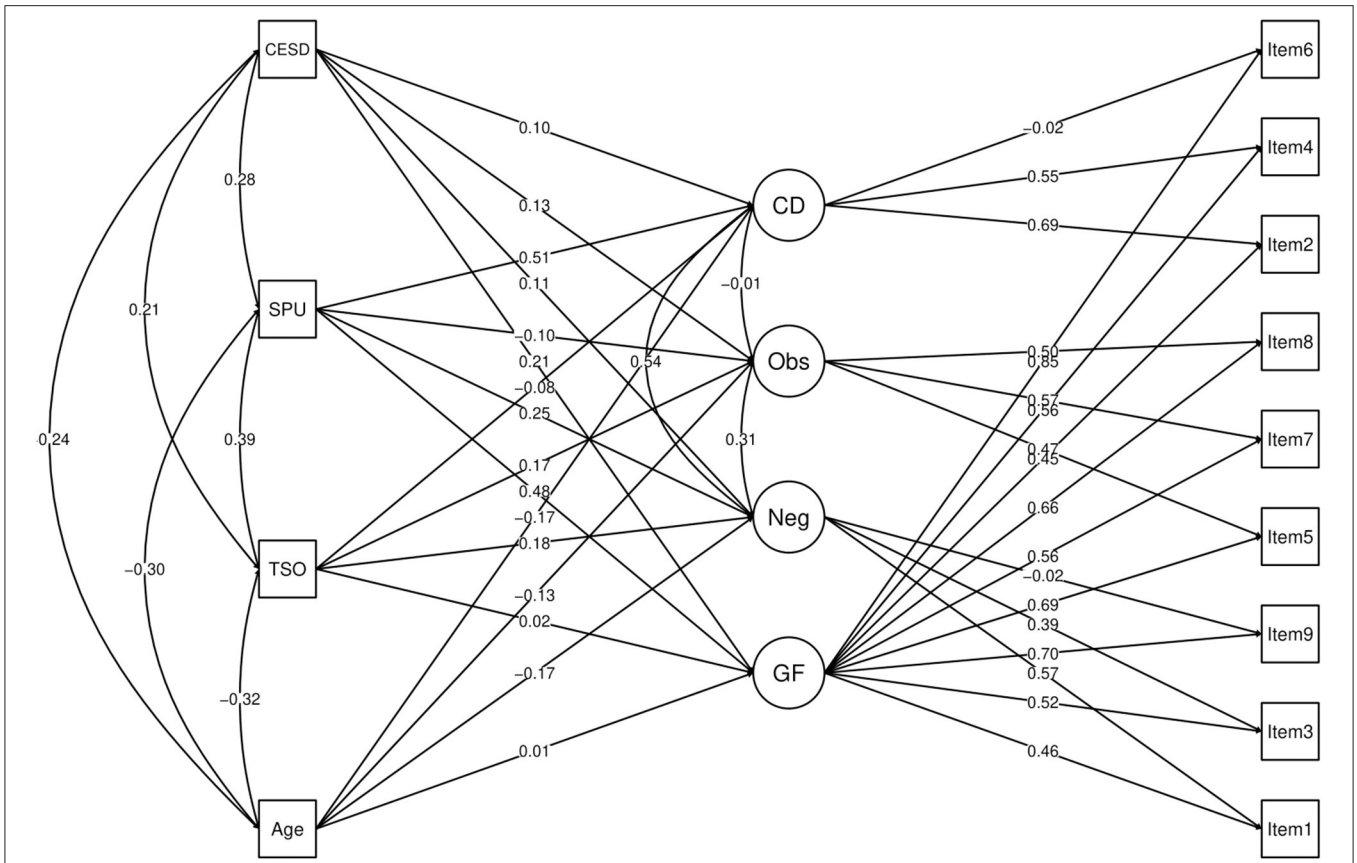

FIGURE 1 | Diagram of the MIMIC model of the PIUQ-SF-9 general factor and specific dimensions and the age of the respondents, time spent online, self-perception of problematic internet use, and depressive symptoms. MIMIC, Multiple Indicators Multiple Causes; CESD, Center for Epidemiologic Studies-Depression Scale; SPU, Self-perception of Problematic Use; TSO, Time Spent Online; CD, Control Disorder; Obs, Obsession; Neg, Neglect; GF, General Factor. A detailed measurement model assessment as **Supplementary Material** can be found on the following link: https://github.com/wagnerLM/PIUQ/blob/main/PIUQ-SF-9_fit.

with higher levels of education (6), convenience sampling may have also influenced this finding.

In summary, based on the process of the adaptation of the PIUQ-SF-9 into Brazilian Portuguese and the validation evidence examined, the PIUQ-SF-9 seems to be a valid and reliable instrument to be used in future studies on problematic internet use in Brazil. The availability of a culturally validated instrument with sound psychometric properties will allow us to estimate and monitor the risk of problematic internet use in our population, to examine the effectiveness of prevention and treatment protocols, and also to compare these data with findings from other countries. Due to its brevity, the PIUQ-SF-9 can easily be included in research protocols without increasing significantly the completion time. This can also increase participants' compliance, especially those with more severe patterns of problematic internet use. In order to increase the PIUQ-SF-9 evidence of validation, future research should explore the instrument's measurement invariance, its performance in clinical samples and populations of different stages of development (e.g., teenagers), and also its possible gender differences in problematic internet usage (40).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/**Supplementary Material**.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Research Ethics Committee of the Hospital de Clínicas de Porto Alegre (Protocol Number 89702318.2.0000.5327). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

DS, WLM, SL, KK-C, ZD, OK, IP, and SH contributed to the conception and design of the study. DS, VA, CP, and PL organized the database. DS, WLM, MY, and OK performed the statistical analysis. DS and MY wrote the first draft of the manuscript. SL, KK-C, PL, OK, ZD, and SH wrote sections of the manuscript. All

authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.660186/full#supplementary-material

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Stress and Problematic Smartphone Use Severity: Smartphone Use Frequency and Fear of Missing Out as Mediators

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Problematic smartphone use (PSU) has been linked with stress. Higher levels of stress likely increased problematic smartphone use. We investigated relations between stress, fear of missing out, and problematic smartphone use. The aim of the current study was to analyze the mediating role of fear of missing out (FOMO) and smartphone use frequency (SUF) between stress and PSU. We surveyed a broad sample of 2,276 Chinese undergraduate students in July 2019, using the FOMO Scale, Smartphone Addiction Scale-Short Version, Smartphone Use Frequency Scale, and Depression Anxiety Stress Scale-21. The results showed that stress was associated with PSU severity. Gender differences were found in PSU severity. Furthermore, FOMO was positively associated with SUF and PSU severity. Structural equation modeling demonstrated that FOMO acted as a mediator between stress and PSU severity. FOMO and SUF acted as a chain of mediators between stress and PSU severity. SUF did not account for relations between stress and PSU severity. The study indicates that FOMO may be an important variable accounting for why some people with increased stress levels may overuse their smartphones.

Keywords: stress, problematic smartphone use, fear of missing out, depression, anxiety, Suf

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INTRODUCTION

Smartphone has become an integral part of people's lives, and people engage in many different types of activities (e.g., gaming, mobile payments, and social networking) on their smartphones (1, 2). A series of interactive behaviors with one's smartphone has become part of the routine for most individuals, which is ubiquitous, especially for young people (3, 4). The use of smartphones has greatly facilitated our lives. However, the emergence of smartphone use can create some negative effects, such as problematic smartphone use (PSU). The prevalence of PSU among Chinese undergraduates was estimated to be 21.3% (5). The current study focuses on the impact of stress, common among undergraduates, on PSU severity, and the mediating roles of fear of missing out (FOMO) and smartphone use frequency (SUF).

Background on Problematic Smartphone Use and Stress, Fear of Missing Out

Problematic smartphone use (PSU) refers to the excessive use of smartphones with associated dysfunction, withdrawal difficulties, and other phenomena similar to substance addiction (6, 7).

Studies have shown that prolonged use of mobile phones can cause cervical back and neck pain (8), increased risk of car accidents (9), and delay and impairment in academic and work performance (10). In addition, PSU is also highly correlated with anxiety, depression, and other mental health symptoms (7, 11). In previous studies, this construct has been similarly labeled as "smartphone addiction," and "excessive smartphone use" (12). Smartphone addiction should describe a pathological symptom, and we are only measuring a relative intensity, not a criterion to classify addiction; it is not applicable. Excessive smartphone use should only describe smartphone use, and excessive smartphone use is not necessarily a problem. Therefore, we think PSU is the most suitable in this study.

Stress is an agitated state arising from a lack of means to attain the many social environmental demands that place a burden on an individual's typical ability to adapt (13). Stress can change people's physical and mental state, and people are more prone to addictive behavior in stressful situations (14–18). With the popularity of smartphones, more people use electronic devices to engage in social networking sites and watch videos to relieve stress when they are under pressure, which often brings negative consequences (19–21). Jie et al. (22) reported that stress from interpersonal relationships, school-related problems, and anxiety symptoms were significantly associated with excessive Internet use. Stress and PSU severity are also closely related [reviewed in Vahedi and Saiphoo (23)] with specific studies demonstrating such a relationship (24–26). In fact, social stress (26) and emotional stress (24) positively influence PSU severity. Furthermore, Cho et al. (25) demonstrated that stress had a significant influence on PSU severity in adults. As stress increases, self-control decreases, which leads to increased PSU severity (25). Therefore, we pose the following first hypothesis.

H1: Stress should be positively associated with PSU symptoms.

Studies have shown that the prevalence of PSU is about 30% among men and 29% among women (25). Factors linked to PSU among male college students include gaming app use, anxiety, and poor sleep quality (27). PSU among female college students has been linked to the use of multimedia apps, social networking services, depression, anxiety, and poor sleep quality (28). Both stress and gender can play a role in PSU (26, 29, 30). Social stress positively influences problem smartphone use, and women experience more social stress and use smartphones more for social purposes than men, and thus, women are more likely to develop habitual or addictive smartphone behaviors (26).

H2: Women should evidence greater levels of PSU.

FOMO is defined as a pervasive worry that others might be having rewarding experiences from which one is not part of and the desire to stay connected with what others are doing continually (31). FOMO involves anxiety about missing out on learning that others have experienced valuable experiences and a desire to maintain ongoing connections with others (31). SUF means the frequency of smartphone use. Many studies have found that FOMO has a close relationship with SUF and PSU severity. People who score higher in FOMO are more likely to overuse their smartphones to satisfy the desire to stay connected (32). FOMO and PSU are positively correlated, and higher FOMO can be a driver of PSU (33). A study by Elhai et al. (34) found that FOMO is closely related to negative emotions, social use of smartphones, and PSU severity. Also, FOMO and greater SUF were related to PSU severity. FOMO was associated with increased SUF (a small effect) and PSU (a large effect) (7). FOMO was also found most closely related to PSU severity and social stress (8).

H3: FOMO is positively associated with SUF (H3a) and PSU severity (H3b).

FOMO and SUF play an important mediating role between stress and PSU. Many studies have shown that anxiety and depression have important effects on problematic Internet and smartphone use (35–37). One study found that social anxiety and loneliness were significantly correlated with excessive use of online games, but when stress levels were controlled, the significant relationship disappeared (36). This finding shows that stress plays a significant role in overuse of the Internet. Studies have shown that stress is directly associated with PSU severity (24–26). At the same time, other psychological factors may play an important role between stress and PSU. For example, a study found that all predictors of Internet overuse lost statistical significance, including the effect of stress on online game overuse, after controlling for avoidance motivation and achievement motivation (36). Therefore, the SUF may play a mediating role between stress and PSU severity.

In addition, many empirical studies have examined the mediating role of FoMO in the relationship between psychological variables and PSU. For example, many studies have found that FOMO mediates relations between negative emotions (such as anxiety and depression) and PSU severity (35, 37). It has also been found that FOMO plays a mediating role in maximization and PSU (33). Therefore, we can assume that FOMO plays a mediating role between stress and PSU severity. Meanwhile, many studies have shown that elevated FOMO and elevated SUF are positively correlated, and SUF is a significant predictor of PSU severity (35). Therefore, we infer that there is another pathway that FOMO and SUF play a chain mediating role between stress and PSU severity. It is high FOMO and high SUF at high stress levels that lead to PSU.

H4: FOMO acts as a mediator between stress and PSU severity.
H5: SUF acts as a mediator between stress and PSU severity.
H6: FOMO and SUF act as a chain mediator between stress and PSU severity.

Theory

The uses and gratifications theory (UGT) (38) was an early theory based on mass communication research to explain why people use media. According to this theory, people use particular types of media to satisfy specific needs they have. For example, individuals who feel lonely can use social apps to meet their social needs by interacting with friends or strangers. For this study, this theory may also explain the relationship between stress and PSU severity. For example, increased stress may lead individuals to use their smartphone for recreation and, thus, make themselves feel temporarily happy and relaxed. Meanwhile, an important

characteristic of FOMO is the need to stay in constant contact with what others are doing (31). Przybylski et al. (31) argue that FOMO stems from a lack of need satisfaction, such as the need for social connection, and the use of smartphones allows people to get frequent social networking sites to get the status of life of people they follow, updates, and social hotspots, and to get satisfaction by doing so. Previous studies have also shown that individuals with high levels of FOMO have higher levels of SUF and PSU severity (27, 39, 40). Therefore, the UGT theory may be able to explain this phenomenon.

The compensatory Internet use theory (CIUT) (20) is a theory proposed for excessive Internet use. The CIUT suggests that when individuals face adversity (such as stress and negative emotions), they often use the Internet to relieve negative emotions such as stress, although this may adversely lead to Internet overuse. Nowadays, smartphones are so common and available that when people are unhappy and under pressure, they often unconsciously unlock their phones, watch a video, surf social networking sites, or play games (28), which also lead to increased PSU severity. CIUT theory is supported by empirical studies in PSU research (30).

The Interaction of Person-Affect-Cognition-Execution (I-PACE) model (41) is a comprehensive theory explaining problematic Internet use. This theory describes the process of developing excessive Internet use, involving a cycle, from core traits (such as genetic, biological, social cognition, personality, and specific motivation), to the subjective perception of emotional and cognitive reactions, the decision to use the Internet, and then obtain satisfaction, in turn, affecting the core traits. Each step of the process is closely related to whether it ultimately leads to problematic Internet use. The updated I-PACE model (42) has become more sophisticated, and suggests that the development of addictive behaviors is the result of interactions between inducing variables, emotional and cognitive responses to specific stimuli, and executive functions such as inhibitory control and decision making. The stages of Internet overuse were divided into early and late stages, and corresponding brain mechanisms were summarized. In I-PACE, FOMO is a prominent response variable to personal factors. It has been suggested that FOMO is well-suited as a response variable in I-PACE, representing a cognitive or affective bias mediating variable between personal factors and excessive Internet use (37, 43). Recent studies have found that FOMO mediates the relationship between negative emotions such as anxiety and depression and PSU severity (34, 43).

