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Problematic Media Use: Comparisons by Media Type and With Other Addictive Behavior and Substance Use Domains

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While many hesitate to classify problematic media use as a behavioral addictive disorder, it remains clear that there are overlaps in antecedents and consequents. However, there is still a great deal unknown about individual difference factors for developing problematic behaviors. Nor is there a comprehensive understanding of how the relationships between problematic uses of media and other problematic addictive behaviors and substance use comparatively influence health and well-being outcomes. It is also unclear the extent to which domains of problematic addictive disorders may relate to one another—are the media domains distinct from the other domains, or do they fit together into a more general addictive behavior dimension? The present study surveyed 1,227 U.S. adults, assessing their addictive behaviors across a variety of domains, individual differences, and health and well-being. Findings suggest that media domains are in many cases similarly, and sometimes even more strongly, associated with negative health and well-being measures compared even to problematic substance use. In addition, cluster analysis finds that media domains do not separate from other domains of addiction, but instead there are two clusters with a mix of domain types. Additionally, only age and impulsivity were individual variables associated with both domain clusters, which were associated with worse mental health, lower life satisfaction, lower sleep quality, and less healthy dietary behavior.

Keywords: media use, addictive behaviors, substance use disorders, addiction, cryptocurrency

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Problematic media and technology use is often associated with negative health outcomes such as worse sleep quality, worse diet quality, and negative mental health outcomes such as increased depression, anxiety, stress, and isolation/loneliness (Eden et al., 2021; Flayelle et al., 2022; Griffiths & Nuyens, 2017; Huang, 2022; Meshi & Ellithorpe, 2021; Meshi et al., 2020; Spada, 2014; Tham et al., 2020). The potential harms of problematic media use are not restricted only to the users but also affect parents and partners (Szász-Janocha et al., 2023), and adolescents who exhibit problematic media use can influence their peers to also be more likely to exhibit such behaviors (Gunuc, 2017; Lee et al., 2017).

While many kinds of media use have been studied with respect to their problematic use, perhaps the most studied is problematic video gaming—the only media domain to have been officially recognized as a disorder ("Gaming Disorder") according to the World Health Organization's *International Classification of Diseases*–11. The American Psychiatric Association has not officially recognized "Internet Gaming Disorder" as a disorder in their *Diagnostic and Statistical Manual of Mental Disorders–Fifth Edition* but has included it as a condition meriting further research; it is the only media domain to be included. Amidst debates regarding other types of media and whether they, too, should be included in the

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next iterations of the *International Classification of Diseases* and *Diagnostic and Statistical Manual of Mental Disorders*, scholars have pointed to the features of the technologies that are most likely to be associated with the development of an addiction like dependency (Flayelle et al., 2023). These include inconsistent reinforcement (e.g., random gifts or loot boxes with valuable content in gaming, the ability to infinitely scroll and find a gem of a post amidst the mundane in social media), personalized triggers (e.g., push notifications), overvaluation of positive elements (e.g., realistic graphics and interactivity), features that interfere with deliberation (e.g., time-limited decisions in gaming, autoplay in streaming television), partial goal fulfillment (e.g., points programs, infinite renewal of new content), and taking advantage of cognitive biases (e.g., near misses in loot box gaming, fear of missing out in social media and binging television). These aspects inherent to the technologies give media use an increasingly addictive potential (Flayelle et al., 2023).

When Are Media and Technology Behaviors "Problematic"?

It must be pointed out that media use is not inherently problematic. Problematic use of media usually goes beyond high engagement or time spent to a point where individuals experience psychological distress and/or an impairment in daily functioning (Griffiths, 2005). These individuals experience symptoms similar to those with substance use disorders (e.g., preoccupation, tolerance, mood modification, withdrawal, relapse, jeopardizing jobs and relationships, loss of interest in hobbies and other experiences; Griffiths et al., 2017). Indeed, a recent study specifically recruited highly engaged video gamers (defined as playing 30+ hr per week) and found that in a sample of 403 such heavy users, only 131 (32.5%