METHODS

Procedure

We conducted an online survey at Tianjin Normal University in the fall of 2018 and spring of 2019. Institutional Review Board approval was first granted by the university. The university's Psychology Department recruited student participants through local online information on college bulletin boards and social networking accounts. These participants were directed to an informed consent statement and (for those who agreed) an online survey on wjx.cn, a Chinese online survey platform. All tests were conducted in Mandarin Chinese. There were 2,278 people who enrolled, but 15 participants who reported being younger than 15, or older than 27, were excluded. We also removed participants whose response time was substantially short or long. The remaining sampled included 2,263 participants, with an effective rate of 99.34% of those enrolling.

Participants

Among the 2,263 participants, the average age was 19.35 years (SD = 1.36). A majority were women (n = 1,666; 73.6%), with 597 (26.4%) men. Most were of Chinese Han ethnicity (n = 2,075; 91.7%). A majority were freshman (n = 1,302, 57.5%) or sophomores (n = 669, 29.6%). Most were majoring in social/natural sciences (n = 1,668, 73.7%), language/humanities (n = 258, 11.4%), or engineering (n = 198, 8.7%). A majority reported being single/not in a romantic relationship (n = 1,699, 75.1%), with 541 (23.9%) participants in a relationship but not married.

Instruments

Demographics

We queried gender, age, grade, race/ethnicity, relationship status, major, and years of smartphone use. Subsequently, the following psychological scales were administered.

Smartphone Use Frequency Scale

The SUF (44) was developed as an 11-item measure querying frequency of using specific smartphone features, with response options from 1 = Never to 6 = Very often. The features queried included "video and voice calls (making and receiving)," "text/instant messaging (sending and receiving)," "email (sending and receiving)," "social networking sites," "Internet/websites," "games," "music/podcasts/radio," "taking pictures or videos," "watching videos/TV/movies," "reading books/magazines," and "maps/navigation." We used the Chinese scale version, translated and validated previously, adding a 12th item tailored to this population: "educational learning." Internal reliability for the Chinese scale is adequate (35). Cronbach's alpha in our sample was 0.819.

Depression Anxiety Stress Scale-21

Stress was measured by the Chinese version (17) of the 21-item DASS-21 (45). Each subscale is measured by seven items rated over the past week, with options from 0 = Did not apply to me to 3 = Applied to me very much or most of the time. We used the entire DASS-21 questionnaire for measurement, but the scores for stress in the model were scores for the dimension stress only. Internal consistency for the stress scale in this sample was 0.889.

Fear of Missing Out Scale

FOMO was measured by the Fear of Missing Out scale (FOMO) (31), which consists of 10 items (e.g., "I get anxious when I don't know what my friends are up to."). Each item was rated from "1 = Not at all true of me" to "5 = Extremely true of me," with higher total scores indicating higher levels of FOMO. We used the Chinese version, translated and validated previously (46). In the present study, Cronbach's α for the scale was 0.892.

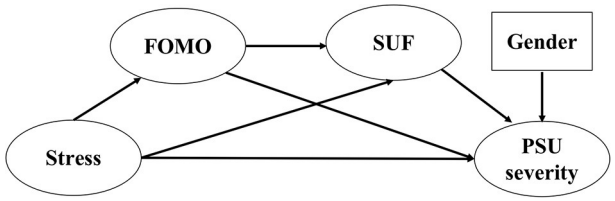

FIGURE 1 | Hypothetical model diagram.

Smartphone Addiction Scale—Short Version

We used the SAS-SV (47) to measure the severity of PSU by self-report, tapping health and social impairment, withdrawal, and tolerance components. The SAS- SV is the short version of the original SAS (47). The SAS-SV contains 10 items, with responses ranging from 1 = Strongly disagree to 6 = Strongly agree. Studies confirmed the reliability of the scale (48). A higher score means a higher degree of PSU. We used the Chinese version, which was previously translated and supported (28, 35). Cronbach's alpha in this study was 0.924.

Data Analysis

SPSS 23.0 software was used for data processing, correlation, and descriptive analysis. We had no missing item-level data, as the web survey prompted participants to input responses for skipped items. We summed each scale's items for total scores. Scale scores were normally distributed, with the largest value for skewness being 1.12 (Stress) and for kurtosis being 1.99 (SUF).

We used Mplus version 7 (Muthén & Muthén, 1998–2019) for confirmatory factor analytic (CFA) and structural equation modeling (SEM) analyses. We performed CFA for each scale in **Figure 1**, using item-level data, in order to test the scale's factor structure. We treated each scale's items as ordinal, using polychoric covariance matrices, weighted least squares estimation with a mean- and variance-adjusted chi-square (WLSMV), and probit-based factor loadings (49). Residual covariances were fixed to zero; all factor loadings were freely estimated, with factor variances fixed to a value of 1. We report fit indices including the comparative fit index (CFI) and Tucker–Lewis index (adequate fit between 0.90 and 0.94; excellent fit >0.94), standardized root mean squared residual (SRMR; adequate fit < 0.08, excellent fit < 0.05), and root mean square error of approximation (RMSEA, adequate fit from 0.07 to 0.08; excellent fit < 0.07) (50).

We tested the hypothetical model in **Figure 1**. We discuss our use of latent variables below. The path from stress to PSU severity tests H1. The path from FOMO to PSU tests H3. The path from FOMO to SUF tests H4.

We tested mediation, computing the cross-product of direct path coefficients. We estimated standard errors for indirect (mediation) path coefficients using the delta method, with 1,000 bootstrapped, non-parametric samplings (51). We tested SUF as a mediator between FOMO and PSU severity (H5). We tested FOMO as a mediator between stress with PSU (H6). Finally, we tested FOMO as a mediator between stress with SUF (H6).

TABLE 1 | Mean, standard deviation, and correlation analysis of each variable.

	M	SD	1	2	3	4	5
Stress	5.81	4.63	–				
FOMO	24.64	7.65	0.55***	–			
SUF	50.07	9.11	0.15***	0.22***	–		
PSU severity	36.25	10.94	0.49***	0.37***	0.35***	–	
Gender	1.74	0.44	−0.03	0.00	0.10**	0.15**	–

*FOMO, Fear of Missing Out Scale; PSU, problematic smartphone use; SUF, smartphone use frequency. **p < 0.01; ***p < 0.001.*

TABLE 2 | *T*-test for each variable on gender.

	Male	Female	*t*	*p*
PSU severity	33.52	37.23	51.83	0.000
SUF	48.49	50.64	24.57	0.000
Stress	6.05	5.72	2.20	0.138
FOMO	24.61	24.64	0.01	0.920

TABLE 3 | Mediating effect tests.

Path	*β*	SE	*z*	95% CI of *β*	*p*
Gender → PSU (direct effect)	0.13	0.020	6.774	0.231:0.421	0.000
Stress → PSU (direct effect)	0.45	0.026	17.186	0.790:0.988	0.000
Stress → FOMO → PSU	0.04	0.016	2.296	0.005:0.068	0.022
Stress → SUF→ PSU	0.01	0.009	0.880	−0.008:0.025	0.379
Stress → FOMO → SUF → PSU	0.04	0.007	5.554	0.026:0.053	0.000
Total mediating effect	0.08	0.017	4.854	0.051:0.117	0.000
Total effect	0.53				

RESULTS

Descriptive Statistics and Correlations

The descriptive and correlational results are shown in **Table 1**. The results showed that correlations between stress, FOMO, SUF, and PSU severity between the two reached a significant level ($p < 0.001$). The correlation between gender and SUF, and between gender and PSU severity reached a significant level ($p < 0.01$).

Analysis of the Difference Test on Gender

Gender difference tests were done for PSU severity, SUF, stress, and FOMO. It was found that there were gender differences in PSU severity and SUF, and females scored significantly higher than males in PSU severity and SUF ($p < 0.001$). The gender differences in the scores of stress and FOMO were not significant (see **Table 2**).

SEM Results

Since gender has a significant influence on PSU, we controlled PSU for gender (8). There are three mediating pathways—one sequence mediating and two parallel mediating paths. The first parallel mediating path is stress → FOMO → PSU; The second

parallel mediating path is stress → SUF → PSU. The sequence mediating path is stress → FOMO → SUF → PSU.

Structural equation modeling showed that the hypothesized model yielded a good fit, $\chi^2(113) = 1070.079$, $\chi^2/df = 9.47$, RMSEA = 0.061, SRMR = 0.040, CFI = 0.959, and TLI = 0.951. In general, if $\chi^2/df > 3.84$, RMSEA < 0.08, SRMR < 0.05, and CFI/TLI > 0.90, the structural equation model may be supported. In this study, the model fits the data well, which confirmed the multiple pathways model. We next found from the model path diagram (as shown in **Table 3**) that, except for the path "stress → SUF," all the other paths reached significance ($p < 0.05$).

The results of bootstrapping for deviation correction (as shown in **Table 3** and **Figure 2**) showed that both the direct effect and total mediating effect reached a significant level $p < 0.001$). In addition, the 95% confidence interval of bootstrap did not include 0, indicating that both the mediating effect and direct effect were supported.

The mediating effect of SUF between stress and PSU severity was 0.01, and the confidence interval contains 0, so the mediating effect was not significant. The mediating effect of FOMO between stress and PSU was 0.04, and the confidence interval does not contain 0, so the mediating effect was significant. The effect size for the mediation sequence between stress and PSU by FOMO and SUF was 0.08, and the confidence interval does not contain 0, indicating that this mediation sequence was significant.

DISCUSSION

The results of the study provide support that stress is associated with PSU severity in Chinese undergraduate students, supporting H1. Gender correlated with PSU severity, supporting H2. FOMO was positively associated with SUF and PSU severity, supporting H3. FOMO acted as a mediator between stress and PSU severity, supporting H4. FOMO and SUF acted as a chain of mediators between stress and PSU severity, supporting H6. Finally, SUF did not mediate relations between stress and PSU severity, thus rejecting H5.

Stress can predict PSU severity, supporting H1. This finding is in line with the CIUT (20) and UGT (38) that people will use smartphones more to meet their needs in the face of life adversity (e.g., high pressure), which may produce poor consequences. This result is also consistent with previous studies, which showed that people with higher stress use the Internet as a coping mechanism to relieve stress, thus, more likely to generate problematic Internet use (24–26, 52). The results of a systematic review suggest that stress is positively correlated with PSU severity use, with a small-to-moderate effect ranging from $r = 0.20$ to $r = 0.30$ (11). However, in our study, the correlation between stress and PSU was as high as 0.49, which may be related to the cultural phenomenon that Chinese college students have higher academic pressure from their parents and family (53) compared with students from other countries. One study has shown that the prevalence of PSU among Chinese college students is as high as 21.3%, and high stress is one of the risk factors for PSU among Chinese college students (5). Therefore, in Chinese college students, the relationship between stress and PSU may be stronger than in other cultural groups.

Gender was associated with PSU severity, supporting H2. Previous studies have shown that men and women differ in the degree of PSU and upper emphasis on smartphone use (54). Women are more likely to use social activities, while men are more likely to use procedural apps (such as games) (26). Overall, women spend more time on their smartphones. However, one study found that men had greater PSU severity (55). Nevertheless, in our study, we found that women had a higher degree of PSU severity. In order to more clearly verify the role of FOMO in the stress–PSU relationship, we controlled for the influence of gender on the degree of PSU severity.

The results showed that FOMO and SUF, FOMO, and PSU were significantly and positively correlated, supporting H3a and H3b. FOMO is a newly emerging and important psychological construct closely correlated with SUF and PSU severity (8, 27, 31, 39). Studies have shown that FOMO is highly correlated with negative emotions (such as anxiety and depression) (30). In this study, FOMO showed a moderate correlation with stress, $r = 0.55$. According to UGT (38), smartphones are used to satisfy their specific needs, so when individuals experience stress, they need to use certain features of smartphones to satisfy their needs to relieve stress and pursue relaxation and happiness.

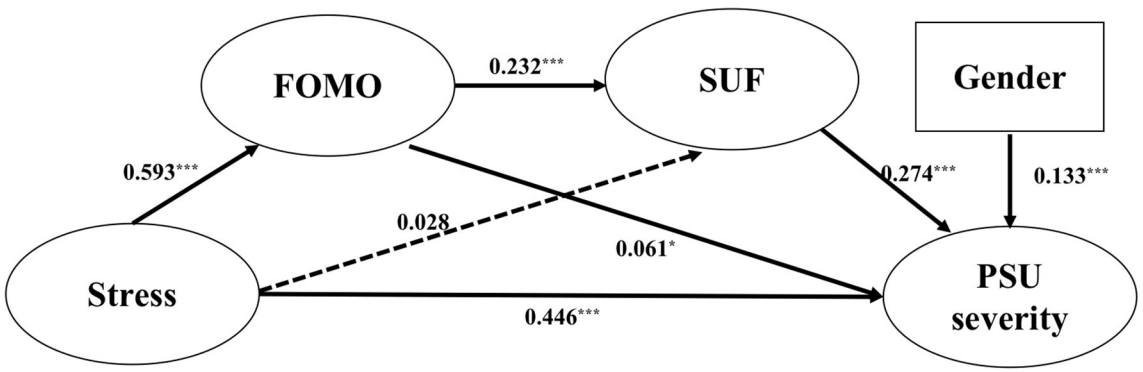

FIGURE 2 | Results of the structural equation model. *$p < 0.05$; ***$p < 0.001$.

Also, high FOMO motivates individuals to use smartphones to satisfy the need to worry about missing cell phone messages, important news, etc. According to CIUT (20), when individuals face adversity (such as stress and negative emotions), they tend to use the Internet to relieve negative emotions such as stress. FOMO correlates with SUF and PSU severity, possibly because FOMO has components involving negative emotions. Previous studies have shown that FOMO was a predictor of SUF and PSU severity (35, 39, 40), which is consistent with our findings.

FOMO played a mediating role between stress and PSU severity, supporting H4. The result is consistent with the I-PACE model, proposing cognitive or affective bias variables such as FOMO (37, 41, 43) as mediating between subjectively perceived situations (stress) and problematic Internet use (37, 41, 42). When studying the relationship between levels of stress and PSU severity previously, studies often treated stress similarly to depression and anxiety (35), but there are differences. In the I-PACE model, stress is in a different position from anxiety and depression. Stress belongs to subjectively perceived situations, while anxiety and depression belong to the pathological components of an individual's core traits. Therefore, treating stress differently from anxiety and depression can help us better understand the important role of stress in PSU. Studies have shown that FOMO mediated relations between psychopathology symptoms (such as depression/anxiety) and PSU severity (35, 56). However, a few studies have been conducted on the relationship between FOMO and both subjectively perceived situations and PSU. Our research explored the relationship between the subjectively perceived situation and PSU severity and found that FOMO played a mediating role between stress and PSU severity, which fills the gap in this field and further verifies and expands the I-PACE model.

FOMO and SUF acted as a chain-mediating sequence between stress and PSU severity, supporting H6. The results are consistent with the I-PACE model, proposing cognitive bias variables such as FOMO (37) and also examining SUF mediating between subjectively perceived situations (stress) and problematic Internet use (41, 42). The reason is that the influence of FOMO on stress may be manifested by the increasing and habitual frequency of using mobile phones to form PSU (57).

However, surprisingly, the mediating path of stress to PSU severity via SUF was not significant, which is inconsistent with our hypothesis (H5). The results are also inconsistent with UGT's (38) conceptualization that individuals will seek satisfaction from media in the face of negative events. The findings suggest that stress does not directly lead to PSU severity by increasing SUF. Because unlike anxiety and depression, which are mental disorders, milder amounts of stress can be positive in some situations. For example, when individuals face deadlines, the sense of pressure may improve their work efficiency, so that they can complete the task in a short time with high quality. However, FOMO may play an important role in the relationship between stress and PSU. This conceptualization supports CIUT (20). In the empirical study that proposed this theory, stress did not directly lead to excessive Internet use, but required the mediating effect of motivation (36). The increase in pressure does not directly lead to increased SUF, which is also consistent with the I-Pace model. Since stress is a subjective feeling generated by an individual toward the external environment, cognitive and emotional responses are also needed between the stress and the decision to use a smartphone (41).

The present study had several limitations. First, although using a relatively large sample of undergraduates, all participants were from a single university in China, limiting generalizability regarding other countries. Second, the design was cross-sectional, and we cannot conclude that variables such as stress "predicted" or "caused" PSU severity, as only experimental or longitudinal designs could test such a research question. Third, our measures involved self-report rather than diagnostic interviewing, and our measures of smartphone use and PSU did not assess objective smartphone use through phone logs (34, 58). Nonetheless, the present study offers important insights into psychological constructs associated with PSU severity and possible mediating variables explaining such relationships.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The ethics committee at Tianjin Normal University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

HY designed the study protocol. JF conducted data collection and conducted data management, cleaning, and analysis. BL and JF wrote the first draft of the paper. BL and HY substantially revised the manuscript. All authors contributed to the article and approved the submitted version.

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Individual Differences in Tendencies Toward Internet Use Disorder, Internet Literacy and Their Link to Autistic Traits in Both China and Germany

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Recent evidence demonstrates that Internet Use Disorder tendencies (IUD; formerly known as Internet Addiction) are associated with higher tendencies toward autistic traits. In the present study, we aimed to further explore this association between IUD tendencies and autistic traits in a large cohort of German and Chinese subjects (total $N = 1{,}524$; mostly student background) who completed the short Internet-Addiction-Test, the Autism-Spectrum-Quotient, and the Internet-Literacy-Questionnaire. Moreover, the present research also enabled us to study potential differences in the investigated variables between the Chinese and German cultures. First, the results indicated higher occurrence of IUD symptoms in China. Moreover, Chinese subjects scored significantly higher on all ILQ dimensions than German participants, with the exception of *self-regulation* where the reverse picture appeared. Second, results confirmed a positive association between IUD tendencies and autistic traits both in China and Germany, although effect sizes were low to medium (China: $r = 0.19$ vs. Germany: $r = 0.36$). Going beyond the literature, the present study also assessed individual differences in Internet Literacy and shows in how far variables such as *technical expertise, production and interaction*, *reflection and critical analysis* as well as *self-regulation* in the realm of the Internet usage influence the aforementioned association between IUD tendencies and autistic traits. Although the present study is limited by being of correlational nature it is discussed how the association between IUD tendencies and autistic traits might be explained.

Keywords: internet use disorder, internet addiction, autistic traits, internet literacy, China, Germany

INTRODUCTION

Currently, 65.6% of the world's population have access to the Internet[1]. The rapid increase in available digital technologies has brought many advantages such as access to useful information, entertainment and the possibility of exchanging texts, pictures and video messages almost anywhere at any time. In particular, it has made long-distance communication far easier and cheaper. However, in addition to these positive aspects there is increasing concern and on-going debate over whether over-usage of online channels may represent a threat to mental health (1). Indeed, excessive usage of the Internet has been associated with attention deficit hyperactivity disorder (ADHD), depression, and social phobia (2–4) as well with autistic traits [e.g., (5)]. However, whether over-usage of the Internet contributes causally to these disorders is largely unresolved.

Since the initial report of a female patient potentially being "addicted" to the online world (6), a rapidly growing body of evidence demonstrates that excessive use of the Internet could indeed represent a mental health problem [for a recent overview see the work by (7)]. In this context it is of importance to mention that the term "Internet Addiction" is heavily criticized and most researchers in the field currently prefer to use the term problematic Internet use or, in line with recent developments in ICD-11, Internet Use Disorder [IUD; e.g., (8)]: In 2013 the American Psychiatric Association (APA) added Internet Gaming Disorder as an emerging disorder in section 3 of DSM-5's appendix (9). Here, Internet Gaming Disorder as a specific form of IUD was recognized for the first time as a potential mental health problem by an official health organization. The inclusion of this scientific working term triggered more structured research in the field, with the outcome that the World Health Organization (WHO) has now even included Gaming Disorder as an officially recognized disorder in ICD-11[2]. In line with this terminology the I-PACE model by Brand et al. (10, 11) perhaps currently represents the most comprehensive model for understanding and studying IUD. The model proposes that an interaction of person, affect, cognition and execution variables can explain how individuals develop from habitual to pathological online use and it also draws on an older model by Davis (12) which makes the important distinction between unspecified (generalized) and specific IUDs. Whereas, unspecified IUD (also at the heart of this work) might function as an umbrella term describing individuals being hooked to several online channels such as online gaming and online social media, specific IUD explicitly refers to over-usage of only one online channel. The importance of distinguishing between specific and unspecific/unspecified IUDs has also been shown empirically by correlating different forms of online addictive behaviors with each other [showing only in parts high overlap (13, 14)]. In the present study, we mainly want to explore the development of unspecific IUD. Although no consensus has been reached on how to best diagnose and assess IUD, many researchers rely on measures based on an addiction background and also the compulsive-obsessive spectrum (15, 16). This all said, the term IUD itself is not officially recognized by the WHO or the APA. We explicitly mention that we use this term in the present manuscript to aim at unification of terms in the literature (in line with the aforementioned official Gaming Disorder diagnosis as a guiding light). In the realm of this discussion, it is of importance to mention that we do not want to over-pathologize everyday life behavior (17) and we also mention a recent paper by Elhai et al. (18) advocating for fairness principles in labeling Internet Use Disorders. In the present study, we mainly want to explore variables of potential interest for the development and maintenance of unspecific IUD.

Interestingly the prevalence rates of unspecific IUD are much higher in Asian countries (19), in particular higher numbers have been reported for Taiwan [around 13.8% (20)] and South Korea (around 10.7%) compared to lower numbers in European countries [around 4.4% (21, 22)]. Although clearly differences in prevalence rates across countries could be influenced by cultural background, they might also result from different measures used to assess IUD in previous studies and their respective sample characteristics. Cultural differences can be hard to detect due to the importance of samples from different countries being recruited in parallel and with matched socio-demographic variables such as age, gender and education. Nevertheless, Montag (23) has proposed that cross-cultural research can actually be an effective solution for resolving the replication crisis in psychology and the life sciences: if the same results can be observed across samples from different cultural backgrounds (especially, when the samples are also different in terms of gender and/or age, etc.), this provides compelling support for globally valid effects.

Although much research has been conducted on IUD tendencies in the last 20 years, only a few studies have attempted to link autistic traits with excessive online usage. Such a link is imaginable, because aside from links to ADHD and depression, IUD has been associated with both lower empathy and higher social anxiety (24–27). The latter psychological constructs are clearly known to play a relevant role to understand the autistic condition (28–30). Given the links between low empathy/high social anxiety and higher autistic traits—and against the background of the mentioned research—it seems likely that IUD and autistic traits could be related. Indeed, Finkenauer et al. (31) reported that strong autistic traits could predict compulsive Internet use in adults. Romano et al. (5) further found that higher levels of IUD were associated with higher levels of autistic traits and this association was particularly pronounced in participants with higher anxiety levels. Given the scarce literature on this topic, we revisited with the present research the question on the relationship between autistic traits and IUD tendencies. Please note that we investigated autistic traits in subclinical samples in the present work, but we are also referring to recent clinical work showing either elevated compulsive Internet use in patients with Autism Spectrum Disorder (ASD) rated by parents (32) or high prevalence of IUD in patients with ASD [10.8% (33)]. Of further interest, the existing studies investigating links between the autistic traits and IUD tendencies did not investigate how facets of the autistic traits are linked to individual differences

[1]https://www.internetworldstats.com/stats.htm (accessed July 22, 2021).
[2]https://icd.who.int/browse11/l-m/en#/http://id.who.int/icd/entity/1448597234 (accessed May 11, 2021).

in tendencies toward IUD. The questionnaire measuring autistic traits (the Autism Spectrum Questionnaire; AQ) can be split into facets called *social skills, attention switching, attention to details, communication* and *imagination* (34). Against the background of studying individual differences in IUD tendencies, we believe the AQ facets *social skills* and *communication* to be of particular importance. Individuals scoring high on AQ's *social skills* among others prefer to do things alone and do not like social situations. Individuals scoring high on the AQ's *communication* among others describe themselves as being recognized as impolite by others and having difficulties to keep a talk going. Although speculative, one could expect that in particular problems in *social skill/communication* areas might go along with higher IUD tendencies, because the Internet might be seen by persons with higher autistic traits as enabling communication without being directly confronted with others. This might be in ways good (as a first solution to enable communication). But when habits are formed to only live one's own life via the Internet, social withdrawal together with IUD patterns might result in pronounced negative affect.

Next to investigating the associations between IUD and autistic tendencies including various facets of autistic tendencies and going beyond the already published works in the field, we aimed to understand whether the association between IUD tendencies and autistic traits would be illuminated by different dimensions of Internet Literacy. In older work by Stodt et al. (35), it was already demonstrated that the facets of Internet Literacy *technical expertise* and *knowledge about production and interaction* in the context of Internet use are positively associated with IUD tendencies, whereas the facet of Internet Literacy called *self-regulation* is negatively associated with IUD tendencies both in China and Germany. The present work re-examines this question in new, larger samples from China and Germany, and additionally takes into account the variable of autistic traits. We hypothesized that the aforementioned variables from Internet Literacy might influence the association between IUD tendencies and autistic traits. E.g., such an association might be stronger in individuals scoring lower on *self-regulation* and higher on *production and interaction* (which might be related to systemizing tendencies in autistic traits). In particular, Internet Literacy's *production and interaction* could be a moderator variable between autistic traits and IUD tendencies, because high scorers on this facet prefer online-over offline-communication, which is something very likely to occur in individuals scoring high on autistic traits and being drawn to overuse the Internet. Beyond this, variables related to Internet Literacy could be of special importance in the study of autistic traits and IUD tendencies, because according to a work by Stodt et al. (36) teaching self-regulation skills might help Internet users to reduce problems with overuse of the Internet, although this study did not deal with autistic traits. The ILQ part of the present work is of an exploratory nature and correction procedures for multiple testing will be applied to lower the chance for false positive findings. We also revisit the finding from Romano et al. (5) reporting that the association between AQ and IUD tendencies is particularly pronounced in individuals characterized by high trait anxiety. These findings are presented in the Supplementary Material (part 2). In summary, the main rationale for investigating autistic traits in the context of IUD might be grounded in the idea that the Internet facilitates communication for individuals with higher autistic traits, as the Internet offers more ways to indirectly communicate without complex non-verbal cues (37). This in turn might in some cases result in higher tendencies toward IUD. We already provided some thoughts on possible associations between AQ's facets *social skills/communication* and IUD tendencies, but also mention the exploratory character of the present study, here.

METHODS

Participants

We invited participants from China and Germany to take part in the online surveys. Since we mainly followed a dimensional approach in the present study investigating tendencies toward IUD and autistic traits (vs. "only" focusing on clinical diagnoses), we had no exclusion criteria at the recruiting stage with respect to mental health or other medical conditions. A total of 1,524 participants (865 males, 659 females) were included in our study (please note that before getting to this final sample size, most prominently $n = 2$ individuals in the German sample and $n = 53$ individuals from the Chinese sample were excluded due to careless responding (filling in same answers >80% of the variables regarding the AQ scores, where inverted items can be found). Further reasons to be excluded were minor age, participating in the study by Stodt et al. (35) and participating twice (in the context of participating twice one data set was eliminated). Please note that this rate of careless responding is lower than what has been reported elsewhere (38, 39), but in the context of various operationalizations of careless responding such comparisons need to be considered with caution. A subgroup of the here analyzed participants of the present samples from China/Germany has been investigated in the context of molecular genetics of autistic traits and experimental research (40, 41). Moreover, an overlap exists between the present sample and the sample reported in a recent work by Sindermann et al. (30) investigating autistic traits and empathy in a German sample.

The mean-age of the whole sample was M = 22.13 years old (SD = 5.46). The whole procedure was the same in China and Germany including protocols for questionnaires analyzed in our work and the online platform, which subjects used to fill in the questionnaires.

All Chinese participants were recruited as part of the Chengdu Gene Brain Behavior Project (CGBBP) and included 929 participants (sex: 696 males, 233 females; age: M = 21.48 years, SD = 2.29, range: 18–32). The majority of subjects were university students, in detail: 91.6% of the sample. The study was approved by the local ethics committee at the University of Electronic Science and Technology of China (UESTC). All subjects provided electronic informed consent and received monetary compensation for their participation.

The 595 German subjects recruited for the current study were recruited in course of the Ulm Gene Brain Behavior Project (UGBBP) (sex: 169 males, 426 females; age: M = 23.16, SD = 8.15, range: 18–82). Participants were recruited mainly from

TABLE 1 | The reliabilities (Cronbach's α) of the short Internet Addiction Test (s-IAT), Internet Literacy Questionnaire (ILQ), and the Autism Spectrum Quotient (AQ) and their subscales in the Chinese and German samples.

Domain/variable	China	Germany	Scale range[a]
Short Internet Addiction Test (s-IAT)	0.885	0.851	12–60
sIAT Loss of control/time management	0.821	0.794	6–30
sIAT Craving/social problems	0.798	0.757	6–30
Internet Literacy Questionnaire (ILQ)			
ILQ Technical expertise	0.770	0.784	0–5
ILQ Production and interaction	0.811	0.817	0–5
ILQ Reflection and critical analysis	0.717	0.784	0–5
ILQ Self-regulation	0.754	0.783	0–5
Autism Spectrum Questionnaire (AQ)	0.674	0.725	0–50
AQ Social skills	0.711	0.709	0–10
AQ Attention switching	0.278	0.426	0–10
AQ Attention to details	0.478	0.513	0–10
AQ Communication	0.526	0.571	0–10
AQ Imagination	0.359	0.381	0–10

[a] *Scale range means the possible range of each questionnaire scale.*
Reliabilities were calculated on complete data sets provided by the participants, hence, participants who provided missing data were excluded from the calculations of reliabilities of the scales.

Ulm, Germany by advertisements and 86.6% of the participants were university students. Some questionnaire data was missing from 10 subjects in the German sample (<2%) and their missing data was handled by imputation from the mean (42). All participants provided electronic informed consent and received monetary compensation for their efforts. The German part of the study was approved by the local ethics' committee of Ulm University, Ulm, Germany.

Self-Report Measures

The online platform SurveyCoder programmed by Christopher Kannen (ckannen.com) was used to collect subjects' self-report information via the administration of the below mentioned questionnaires. Although both the CGBBP and UGBBP included a large battery of self-report questionnaires to grasp individual differences in different traits, in the present work, we focused on the Adult Autism Spectrum Quotient (AQ) (mentioned above), the short Internet Addiction Test (s-IAT) and due to the work by Stodt et al. (35) on the Internet Literacy Questionnaire (ILQ). Chinese and German versions of all questionnaires were already available [e.g., as used in (35)]. In this study, all questionnaires and their subscales revealed a good internal consistency with all Cronbach's $\alpha > 0.700$, except for AQ total scores in the Chinese sample, and several AQ subscales in both samples (**Table 1**).

Autism Spectrum Quotient (AQ)

Based on the hypothesis that autism is a dimensional rather than a categorial variable (i.e., can be measured in healthy as well as patient populations), Baron-Cohen et al. (34) developed the widely used AQ, which assessed individual differences in autistic traits in subclinical groups. It contains 50 items and all of the answers are based on a four-point Likert scale (from "definitely agree" to "definitely disagree;" with response options reduced to a scoring of 0/1 during data analysis as described in the original works). The AQ also includes items with reverse statements requiring recoding in the opposite way (from definitely disagree to definitely agree). The test-retest reliability of this questionnaire is 0.70, and the internal consistency has previously been found to be 0.82 (34). Internal consistencies for the present data are presented in **Table 1** (please see that internal consistencies of most AQ subscales are in the low area of acceptability both in China and Germany).

With respect to the analysis of AQ scores presented in the results section, a quartile categorization method was used to divide participants into three different subgroups: low AQ scoring group (25% of participants below 25th quartile), medium AQ scoring group (50% of participants between 25th and 75th quartile) and high AQ scoring group (25% of participants above 75th quartile) in both countries. Participants with the same AQ scores were included in the same group and thus the groups do not exactly comprise the stated percentages of participants. It is worth noting that we mainly focused on the low and high scoring groups to explore associations with IUD tendencies and potential interactions with Internet Literacy. For reasons of completeness, we present results (means and standard deviations) contrasting s-IAT, AQ and ILQ variables according to clinical-/screening-cut-off-scores for the ASD (43) in the **Supplementary Material**.

Short Internet Addiction Test (s-IAT)

As already mentioned, currently there is no consistent system for assessing IUD. We decided to choose the short Internet Addiction Test (s-IAT) developed by Pawlikowski et al. (44), which is a short version from Young's original IAT, which has shown excellent psychometric properties (44, 45). The s-IAT includes some of IUD's key elements such as loss of control and daily problems due to one's own excessive Internet usage. The s-IAT contains 12 items and each item is answered via a 5-point Likert scale from 1 ("never") to 5 ("very often"). The questionnaire consists of the two subscales *loss of control/time management* and *craving/social problems*, each consisting of six items. The total scores of the s-IAT theoretically can vary between 12 and 60 points. Higher scores indicate higher problems due to one's own Internet use. According to Pawlikowski et al. (44) a score higher than 30 signifies problematic Internet use and higher than 37 signifies pathological Internet use.

Internet Literacy Questionnaire (ILQ)

In order to assess individuals' competent and adequate dealing with the Internet use, we administered the Internet Literacy Questionnaire [ILQ; please find an early version of this questionnaire in Stodt et al. (36)]. According to a new exploratory factor analysis, a more economical version of the ILQ was used in this study [as presented in (35)]. The shortened version only includes 18 items of the original 24-item version, but also contains four dimensions as does the original version: *technical expertise*, *production and interaction*, *reflection and critical analysis*, and *self-regulation*. The dimension *technical expertise* measures "individuals' specialized knowledge in handling computer hard- and software as well as Internet

applications" [(35), p. 31]; the dimension *production and interaction* explores "how and why an individual uses the Internet to create own content and to interact with others". *Reflection and critical analysis* covers "individuals' ability to evaluate the credibility of online content and behavior of others as well as critically reflecting one's activities on the Internet" [(35), p. 31]. The last dimension *self-regulation* measures the ability to regulate individual's own Internet use to prevent negative consequences for daily life [(35), p. 31]. Each item is rated on a 6-point Likert scale from 0 ("strongly disagree") to 5 ("totally agree"). Please note, that in the present work the mean scores are presented for each dimension. In our samples, the dimensions' internal consistencies (Cronbach's α) were satisfying for the German and Chinese versions (see **Table 1**).

Data Analysis

First, we checked all distributions of s-IAT scores, ILQ dimension scales and AQ scores separately in China and Germany. According to (46), skewness and kurtosis values of |0–2| and |0–7|, respectively can be taken as demonstrating sufficient normality. After checking the distributions of all scales, all scales had a skewness and kurtosis $< \pm 2$, and due to our large sample size, we decided to use parametric tests (47). Histograms as well as information about skewness and kurtosis of distributions are presented in the **Supplementary Material**.

Statistical analyses were performed via the software package IBM SPSS24 (IBM, Armonk, NY, USA). The following procedures describe the overall analysis strategy with findings presented either in the following result section or the **Supplementary Material.**

Descriptive statistics were computed to describe means and standard deviations of all scales. We used *t*-tests for independent samples to examine differences between Chinese and German samples regarding the manifold Internet variables and AQ scores, and Hedge's g as an effect size. According to (48), the reported effect sizes for *t*-tests around 0.20 can be seen as small, around 0.50 as medium and around 0.80 as large. Aside from this we used Pearson's correlations to investigate associations between s-IAT scores, ILQ dimension's scores, and AQ scores in both countries and Fisher's z tests were used to assess differences between two correlations stemming from non-identical sample size (i.e., to compare correlations found in the Chinese and German samples). Moreover, gender differences in each sample and associations of all variables of interest with age were calculated, and we also ran detailed analysis for the AQ/s-IAT and AQ/ILQ correlations depending on AQ facets.

To determine the "influence" (it is a correlational study) of every variable on IUD tendencies, we conducted hierarchical regression models to predict IUD separately in China and Germany. In these two models, s-IAT total scores (not *z*-standardized) were implemented as dependent variable without focusing on its subscales. The independent variables—after being transferred into standardized z-scores—were entered in three blocks. In the first block, participants' social-demographics (e.g., age, gender) were entered. In the second block, the personality variable (AQ score) was entered to examine the influence of autistic traits after accounting for the demographic factor. In the third block, the four dimensions of the Internet Literacy questionnaire were entered as predictors. In addition, moderated regression analyses were used to extend the ILQ-s-IAT findings from Stodt et al. (35). In detail, we explored possible interaction effects between nationality and autistic traits on the one hand (not investigated in the Stodt et al. work) and between nationality and Internet Literacy on the other hand. Aside from this, we also tested whether the effects of the autistic traits on the s-IAT were moderated by Internet Literacy. Moreover, for a clearer understanding of the relationship between autistic traits and IUD tendencies, we compared the AQ total scores as well as AQ subscales' scores within different Internet user groups (e.g., non-problematic Internet users, problematic Internet users and pathological Internet users). Finally, we also considered and calculated two previously described cut-offs for the AQ: the "clinical" threshold of $\geq$32 and the "screening" cut-off of $\geq$26 (34) to investigate differences in s-IAT scores and ILQ dimensions between low autistic traits and high autistic traits.

RESULTS

Descriptive Statistics and Differences Between the Chinese and German Samples

Table 2 shows the descriptive statistics of all questionnaires used (s-IAT, ILQ, and AQ) separately for the Chinese and German samples. The results revealed significant differences in s-IAT, ILQ, and AQ scores between the two samples. The scores on the s-IAT were significantly higher in the Chinese compared to the German sample (large effect size). For Internet Literacy, Chinese subjects showed higher scores in the dimensions of *technical expertise*, *production and interaction* and *reflection and critical analysis* compared to German participants, but lower scores in the dimension *self-regulation* (here with moderate to large effect sizes). Regarding the AQ scores, Chinese subjects again showed significantly higher scores overall than the German subjects.

Occurrence of Autistic Traits

With the AQ-score quartile categorization method described in the method section, we divided our Chinese and German samples into different groups (high, average, and low scoring groups), although we primarily focused on the high and low AQ scoring groups. A total of 239 subjects in the Chinese sample and 126 subjects in the German sample were in the high AQ scoring group, and 233 subjects in the Chinese sample and 132 subjects in the German sample were in the low AQ scoring group.

Occurrence of IUD

Applying the standard cut-off scores of the s-IAT according to Pawlikowski et al. (44) resulted in different prevalence rates in the two samples for the different IUD categories. The distributions of IUD groups differed across the Chinese and German samples [$\chi^2 = 172.30$, df $= 2$, $p < 0.001$]. Problematic use of the Internet was found in 34.3% of the Chinese sample compared to only 17.8% in the German sample. Pathological use of the Internet in the Chinese sample was found in 22.4%, whereas in the German sample it was 5.5%.

TABLE 2 | Means (M) and Standard Deviations (SD) plus *t*-tests investigating all psychometric measures depending on the variable German vs. Chinese sample.

Domain/Variable	China ($n = 929$)		Germany ($n = 595$)		t	p	Hedge's g
	M	SD	M	SD			
Short Internet Addiction Test (s-IAT)							
s-IAT Total scores	32.14	8.09	25.82	7.04	$t_{(1,388.39)} = 16.12$	<0.001	0.82
s-IAT LoC/TM	17.44	4.42	15.66	4.51	$t_{(1,522)} = 7.59$	<0.001	0.40
s-IAT LoC/TM	14.70	4.30	10.16	3.31	$t_{(1,471.94)} = 23.23$	<0.001	1.15
Internet Literacy Questionnaire (ILQ)							
ILQ TE	3.15	0.99	2.44	1.12	$t_{(1,146.66)} = 12.58$	<0.001	0.68
ILQ PI	3.08	0.97	1.85	1.09	$t_{(1,160.73)} = 22.30$	<0.001	1.21
ILQ RCA	2.99	0.86	2.84	0.94	$t_{(1,183.50)} = 3.15$	0.002	0.17
ILQ SR	2.82	0.86	3.31	0.92	$t_{(1,201.94)} = -10.37$	<0.001	0.55
Autism Spectrum Quotient (AQ)							
AQ Total scores	21.71	5.82	16.90	5.68	$t_{(1,522)} = 15.89$	<0.001	0.83
AQ: High scoring group (CH = 239/G = 126)	28.88	2.81	25.23	3.23	$t_{(363)} = 11.20$	<0.001	1.23
AQ: Middle scoring group (CH = 457/G = 337)	21.84	2.24	16.51	2.60	$t_{(657.38)} = 30.26$	<0.001	2.21
AQ: Low scoring group (CH = 233/G = 132)	14.10	2.53	9.95	1.79	$t_{(345.43)} = 18.25$	<0.001	1.81

TE, technical expertise, PI, production and interaction; RCA, reflection and critical analysis; SR, self-regulation; LoC/TM, loss of control/time management; C/SP, craving/social problems; CH, China; G, Germany.

Investigating Associations Between Age/Gender and the Variables of Interest in China and Germany Separately

In line with the different ranges of age in the two cohorts (China, range 18–32; Germany, range 18–82), age differed significantly between two samples [$t_{(654.57)} = -4.91$, $p < 0.001$]. Also, there were different gender distributions found in the Chinese and German samples [China, $n_{male} > n_{female}$; Germany, $n_{male} < n_{female}$, $\chi^2 = 319.76$, df = 1, $p < 0.001$]. Therefore, we further calculated if age and gender influence Internet Literacy, autistic traits and tendencies toward IUD in both samples. For Internet Literacy, we observed significant gender differences in the Chinese sample and the German sample (see **Supplementary Tables 2, 3**). The associations between age and Internet Literacy dimensions turned out to be different in both samples. In the German sample, age was significantly correlated with all Internet Literacy dimensions, but in the Chinese sample the correlation between age and the dimension *production and interaction* was not significant (see **Supplementary Table 4**). Regarding autistic traits, the gender effect was significant [$t_{(593)} = 4.03$, $p < 0.001$] and age was significantly correlated with it [$r = -0.12$, $p = 0.003$], but only in the German sample. Regarding tendencies toward IUD, we observed that age was significantly associated with s-IAT scores, but only in the German sample [$r = -0.22$, $p < 0.001$]. For gender effects, male subjects indicated higher s-IAT scores in both samples, but these differences did not reach significance. For an overview of effects of age and gender on the relevant measured variables, please see **Supplementary Tables 2–4**.

Correlations Between IUD Tendencies, Internet Literacy, and Autistic Traits

Table 3 shows bivariate correlations with s-IAT scores and ILQ dimension scores as well as the AQ scores, divided by country. To summarize the most important findings: Both in the Chinese and German samples ILQ's *production and interaction* was positively associated with s-IAT scores, whereas ILQ's *self-regulation* was negatively associated with the s-IAT. There was no significant correlation between ILQ's *reflection and critical analysis* and s-IAT scores, neither in the German nor in the Chinese sample. *Technical expertise* significantly correlated with (some) s-IAT scores only in the German sample, and the direction of relationships was mostly divergent in the Chinese and German samples. Fisher's z tests indicated significantly different correlation strength for the s-IAT/ILQ's *technical expertise*, for the s-IAT/ ILQ's *production and interaction* and for the s-IAT/ILQ's *self-regulation* associations between the Chinese and the German sample (see **Table 3**).

The positive associations of AQ total scores with s-IAT scores were found in both countries. Moreover, the correlation between total AQ scores and s-IAT scores was weaker in the Chinese sample compared to the German sample. We also ran detailed analysis for the AQ/s-IAT correlations in the lower, middle and higher AQ scoring groups. Here it became apparent, that the correlation strength between AQ scores and s-IAT scores did not significantly differ in the lower AQ scoring groups between the Chinese sample and the German sample, except the correlation between AQ scores and s-IAT's *loss of control* dimension. In the higher AQ score group, interestingly we see opposing correlation patterns (positive associations in Germany and negative associations in China), which might explain why in the complete sample the positive AQ/s-IAT correlations are weaker in the Chinese compared to the German sample. As can be seen in **Table 2** the Chinese and German high AQ scoring groups also differed in terms of the means in each group—the Chinese sample had a significantly higher score. Therefore, it is imaginable that inverse associations between s-IAT scores and AQ scores might also appear in Germany, but only, when much higher AQ scores would be

TABLE 3 | Correlations between s-IAT scores, AQ scores and ILQ dimension scores (Pearson correlations) including Fisher's z comparison.

	China (n = 929)			Germany (n = 595)			Fisher's z		
Domain/Variable	**s-IAT Total**	**s-IAT LoC/TM**	**s-IAT C/SP**	**s-IAT Total**	**s-IAT LoC/TM**	**s-IAT C/SP**	**s-IAT Total**	**s-IAT LoC/TM**	**s-IAT C/SP**
ILQ TE	−0.004	−0.032	0.026	0.113**	0.073	0.140***	−2.23*	−2.00*	−2.18*
ILQ PI	0.184***	0.146***	0.196***	0.348***	0.251***	0.400***	−3.36***	−2.08*	−4.28***
ILQ RCA	−0.025	−0.058	0.013	−0.005	−0.010	0.002	−0.38	−0.91	0.21
ILQ SR	−0.297***	−0.366***	−0.183***	−0.536***	−0.522***	−0.430***	5.55***	3.71***	5.22***
AQ Total scores	0.192***	0.129***	0.229***	0.355***	0.222***	0.452***	−3.36**	−1.83	−4.83***
AQ: High scoring group (CH = 239/G = 126)	−0.121	−0.077	−0.147*	0.361***	0.304***	0.364***	−4.49***	−3.52***	−4.76**
AQ: Middle scoring group (CH = 457/G = 337)	0.151**	0.103*	0.179***	0.219***	0.150**	0.264***	−0.98	−0.66	−1.24
AQ: Low scoring group (CH = 233/G = 132)	0.067	0.004	0.130*	0.153	0.155	0.111	−0.79	−1.38**	0.18

*TE, technical expertise; PI, production and interaction; RCA, reflection and critical analysis; SR, self-regulation; Loc/TM, loss of control/time management; C/SP, craving/social problems; CH, China; G, Germany; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.*

reached (such as in the present Chinese sample). Crossing a certain threshold of AQ scores then might result in contrary correlation patterns (regarding the association with the s-IAT), but such observations need to be backed up by more empirical search and we do not want to over-interpret our findings in this work. Therefore, we will focus in the discussion on the robust positive associations between s-IAT scores and AQ scores observed independently in the complete Chinese and German samples.

For reasons of completeness, we also computed the correlations between ILQ dimensions and AQ scores. **Table 4** shows the results from these analysis. In the German sample, except ILQ's *reflection and critical analysis*, all other ILQ dimensions correlated significantly with the AQ scores. Positive associations could be observed between both ILQ's *technical expertise/production and interaction* and AQ scores, whereas a negative association could be observed between ILQ's *self-regulation* and AQ scores, similar to the relationship with the s-IAT. In the Chinese sample, we only found correlations in the same directions as found in the German sample for the dimensions of *production and interaction* and *self-regulation*, but the latter did not reach significance (and it was rather a null correlation, although negative). The other two dimensions, *technical expertise/reflection and critical analysis* correlated negatively with AQ scores in the Chinese sample. Fisher's z comparisons revealed that associations were significantly different in the Chinese compared to the German sample. We also compared the correlations between ILQ dimensions and the AQ scores in the lower, middle and higher AQ scoring groups. In the Chinese sample, we did not found any significant correlation in the lower, middle or higher AQ scoring groups. In the German sample, the correlation with ILQ's *production and interaction* was significant in the high AQ scoring group, and the correlations with ILQ *technical expertise/ production and interaction* were significant in the middle AQ scoring group.

Regression Analyses to Predict s-IAT Scores

We report the results of hierarchical regression analysis to predict s-IAT scores in **Table 5** for Chinese and German samples. As mentioned before, the gender effect on s-IAT scores was not significant—neither in the Chinese sample nor in the German sample. Therefore, age, AQ scores as well as ILQ dimensions were inserted as independent variables to predict s-IAT scores separately in the Chinese sample and in the German sample.

Comparing the results between German and Chinese samples, we found that age as a predictor could explain 5% of the variance in the s-IAT in the German sample, indicating that younger participants in the German sample were more likely to report more severe symptoms of IUD (model 1). Autistic traits were positively related to IUD in both the Chinese and German samples. In detail this model 2 could explain an increment of variance in the s-IAT (China: 4%, Germany: 11%). As for the influence of Internet Literacy, *production and interaction* was significantly positively related to IUD, and *self-regulation* was significantly negatively related to IUD both in the Chinese and German sample. The model 3 including Internet Literacy accounted for an additional 25% of the variance in the s-IAT in the German sample and 14% in the Chinese sample. The overall models both successfully explained the variance in IUD. More details can be found in the **Table 5**.

The Interaction Effects Between Internet Literacy and Nationality on IUD Tendencies

Based on the relationships observed between certain Internet Literacy facets/domains and s-IAT scores in both samples, we also calculated further moderated regression analyses to revisit Stodt et al.'s findings (for instance, if possible interaction effects between Internet Literacy and subjects' cultural background could predict individual differences in IUD tendencies) (35).

TABLE 4 | Correlations between Internet Literacy and autistic traits (Pearson correlations) including Fisher's z comparison.

Domain/ variable	China (*n* = 929)				Germany (*n* = 595)				Fisher's *z*			
	ILQ TE	ILQ PI	ILQ RCA	ILQ SR	ILQ TE	ILQ PI	ILQ RCA	ILQ SR	ILQ TE	ILQ PI	ILQ RCA	ILQ SR
AQ Total scores	−0.074*	0.130***	−0.075*	−0.024	0.196***	0.332***	0.034	−0.215***	−5.18***	−4.07***	−2.07*	3.69***
AQ: High scoring group (CH = 239/G = 126)	−0.081	−0.029	−0.125	−0.059	0.153	0.291**	0.022	−0.130	−2.12*	−2.96**	−1.33	0.64
AQ: Middle scoring group (CH = 457/G = 337)	−0.055	0.004	−0.074	0.019	0.180***	0.250***	0.034	−0.051	−3.35***	−3.49***	−1.61	0.92
AQ: Low scoring group (CH = 233/G = 132)	0.046	0.115	0.014	0.020	−0.053	0.062	0.006	−0.086	0.89	0.49	0.05	0.96

TE, technical expertise; PI, production and interaction; RCA, reflection and critical analysis; SR, self-regulation, CH, China; G, Germany; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 6 presents the moderation effects. As can be seen, after correction for multiple testing (Bonferroni adjustment for four interaction effects to alpha 0.05/4 = 0.0125) the only meaningful interaction is found for the ILQ's *self-regulation* dimension by country on the s-IAT. For visualization of the results, the moderator variable (*self-regulation*) was additionally split into three levels (see **Figure 1**: low, average and high *self-regulation*). The main effect of *self-regulation* on the s-IAT is similar in both the Chinese and German samples (with lower *self-regulation* going along with higher s-IAT scores), but the association appears to be stronger in the German sample. This finding is also depicted in **Figure 1**.

For reasons of completeness we also report the following: The hierarchical regression with the ILQ's *technical expertise* entered in a first block, country in a second block and the interaction term in a third block explained 14.2% of the variance [Model 1, $F_{(3,\ 1,520)} = 83.86$, $p < 0.001$]. The same procedure with the ILQ's *production and interaction* resulted in 19.2% of explained variance [Model 2, $F_{(3,\ 1,520)} = 120.53$, $p < 0.001$]. Model 3 with a focus on ILQ's *reflection and critical analysis* revealed 13.9% of explained variance [$F_{(3,\ 1,520)} = 81.66$, $p < 0.001$] and Model 4 with a focus on ILQ's *self-regulation* 27.1% of explained variance [$F_{(3,\ 1,520)} = 188.03$, $p < 0.001$].

The Interaction Effects Between the Autistic Traits and Nationality on IUD Tendencies

Following the same procedure, we were also interested to examine an interaction effect between the AQ score and country on individual differences in s-IAT scores. As can be seen in **Table 6** (Model 5) both the main effect of the AQ on the s-IAT and the main effect of country on the s-IAT were significant. Moreover, the interaction term country x AQ also was significant. In more detail and as depicted in **Figure 2**, AQ scores predict higher s-IAT scores in both countries, but the simple slope is steeper in the German sample, which is in line with the higher correlations found in the German compared to the Chinese sample (see **Figure 2**). The overall model 5 explained 19.5% of the variance [$F_{(3,\ 1,520)} = 122.92$ $p < 0.001$].

The Interaction Effects Between Internet Literacy and Autistic Traits on IUD Tendencies in the Chinese and German Samples (Presented Independently)

The relationships between the AQ and the s-IAT, as well as ILQ dimensions and the s-IAT were often significant at the bivariate level. For a deeper understanding of relationships between autistic traits, Internet Literacy, and IUD tendencies, we investigated whether Internet Literacy might moderate the association between autistic traits and IUD tendencies. As the previous hierarchical regression analysis indicated that *production and interaction* and *self-regulatio*n were significantly related to the s-IAT, and age was a significant predictor for the s-IAT in the German sample. We tested the moderated effects with these two dimensions and age, separately in the Chinese and German samples. In block 1, the independent

TABLE 5 | Results of hierarchical regression analysis for variables predicting the s-IAT in China and Germany.

	China ($n = 929$)				Germany ($n = 595$)			
Predictors	**B**	**β**	**R^2 change**	**F change**	**B**	**β**	**R^2 change**	**F change**
Model 1			0.00	0.97			0.05	30.04***
Age	−0.26	−0.03			−1.55	−0.22***		
Model 2			0.04	35.47***			0.11	76.76***
Age	−0.25	−0.03			−1.26	−0.18***		
AQ	1.55	0.19***			2.34	0.33***		
Model 3			0.14	38.00***			0.25	62.11***
Age	−0.00	0.00			−0.76	−0.11***		
AQ	1.37	0.17***			1.21	0.17***		
ILQ TE	0.37	0.05			−0.18	−0.03		
ILQ PI	1.43	0.18***			1.61	0.23***		
ILQ RCA	0.57	0.07			−0.04	−0.01		
ILQ SR	−3.02	−0.37***			−3.23	−0.46***		

*TE, technical expertise; PI, production and interaction; RCA, reflection and critical analysis; SR, self-regulation; ***$p < 0.001$.*
All independent variables (e.g., age, AQ scores, ILQ dimensions) were inserted in the model after z-standardization.

TABLE 6 | Regression coefficients of the moderated regression analyses with s-IAT total scores as dependent variable.

	Domain/Variable	***B***	***SE***	***β***	***t***	***p***
Model 1	ILQ TE	−0.03	0.25	−0.00	−0.11	0.910
	Country	−6.32	0.40	−0.37	−15.66	< 0.001
	Interaction	0.82	0.40	0.06	2.04	0.042
Model 2	ILQ PI	1.49	0.24	0.18	6.08	< 0.001
	Country	−6.32	0.39	−0.37	−16.14	< 0.001
	Interaction	0.96	0.39	0.07	2.46	0.014
Model 3	ILQ RCA	−0.20	0.25	−0.02	−0.79	0.428
	Country	−6.32	0.40	−0.37	−15.63	< 0.001
	Interaction	0.16	0.40	0.01	0.40	0.689
Model 4	ILQ SR	−2.41	0.23	−0.29	−10.34	< 0.001
	Country	−6.32	0.37	−0.37	−16.99	< 0.001
	Interaction	−1.37	0.37	−0.10	−3.68	< 0.001
Model 5	AQ	1.56	0.24	0.19	6.36	< 0.001
	Country	−6.32	0.39	−0.37	−16.17	< 0.001
	Interaction	0.94	0.39	0.07	2.41	0.016

TE, technical expertise; PI, production and interaction; RCA, reflection and critical analysis; SR, self-regulation.
All independent variables (e.g., country, AQ scores, ILQ dimensions) were inserted in the model after z-standardization.

variable, AQ was entered into the model. In block 2, the potential moderators, age, *production and interaction* and *self-regulation* were entered into the model. In block 3, the interaction terms with AQ scores were added to the model. Detailed statistical results are presented in **Table 7**. A summary of model 3: The age effect on the s-IAT was only presented in the Germany sample ($\beta = -0.12$, $p = 0.001$), the interaction of AQ × age was not significant, neither in the Chinese nor German sample. In the Chinese sample, the interaction of AQ × *self-regulation* was significant ($\beta = 0.06$, $p = 0.038$) whereas in the German sample, the interaction of AQ × *production and interaction* was significant ($\beta = 0.08$, $p = 0.011$). Beyond that robust associations between the AQ and s-IAT scores, but also between ILQ's *production and interaction*/ILQ's *self-regulation* scores and s-IAT scores appeared in both China and Germany.

In order to give insights into associations between facets of the AQ and s-IAT scores, we provide correlation patterns in the **Supplementary Table 5**. Moreover, we present in **Table 8** a regression model conducted in the same fashion as the regression model in **Table 7** with the exception that in **Table 8** the facets of the AQ have been included instead of AQ total scores.

As can be seen in **Table 8** in model 3 in particular the AQ facet called *communication* predicts s-IAT scores both in the Chinese sample and German sample. Beyond that in both countries a robust interaction between AQ's *social skills* and ILQ's *production*

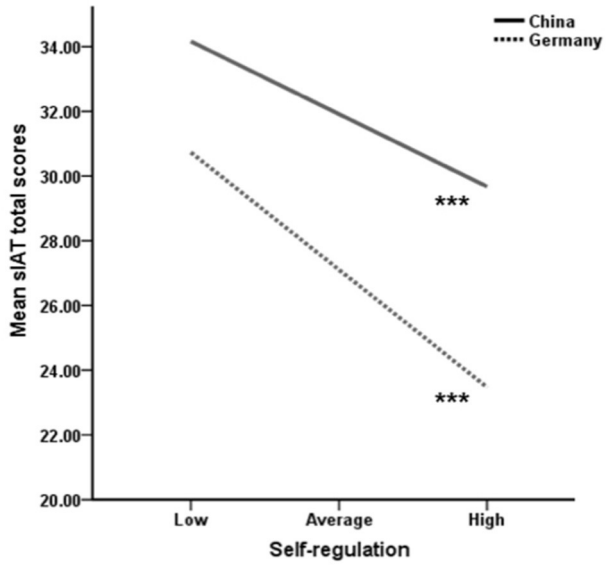

FIGURE 1 | Simple slopes to illustrate the interaction effect between *self-regulation* and country on s-IAT total scores. Note: *** indicates that the s-IAT change from low to high *self-regulation* was significant ($p < 0.001$).

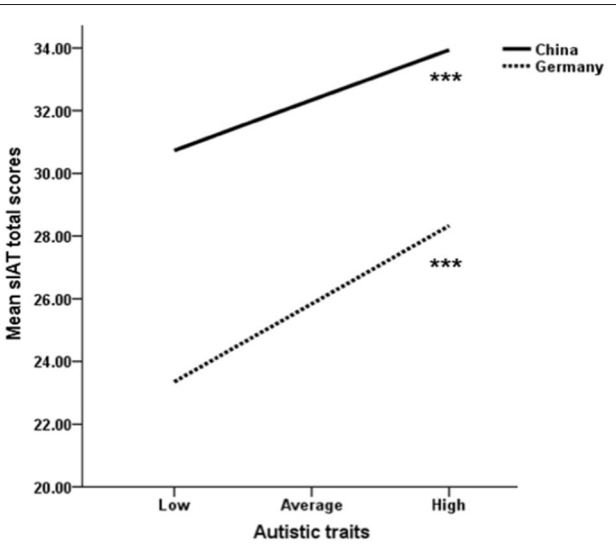

FIGURE 2 | Simple slopes to illustrate the interaction effect between autistic traits and country on the s-IAT total scores. Note: *** indicates that the s-IAT change from low to high autistic traits was significant ($p < 0.001$).

and interaction on s-IAT scores was visible (China, $\beta = -0.12$, $p = 0.002$; Germany, $\beta = 0.10$, $p = 0.034$; see **Figure 3**).

DISCUSSION

This study's goal was to further investigate individual differences in tendencies toward unspecific IUD, and their link to Internet Literacy and autistic traits in two large samples stemming from different cultural backgrounds (China and Germany). Before discussing the results in light of our proposed hypothesis, we should emphasize that in line with previous literature, we observed that IUD levels differed significantly between the Chinese and German samples (26). Against the background of s-IAT scores (assessing IUD) 22.4% of the Chinese sample reported pathological use of the Internet, whereas only 5.5% of the German sample did so. This result is in line with former studies reporting that the prevalence of IUD is higher in Eastern than Western civilizations (rough estimate) and might reflect cultural differences (49). Cultural differences were also observed for the Internet Literacy variable. The current results indicated higher *technical expertise*, higher *production and interaction*, higher *reflection and critical analysis* as well less *self-regulation* skills in the Chinese sample compared to the German sample. These results were in line with observations of a previous study except the dimension *reflection and critical analysis*. In the earlier work by Stodt et al. (35) in the German sample higher scores on this scale compared to the Chinese sample were reported. Regarding higher scores in the ILQ variables *technical expertise/production and interaction* in the Chinese compared to the German sample we think this might reflect a keen focus in Chinese education on technical skills, but this idea needs further empirical backup.

In general, the results of the present work confirm earlier observations that higher autistic traits are linked to higher tendencies toward IUD (5, 31). In the present study, positive correlations between autistic traits and IUD tendencies were found in both the Chinese and German sample, with correlations of 0.19 (China) and 0.36 (Germany), indicating robust although low to medium effect sizes. The analysis of AQ facets revealed that higher communication problems are in particular related to higher IUD tendencies (see **Supplementary Table 5**). As this is (according to our best knowledge) the first study also reporting associations between AQ's facets and s-IAT scores, these findings need to be replicated and should be seen as preliminary. We earlier mentioned the exploratory character of our study, here.

Stodt et al. (35) previously also investigated the association between Internet Literacy and IUD in independent samples of both Chinese and German subjects using comparable methods as in the present work regarding the assessment of these variables (administration of the ILQ's self-report and the s-IAT measures). They observed in both their Chinese and German samples that ILQ's *technical expertise/production and interaction* were positively linked to IUD tendencies. Therefore, we also wanted to revisit these findings again. In the present study again positive association between ILQ's *technical expertise* and IUD tendencies could be observed in the German sample while this association was close to zero in China. In the present study again positive associations between ILQ's *production and interaction* and IUD tendencies could be observed in both countries. Hence, this finding is very robust. High scores on this facet describe individuals who state that the Internet is a good place to make contacts and to interact with others, even preferable to the offline world. Individuals with high ILQ's *production and interaction* also mention that they find it easier to be creative online and formulate an opinion online compared to the offline world. It is very

TABLE 7 | Regression coefficients of the moderated regression analyses with s-IAT total scores as a dependent variable, AQ total scores, age and ILQ dimensions as independent variables.

Domain/ Variable	China (n = 929)				Germany (n = 595)			
	B	β	R^2 change	F change	B	β	R^2 change	F change
Model 1			0.04	35.53***			0.13	85.36***
AQ	1.56	0.19***			2.50	0.35***		
Model 2			0.13	48.41***			0.28	93.27***
AQ	1.26	0.16***			1.20	0.17***		
Age	0.05	0.01			−0.75	−0.11**		
ILQ PI	1.76	0.22***			1.55	0.22***		
ILQ SR	−2.67	−0.33***			−3.24	−0.46***		
Model 3			0.01	2.08			0.01	3.21*
AQ	1.24	0.15***			1.01	0.14***		
Age	0.02	0.00			−0.84	−0.12**		
ILQ PI	1.75	0.22***			1.49	0.21***		
ILQ SR	−2.67	−0.33***			−3.22	−0.46***		
AQ × age	0.23	0.03			−0.05	−0.01		
AQ × ILQ PI	−0.30	−0.04			0.53	0.08*		
AQ × ILQ SR	0.52	0.06*			−0.32	−0.05		

*PI, production and interaction; SR, self-regulation; *p < 0.05; **p < 0.01; ***p < 0.001.*
All independent variables (e.g., age, AQ scores, ILQ PI/SR) were inserted in the model after z-standardization.

straightforward to propose that high scores on this facet would go along with higher autistic traits, although we did not set up such a hypothesis. Indeed, results from **Supplementary Table 6** supports this notion with positive associations between ILQ's *production and interaction* and AQ scores both in China and Germany. Furthermore, our moderated analyses at least for the German sample provide support for the idea that higher autistic traits might lead to a greater preference for online interactions (hence *production and interaction*) and thereby result in a greater risk of developing IUD. We also mention that the current study showed significant differences in the strength of effects sizes regarding all Internet Literacy dimensions and IUD tendencies associations between the Chinese and German samples (lower in China compared to Germany), except the association between ILQ's *reflection and critical analysis*. Beyond these insights, it needs to be mentioned that ILQ's *self-regulation* was negatively associated with IUD in China and Germany.

The current study has some limitations, which should be mentioned. First of all, the present work relied on self-report questionnaires and answers given may be influenced by tendencies to answer in a socially desirable manner. Second, we did not investigate clinical samples in China and Germany and findings might differ in individuals diagnosed with autism, even though the dimensional approach to understand psychopathological phenotypes is well-established in a range of psychopathological conditions. Third, samples recruited in China and Germany differ in some socio-demographic variables. Hence it is not clear whether differences in both samples are due to culture or other variables. Socio-demographic variables could have been also assessed beyond age, gender and education, but our study is limited by a focus on rather young participants (mostly student background). Next, comorbid other relevant psychiatric symptoms such as depressive tendencies (but see some analysis in the **Supplementary Material** (part 2) regarding depressive tendencies) have not been taken into account in the present work. Finally, our findings are only of correlational nature and no specific causality can be derived. We also want to mention recent discussions about the best way to analyze facets of the AQ: English et al. (50) provided evidence to analyze the AQ with a three factor solution. Of note, as the present work in particular focused on the AQ facets *social skills* and *communication*—and we here observed reasonable internal consistencies—we stuck with our analysis method (taking into account five facets although some of them showed weak psychometrics). But again, a three factor solution as proposed by English et al. (50) with the factors *social skill, patterns/details* and *communication/mindreading* would be also interesting. Finally, we mentioned earlier that the ILQ findings should be seen as of preliminary nature.

In summary, we have provided further support for an association between higher autistic traits and higher tendencies toward IUD. As demonstrated from our moderation analysis, this association might be explained by autistic individuals favoring online vs. offline social interactions providing them with a more secure and comfortable environment in which to communicate (at least this is supported by the German data). A negative side effect of such an adaptation could however be the development of unhealthy online behaviors.

TABLE 8 | Regression coefficients of the moderated regression analyses with s-IAT total scores as dependent variable, AQ subscales' scores and ILQ dimensions as independent variables.

Domain/ Variable	China (n = 929)				Germany (n = 595)			
	B	β	R^2 change	F change	B	β	R^2 change	F change
Model 1			0.05	9.47***			0.15	21.34***
AQ SS	0.37	0.05			0.58	0.08		
AQ AS	0.60	0.07*			0.86	0.12**		
AQ AD	−0.03	−0.00			0.11	0.02		
AQ CO	1.30	0.16***			1.85	0.26***		
AQ IM	0.08	0.01			0.26	0.04		
Model 2			0.13	71.63***			0.25	124.83***
AQ SS	−0.04	−0.00			−0.05	−0.01		
AQ AS	0.22	0.03			0.85	0.12***		
AQ AD	0.17	0.02			0.21	0.03		
AQ CO	1.30	0.16***			0.86	0.12**		
AQ IM	0.33	0.04			0.10	0.01		
ILQ PI	1.74	0.21***			1.64	0.23***		
ILQ SR	−2.70	−0.33***			−3.29	−0.47***		
Model 3			0.02	2.53**			0.02	1.63
AQ SS	−0.02	−0.00			−0.36	−0.05		
AQ AS	0.27	0.03			0.94	0.13***		
AQ AD	0.13	0.02			0.22	0.03		
AQ CO	1.28	0.16***			0.73	0.10*		
AQ IM	0.27	0.03			0.07	0.01		
ILQ PI	1.72	0.21***			1.62	0.23***		
ILQ SR	−2.68	−0.33***			−3.31	−0.47***		
AQ SS × ILQ PI	−0.92	−0.12**			0.60	0.10*		
AQ SS × ILQ SR	0.18	0.02			−0.11	−0.02		
AQ AS × ILQ PI	0.31	0.04			−0.23	−0.03		
AQ AS × ILQ SR	0.07	0.01			−0.17	−0.02		
AQ AD × ILQ PI	−0.63	−0.08*			0.08	0.01		
AQ AD × ILQ SR	−0.28	−0.03			0.02	0.00		
AQ CO × ILQ PI	0.71	0.09*			0.05	0.01		
AQ CO × ILQ SR	0.32	0.04			−0.31	−0.05		
AQ IM × ILQ PI	−0.20	−0.03			0.27	0.04		
AQ IM × ILQ SR	0.22	0.03			0.07	0.01		

AQ facets: SS, social skills; AS, attention switching; AD, attention to details; CO, communication; IM, imagination; ILQ facets: PI, production and interaction, SR, self-regulation; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

All independent variables (e.g., AQ facets, ILQ PI/SR) were inserted in the model after z-standardization.

CONCLUSION

The present study revisited previous findings on IUD tendencies and autistic traits (5, 31), additionally taking into account interaction effects between ILQ domains and autistic traits in China and Germany. The association between IUD tendencies and autistic traits in parts were moderated by facets of Internet Literacy.

The prevalence of IUD was higher in the Chinese compared to the German sample, which is in line with previous studies. In addition, higher autistic traits were linked to higher tendencies toward IUD in both the Chinese and German samples and this link is moderated by Internet Literacy domains such as *production and interaction* and *self-regulation* (with different observations in China and Germany). In so far, the present study provides evidence that cultural differences may also play a role in the development and maintenance of IUD. Against the background of the correlational nature of the present study, next steps would be to run longitudinal studies to get insights into causality between variables such as IUD tendencies and autistic traits. Such an approach would be interesting to be conducted also in samples with different cultural background (such as from China and Germany) to

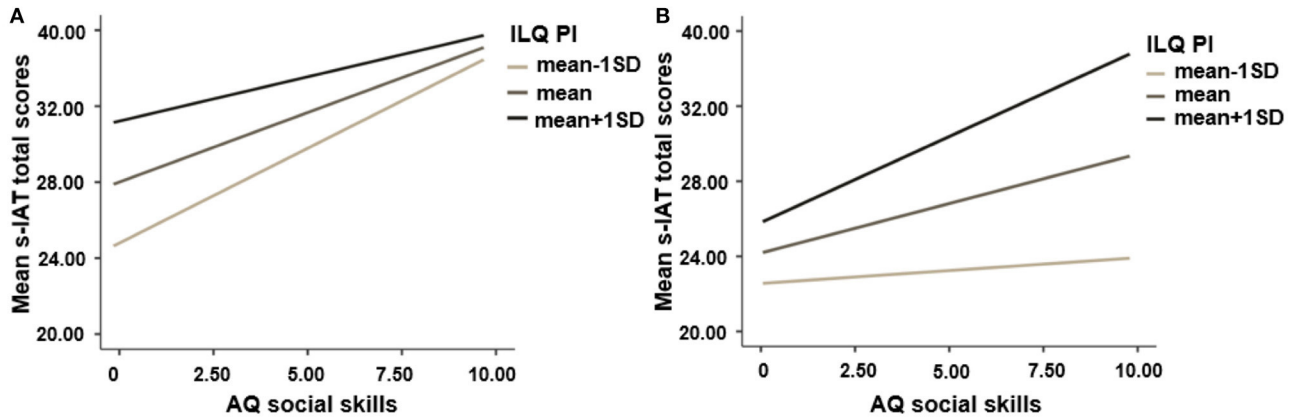

FIGURE 3 | Simple slopes to illustrate the interaction effect between social skills of autistic traits and Internet Literacy *production and interaction* dimension on s-IAT total scores. **(A)** Chinese sample; **(B)** German sample.

investigate if same causality applies perhaps even independent of cultural aspects.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, upon scholarly request.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the ethic committees at UESTC and Ulm University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CM and YZ designed the present study. YZ wrote the first version of the manuscript and conducted the statistical analysis. CS double checked the statistical analysis. CM, BB, KMK, and CS critically revised the manuscript and approved the final version of the manuscript for submission. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyt.2021.638655/full#supplementary-material

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The Effect of College Students' Adaptability on Nomophobia: Based on Lasso Regression

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Smartphones can improve our lives, but also consume our lives. It is known that problematic mobile phone use, such as nomophobia, can lead to some mental health problems. So far, psychological factors behind nomophobia were yet to be fully discovered. Previous studies showed that individuals' adaptability was closely related to nomophobia. However, adaptability was a complex construct that contains various components, and it was unclear whether these components contributed equally to nomophobia. This study investigated 678 college students by using Chinese versions of the nomophobia questionnaire, mobile phone addiction tendency scale, and freshmen adaptability scale. Lasso regression was used to further explore the key factors that could affect nomophobia. Model results showed that the value of λ+1se was [0.303, 0.423] at the minimum mean squared error in the training data. Emotional adaptability significantly predicted the fear of being unable to access information ($\beta = -0.022$, $p < 0.001$), losing convenience ($\beta = -0.067$, $p < 0.001$), and losing Internet connection ($\beta = -0.003$, $p < 0.01$) after λ+1se was included in the testing data, and the R^2 were 0.496, 0.483, and 0.493. Homesickness adaptability significantly predicted the fear of losing contact ($\beta = -0.056$, $p < 0.05$), and R^2 was 0.508. In addition, similar results were obtained by using datasets of mobile phone addiction and adaptability. Therefore, we concluded that the emotional adaptability has an important effect on nomophobia. Additionally, we also found that homesickness adaptability has an important role in predicting fear of losing contact.

Keywords: mobile phone addiction, nomophobia, adaptability, machine learning, Lasso regression

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INTRODUCTION

Adaptability is an important psychological trait for college students (1). It refers to a soft skill that can help people to rapidly learn skills and behaviors in response to changing circumstances (2). Regina et al. (3) found that adolescents' adaptability facilitates positive wellbeing when they need to adapt to a rapidly changing environment.

Quintas-Hijos et al. (4) examined college students' adaptability and its consequences since it significantly influences the development of college students. Yang et al. (5) also found that there was a significant association between adaptability and coping style. Xie et al. (6) also

showed similar findings that students' adaptability in school could significantly predict their academic performance. Chen et al. (7) discovered that adaptability could significantly influence college students' life satisfaction and mental health symptoms, such as anxiety and depression (8). Altogether, adaptability is a possible contributing factor that affects development of early adulthood (9, 10).

Researchers have extensively studied the associations between adaptability and mobile phone use and they found that there was a close link between them (11). Meghan et al. (12) found that adaptability was an important predictor for social media addiction by using a traditional regression model. Other studies also supported this conclusion by using different datasets in different studies (13, 14).

There were many studies about mobile phone addiction (15), but no universally acknowledged criterions or symptoms for mobile phone addiction in DSM-V or ICD-11 (16, 17). Gradually, the concept of mobile phone addiction was discarded (18) and replaced by problematic mobile phone use (PMPU) (19). Recently, nomophobia, a newer PMPU-related notion, has been proposed based on the Fear of Missing Out Theory (FOMO) (20–22). It was defined as distress or anxiety when an individual loses access to their mobile phone, such as from battery drain or inability to use while in class (23, 24). It has been widely studied as a by-product of emerging technologies (25).

There were many studies about adaptability and mobile phone addiction (11), but only one study was about adaptability and nomophobia. A study of Bragazzi et al. (26) discovered that individual's maladaptive coping style could significantly predict nomophobia. Theoretically, the relationship between nomophobia and adaptability could be explained by the Interaction of Person-Affect-Cognition-Execution (I-PACE) model.

The Interaction of Person-Affect-Cognition-Execution (I-PACE) Theory (27) described the psychological and neurobiological processes underlying the development of mobile phone overuse, such as gaming, gambling, viewing pornography, buying shopping, and social-networking addictions. A great number of studies had supported I-PACE in modeling mobile phone overuse (28). I-PACE proposed that many factors could affect mobile phone overuse (e.g., mobile phone addiction and nomophobia), including biological factors (e.g., gender), personality factors, and psychological factors (e.g., adaptability). The present study, therefore, was carried out to examine the extent to which adaptability affected nomophobia by establishing the I-PACE model.

In general, many investigators have used ordinary least square (OLS) to estimate the relationship among variables in the regression model (29). The proposed method provides the most accurate and unbiased estimation by the sum of the minimum residuals (30), but it also has some shortcomings, such as overfitting results and poor predictions on future observations (31). In fact, those problems are even more serious when there are many predictors in a regression model (29, 32, 33).

Regularization methods, such as ridge regression and Lasso regression, in machine learning have been used to make up for the limitations of OLS. Algorithms in machine learning are divided into supervised and unsupervised algorithms (34). In unsupervised learning, the machine uses unlabeled data and learns by itself without any supervision (35). It can be further grouped into clustering and association (36). In supervised learning, the machine learns under supervision, and it has training data and testing data (37). The computer learns and chooses an optimal model by using training data and then gets the final results by fitting the optimal model with testing data. Supervised learning is divided into classification and regression (34). Lasso regression (32, 38) used in this study is a kind of regression that used least angle regression algorithm instead of least squares.

Least absolute shrinkage and selection operator (Lasso) (38) is one of the best regularization methods to deal with overfitting problems and get more accurate results (39). The proposed method can shrink the small coefficient toward zero by adding a penalty term in the process of model estimation (40). Consequently, it can obtain higher model prediction accuracy and model generalizability (32). Moreover, Lasso regression can help researchers to perform variable selection and help them to get more concise and more efficient models (32, 41). This method plays an important role in the construction and perfection of psychological theory. The Lasso formula can be described as follows.

$$\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\left|\beta_j\right|=RSS+\lambda\sum_{j=1}^{p}\left|\beta_j\right|$$

where $i = 1, \ldots, n$ denotes the number of the observations; $j = 1, \ldots, p$ denotes the number of the predictors; β_0 denotes the intercept in the linear regression model; β_j denotes the regression coefficient about the jth predictors and response; λ denotes the penalty parameter.

Present Study

The main purpose of this study was to explore the effect of adaptability on nomophobia. Moreover, both adaptability and nomophobia were multidimensional. Cao and Mao (2) proposed a six-dimension construct for adaptability, and Ren et al. (42) proposed that nomophobia contained four dimensions. How different dimensions of adaptability could affect the different nomophobia facets was a main issue to discuss in this study. We believed that individuals' emotional cognition could affect their decisions and behaviors, and then resulted in some problematic mobile phone use behaviors according to the I-PACE (43). Therefore, we assumed that individuals' gender and adaptability could affect nomophobia.

Researchers usually used ordinary least square to explore the relationships between variables in previous studies. It led to model-data overfit and multi-collinearity when many predictors were included in models. Therefore, the Lasso regularization method in machine learning was conducted in our empirical study to explore the key predictors that affect nomophobia.

Aims

Our primary aim was to explore the key factors (dimensions) of adaptability that could predict nomophobia by using the

Lasso regularization method based on a sample of Chinese college students. Then, we re-examined the role of those key dimensions in the relationship between mobile phone addiction and adaptability. We hypothesized that there were significant associations between nomophobia and adaptability, and emotional adaptability and homesickness adaptability could significantly predict nomophobia. The current study examined the extent to which individuals experience nomophobia and sees whether our finding is generalizable.

METHODS

Participants and Procedure

We recruited 678 volunteers to complete a 5–8-min survey through online and paper-and-pencil questionnaires in 2019 before the outbreak of COVID-19. Both online and offline surveys were used in this study. Fifty participants completed their questionnaires as a paper-and-pencil version in a classroom. The other participants completed online surveys through the Wen Juan Xing App (https://www.wjx.cn). Before data analysis, measurement invariance was supported between the paper-and-pencil dataset and the online dataset by a multi-group confirmatory factor analysis. Consequently, those two datasets had been analyzed together.

Before we analyzed our data, five participants (0.74%) were removed because of missing more than 20 items. Missing values were imputed by expectation maximization (EM) method due to the fact that missing values were missing completely at random (MCAR). A total of 673 participants were included in the data analysis (20.5% men, 79.5% women; $M = 20.4$, $SD = 1.3$). One hundred sixty students were freshmen, as well as 196 sophomores, 210 juniors, 71 seniors, and 36 post-baccalaureates. The study involving human participants was reviewed and approved by the ethics committee of Tianjin Normal University in China (Ethical review number: XL2020-08). The participants provided their written informed consent to participate in this study.

Measures

Instruments

Chinese Version of the Nomophobia Questionnaire

Based on the original nomophobia questionnaire of Ren et al. (42) and Yildirim and Correia (44) revised the Chinese version of the nomophobia questionnaire (NMP-C). In that study, exploratory structural equation modeling (ESEM) and item response model (IRT) were used to perform item selection and to explore the structure of nomophobia scale, and confirmatory factor analysis (CFA) was conducted to verify this structure. The NMP-C contains 16 items and four dimensions, including fear of being unable to access information, losing convenience, losing contact, and losing Internet connection. It used a seven-point Likert scale, ranging from 1 ("Not meet at all") to 7 ("Completely in conformity with") (42). Cronbach's α for the whole scale was 0.931 and that for the four dimensions ranged from 0.789 to 0.901; the ω of the whole scale was 0.931 in this study.

Mobile Phone Addiction Tendency Scale

We wanted to re-examine the role of those key dimensions in the relationship between mobile phone addiction and adaptability. So, we also used Mobile Phone Addiction Tendency Scale (MPATS) to improve the accuracy and reliability of results. MPATS was developed by Xiong et al. (45). The MPATS is composed of 16 items and four factors, including withdrawal symptoms, salience, social comfort, and mood changes. It was a five-point Likert scale, ranging from 1 ("Extremely inconsistent") to 5 ("Extremely consistent"). Jang and Bai (46) found that the Cronbach's α of scale was 0.830 and that for the four dimensions ranged from 0.810 to 0.920. Cronbach's α for the whole scale was 0.896 and that for the four dimensions were from 0.615 to 0.803 in this study. The ω of the whole scale was 0.897 in this study.

The Freshmen Adaptability Scale

The freshmen adaptability scale was originally developed for freshmen by Cao and Mao (2), and it was revised by Luo (47). The scale was shown to be both valid and reliable across settings [e.g., (48)]. The scale has 24 items, including learning, professional, homesickness, interpersonal, emotional, and economical adaptability. It was a six-point Likert scale, ranging from 1 ("Extremely inconsistent") to 6 ("Extremely consistent"). Cronbach's α for the whole scale was 0.815 and that for the four dimensions ranged from 0.720 to 0.837 in this study; the ω of the whole scale was 0.771.

Software and Statistical Methods

SPSS26.0 was used for data preprocessing and internal consistency analysis. Traditional multiple linear regression and sparse linear regression model was conducted in R-4.0.5 (49). OLS was used in traditional regression model, and the Lasso shrinkage algorithm in Machine Learning was used in sparse linear regression model. At first, the sample was divided into two halves by using function of sample randomly, one-half as a training dataset ($n = 336$) and the other as a testing dataset ($n = 337$). Next, training data were conducted to get the best λ by using the cross-validation approach, and then the best λ was taken into the testing data to get the final Lasso regression by using *glmnet* packages. Finally, the *covTest* package was used to test the significance of coefficients in Lasso regression.

RESULTS

Correlations Between Nomophobia and Adaptability

Table 1 shows the descriptive statistics of nomophobia and adaptability among our participants. Results showed that fear of being unable to access information showed a mean (M) of 4.162, $SD = 1.272$ (maximum of seven), fear of losing convenience showed $M = 4.215$, $SD = 1.460$, fear of losing contact showed $M = 4.221$, $SD = 1.488$, and fear of losing Internet connection showed $M = 3.759$, $SD = 1.502$. Besides that, learning adaptability showed $M = 3.782$, $SD = 0.923$ (maximum of six), professional adaptability showed $M = 4.014$, $SD = 1.097$, homesickness adaptability showed $M = 3.232$, $SD = 1.117$, interpersonal adaptability showed $M = 4.413$, $SD = 0.895$,

TABLE 1 | Descriptive statistics for the nomophobia and adaptability.

Variable	Total sample ($n = 673$)	
	M	*SD*
Unable to access information	4.162	1.272
Losing convenience	4.215	1.460
Losing contact	4.221	1.488
Losing Internet connection	3.759	1.502
Learning adaptability	3.782	0.923
Professional adaptability	4.014	1.097
Homesickness adaptability	3.232	1.117
Interpersonal adaptability	4.413	0.895
Emotional adaptability	3.987	1.005
Economical adaptability	4.157	1.020

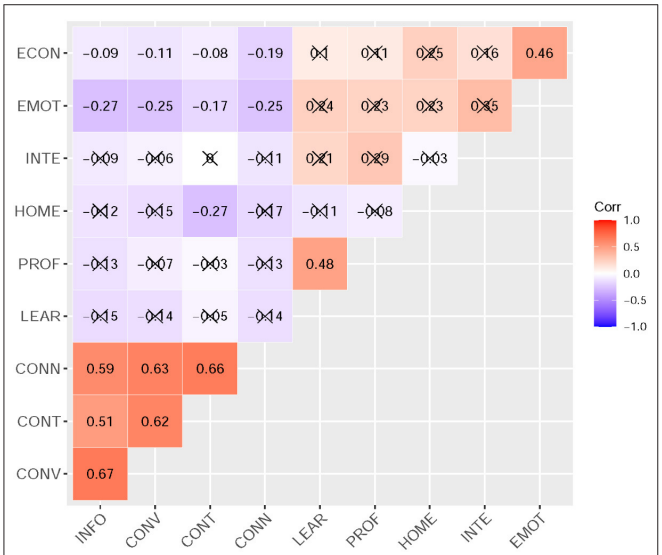

FIGURE 1 | Correlations between nomophobia with adaptability. INFO, unable to access information; CONV, losing convenience; CONT, losing contact; CONN, losing Internet connection; LEAR, learning adaptability; PROF, professional adaptability; HOME, homesickness adaptability; INTE, interpersonal adaptability; EMOT, emotional adaptability; ECON, economical adaptability.

emotional adaptability showed $M = 3.987$, $SD = 1.005$, and economical adaptability showed $M = 4.157$, $SD = 1.020$.

Pearson correlation matrix was conducted to analyze the correlations between variables. Bivariate correlations for summed scores were reported in **Figure 1**. There were significant correlations between homesickness adaptability and fear of being unable to access information ($r = -0.123$, $p < 0.01$), losing convenience ($r = -0.152$, $p < 0.001$), losing contact ($r = -0.274$, $p < 0.001$), and losing Internet connection ($r = -0.168$, $p < 0.001$). Results also showed that emotional adaptability negatively associated with being unable to access information ($r = -0.267$, $p < 0.001$), losing convenience ($r = -0.253$, $p < 0.001$), losing contact ($r = -0.172$, $p < 0.001$), and losing Internet connection ($r = -0.254$, $p < 0.001$). Besides that, learning adaptability and economical adaptability were negatively related to fear of being unable to access information ($r = -0.146$, $p < 0.001$; $r = -0.094$, $p < 0.05$), losing convenience ($r = -0.136$, $p < 0.001$; $r = -0.111$, $p < 0.01$), and losing Internet connection ($r = -0.140$, $p < 0.001$; $r = -0.190$, $p < 0.001$). Meanwhile, professional adaptability and interpersonal adaptability were related to the level of fear of being unable to access information ($r = -0.132$, $p < 0.01$; $r = -0.191$, $p < 0.05$) and losing Internet connection ($r = -0.130$, $p < 0.01$; $r = -0.110$ $p < 0.01$). Other concrete results can be seen in **Figure 1**.

Gender Difference in Nomophobia and Adaptability

t-test was conducted to evaluate the association between gender and our study variables. Results showed that gender was significantly associated with fear of being unable to access information $t_{(671)} = -2.655$, $p < 0.01$ (Men: $M = 3.906$, $SD = 1.223$; Women: $M = 4.228$, $SD = 1.278$), losing convenience $t_{(671)} = -3.288$, $p < 0.01$ (Men: $M = 3.853$, $SD = 1.353$; Women: $M = 4.308$, $SD = 1.474$), and losing contact $t_{(671)} = -3.521$, $p < 0.001$ (Men: $M = 3.827$, $SD = 1.449$; Women: $M = 4.323$, $SD = 1.483$). However, there was no difference in the level of fear of losing Internet connection $t_{(671)} = -1.142$, $p = 0.158$ (Men: $M = 3.598$, $SD = 1.478$; Women: $M = 3.800$, $SD = 1.507$).

In addition, we also found that there was a significant association between gender and homesickness adaptability $t_{(671)} = 5.047$, $p < 0.001$ (Men: $M = 3.652$, $SD = 1.070$; Women: $M = 3.124$, $SD = 1.104$) and economical adaptability $t_{(671)} = -2.480$, $p < 0.05$ (Men: $M = 3.965$, $SD = 1.043$; Women: $M = 4.206$, $SD = 1.010$).

Traditional Multiple Regression Model of Adaptability on Nomophobia

The collinearity diagnostics was used to test multicollinearity among the independent variables before the traditional multiple regression. The VIF values [1.079, 1.519] supported that there was no multicollinearity. Traditional regression, which is based on least squares algorithm, was chosen to explore the factors that could predict nomophobia. Gender was dummy coded before the regression analysis. Gender and six dimensions of adaptability were taken as predictors, and four dimensions of nomophobia were response variables. **Table 2** shows four traditional regression models.

Results about four traditional regression models in **Table 2** showed that emotional adaptability was negatively associated with four dimensions of nomophobia ($\beta \epsilon [-0.190, -0.316]$, $p < 0.01$). Homesickness adaptability was negatively associated with the fear of losing convenience ($\beta = -0.123$, $p < 0.05$), fear of losing contact ($\beta = -0.322$, $p < 0.001$), and fear of losing Internet connection ($\beta = -0.162$, $p < 0.01$). In addition, learning adaptability was negatively associated with the fear of losing convenience ($\beta = -0.159$ $p < 0.05$). Gender was positively associated with the fear of losing convenience ($\beta = 0.341$, $p < 0.05$) and losing contact ($\beta = 0.294$, $p < 0.05$).

TABLE 2 | Traditional multiple regression model about nomophobia and adaptability.

Predicted variables	Response variables			
	Access information	Losing convenience	Losing contact	Losing Internet connection
Intercept	5.579***	5.535***	5.290***	6.349***
Gender	0.226	0.341*	0.294*	0.111
Learning adaptability	−0.100	−0.159*	−0.065	−0.126
Professional adaptability	−0.073	−0.001	−0.033	−0.078
Homesickness adaptability	−0.086	−0.123*	−0.322***	−0.162**
Interpersonal adaptability	0.029	0.067	0.085	−0.022
Emotional adaptability	−0.229***	−0.316***	−0.190**	−0.228***
Economical adaptability	0.045	0.008	0.050	−0.113

****p < 0.001, **p < 0.01, and *p < 0.05.*

TABLE 3 | Lasso regression model of nomophobia and adaptability.

Predicted variables	Response variables			
	Access information	Losing convenience	Losing contact	Losing Internet connection
Intercept	4.252***	4.481***	4.401***	3.771***
Gender	–	–	–	–
Learning adaptability	–	–	–	–
Professional adaptability	–	–	–	–
Homesickness adaptability	–	–	−0.056*	–
Interpersonal adaptability	–	–	–	–
Emotional adaptability	−0.022***	−0.067***	–	−0.003**
Economical adaptability	–	–	–	–

****p < 0.001, **p < 0.01, and *p < 0.05.*

Lasso Regression Model of Adaptability on Nomophobia

Traditional multiple regression results showed that the nomophobia was related to the learning adaptability, homesickness adaptability, emotional adaptability, and gender. Therefore, Lasso regression based on least angle regression algorithm was used to confirm the key factors that could predict the nomophobia by using R package *glmnet*.

Gender and six dimensions of adaptability were taken as predictors, and four dimensions of nomophobia were response variables. Therefore, there were four Lasso regression models for this section, and they are reported in **Table 3**. The values of λ were 0.001, 0.020, and 0.045 and λ+1se values were 0.338, 0.303, and 0.423 at the minimum mean squared error (MSE) through the training dataset when response data were from fear of being unable to access information, losing convenience, and losing Internet connection. λ+1se was considered to be the best λ because the penalty power of λ was too small to solve the problem of overfitting. Finally, results showed that emotional adaptability could predict fear of being unable to access information ($\beta = -0.022$, $p < 0.001$), fear of losing convenience ($\beta = -0.067$, $p < 0.001$), and fear of losing Internet connection ($\beta = -0.003$, $p < 0.01$), and it was accepted by *covTest* package; R^2 values were 0.496, 0.483, and 0.493, and *MSE* values were 1.391, 2.046, and 2.184. λ+1se was 0.345 when responses were from fear of losing contact, and the retained variable was homesickness adaptability ($\beta = -0.056$, $p < 0.05$); R^2 was 0.508, *MSE* was 2.032, and the results can be seen in **Table 3**.

The Lasso Regression Model of Adaptability on Mobile Phone Addiction

The dataset of mobile phone addiction and adaptability was used to verify the role of emotional adaptability and homesickness adaptability. In this part, collinearity diagnostics was used to test multicollinearity. Results showed that there was no multicollinearity among the independent variables in this study (VIFϵ[1.079, 1.519]).

Firstly, we performed the traditional regression model about adaptability and mobile phone addiction. Therefore, gender and six dimensions of adaptability were taken as predictors, and four dimensions of mobile phone addiction were response variables. Gender was dummy coded before the regression analysis.

Multiple regression results in **Table 4** showed that emotional adaptability was negatively associated with the level of withdrawal symptoms ($\beta = -0.193$, $p < 0.001$), salience ($\beta = -0.148$, $p < 0.001$), social comfort ($\beta = -0.321$, $p < 0.01$), and mood changes ($\beta = -0.153$, $p < 0.001$). Homesickness adaptability and learning adaptability were negatively associated with the withdrawal symptoms ($\beta\epsilon[-0.142, -0.073]$, $p < 0.05$),

TABLE 4 | Traditional multiple regression and Lasso regression model of mobile phone addiction and adaptability.

Predicted variables	Traditional multiple regression				Lasso regression			
	Withdrawal symptoms	Salience	Social comfort	Mood changes	Withdrawal symptoms	Salience	Social comfort	Mood changes
Intercept	4.478***	5.330***	5.064***	5.147***	3.326***	4.089***	3.372***	3.336***
Gender	−0.001	0.104	−0.041	0.062				
Learning adaptability	−0.073*	−0.225***	−0.078	−0.111**		−0.159***		−0.007
Professional adaptability	−0.068*	−0.055	−0.012	−0.042		−0.013		
Homesickness adaptability	−0.142***	−0.149***	−0.048	−0.129***	−0.005**	−0.065**		−0.008
Interpersonal adaptability	−0.005	−0.037	−0.035	−0.081*				
Emotional adaptability	−0.193***	−0.148***	−0.321***	−0.153***	−0.102***	−0.134***	−0.130***	−0.133***
Economical adaptability	−0.020	−0.066*	−0.065	−0.121***		−0.030*		−0.046

$^{***}p < 0.001$, $^{**}p < 0.01$, and $^{*}p < 0.05$.

salience ($\beta\epsilon[-0.225, -0.149]$, $p < 0.001$), and mood changes ($\beta\epsilon[-0.129, -0.111]$, $p < 0.01$).

Secondly, we also performed Lasso regression to further confirm the key factors that can affect the mobile phone addiction. Results showed that the values of λ were 0.026, 0.001, 0.017, and 0.001, and λ+1se values were 0.171, 0.086, 0.267, and 0.121 at the minimum MSE through the training dataset when response data were from withdrawal, salience, social comfort, and mood change.

Finally, the retained variables were emotional adaptability, homesickness, and learning adaptability after bringing the best λ into the testing data, and they were accepted by *covTest* package. Results on Lasso regression in **Table 4** show that emotional adaptability was negatively associated with withdrawal symptoms ($\beta = -0.102, p < 0.001$), salience ($\beta = -0.134, p < 0.001$), social comfort ($\beta = -0.130, p < 0.001$), and mood change ($\beta = -0.133$, $p < 0.001$). Homesickness adaptability was negatively associated with withdrawal symptoms ($\beta = -0.005, p < 0.01$) and salience ($\beta = -0.065, p < 0.01$), and learning adaptability was associated with salience ($\beta = -0.159, p < 0.001$).

DISCUSSION

Main Findings

This study used traditional multiple regression to explore the associations between adaptability and nomophobia. Results showed that emotional adaptability, homesickness adaptability, and learning adaptability were significantly related to nomophobia. Emotional adaptability could negatively predict four dimensions of nomophobia (see **Table 2**). That is to say, individuals would exhibit more mobile phone uses when they have some emotional maladjustment (50). Results also showed that homesickness adaptability was negatively associated with fear of losing convenience, losing contact, and losing Internet connection (see **Table 2**). Results in this study were consistent with previous studies (51), which means that individuals, who have homesickness maladjustment, would have more demands for mobile phones, since mobile phones can help them to communicate with their families and friends anytime and anywhere (52) and relieve their homesickness maladjustment. In addition, we found that there was a negative association between learning adaptability and fear of losing convenience (see **Table 2**). Individuals would be more anxious if they could not use their mobile phone to access some learning resources (53, 54). After all, mobile phones had already been the most efficient tool to search for information.

Besides, this study mainly intended to explore which kinds of adaptability were closely related to nomophobia by using Lasso regression. Results showed that emotional adaptability was associated with fear of being unable to access information, losing convenience, and losing Internet connection after shrinking (see **Table 3**). In other words, not only would people be worried because of the dysfunction caused by missing out of mobile phone, but they also suffered from emotional maladjustment because of the absence of convenience provided by mobile phones (55). These viewpoints were verified again by the dataset on mobile phone addiction and adaptability. Those results showed that emotional adaptability was significantly associated with withdrawal symptoms, salience, social comfort, and mood change (see **Table 4**). Meanwhile, homesickness adaptability was negatively associated with withdrawal symptoms and salience (see **Table 4**).

Results also showed that the association between fear of losing contact and homesickness ($\beta = -0.322$, $p < 0.001$) was higher than with the emotional adaptability ($\beta = -0.190, p < 0.01$). That is to say, students' homesickness adaptability would lead to more demands for their phones, because mobile phones helped them to keep in touch with their families and friends (52, 56). We also found that the correlation between homesickness adaptability and fear of losing contact was higher than ($r = -0.274, p < 0.01$) other dimensions in nomophobia ($r = -0.123, -0.152, -0.168$, $p < 0.001$). It can also support the idea that homesickness adaptability predicted fear of losing contact.

This study provided the empirical evidence for the I-PACE model. The I-PACE model (27) supposed that there were many factors, such as biological factors, personality factors, and psychological factors, that affected mobile phone overuse. Our results supported this hypothesis and were consistent with the conclusion of previous studies (28). In sum, individuals' emotional cognition (adaptability in our study) resulted in some

problematic behaviors related to smartphones (nomophobia and mobile phone addiction in this study) (43).

Limitations and Future Directions

It should be noted that this study concluded that college students' academical adaptability, homesickness adaptability, and emotional adaptability could predict the level of nomophobia significantly. We just had found the factors that could affect nomophobia, but did not put forward effective measures to improve individuals' adaptability, because we just conducted a survey for the relationship between them. Therefore, we hope to solve this problem by an interventional study in the future. Besides, the relationship between adaptability and nomophobia was a cross-sectional study in this study. However, adaptability is a state variable to some extent. The results will be more persuasive if a longitudinal study is conducted. Therefore, a longitudinal design together with cross-lagged regression analysis is a good choice to verify the conclusions from this study.

Implications

This study used Lasso regression to explore the relationship between individuals' adaptability and nomophobia. It has several implications. At first, it provided compelling evidence for the assumption of the I-PACE model by using empirical data, which confirmed that individuals' adaptability (psychological factors) could predict nomophobia significantly. Next, previous studies treated adaptability or nomophobia as a simple component (11, 13, 26), when the distinct dimensions of those two psychological traits were clarified. Furthermore, the specific relationships between different dimensions of adaptability and different dimensions of mobile phone overuse (mobile phone addiction and nomophobia) were examined. The key factors, such as emotional adaptability and homesickness adaptability, that affected nomophobia were discovered. Therefore, we further explained why individuals have various manifestations of nomophobia. Thirdly, this study also confirmed that the mobile phones bring both positive and negative effects on the participant. On the one hand, this study found that there were significant associations between mobile phone overuses with emotional adaptability and homesickness adaptability. On the other hand, for some college students, they could get in touch with their family through mobile phones when they suffer from homesickness maladjustment. It indicated that decreasing PUPM could be complex in practice.

CONCLUSION

In conclusion, this study found that emotional adaptability was the key factor that can influence the level of fear of being unable to access information, losing convenience, and losing Internet connection. Homesickness adaptability was an important factor that can affect the fear of losing contact in nomophobia. That is to say, individuals' level of emotional adaptability and homesickness adaptability are important adaptability traits for predicting nomophobia. Individuals would exhibit the fear of being unable to get information, losing convenience, and losing Internet connection in nomophobia if they have some performance about emotional maladjustment. Additionally, they would exhibit the fear of losing contact in nomophobia if they have some performance about homesickness maladjustment.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by XL2020-08. The patients/participants provided their written informed consent to participate in this study. We have informed the participants about the relevant content of the study before the test and have obtained the participants' consent. We also informed the participants that data will only be used for scientific research, and they have the right to automatically withdraw at any time.

AUTHOR CONTRIBUTIONS

JL: methodology and writing—reviewing and editing. SR: conceptualization, methodology, software, writing—original draft preparation, and writing—reviewing and editing. YL: data collection and investigation. TL: conceptualization, methodology, and writing—reviewing and editing. All authors contributed to the article and approved the submitted version.

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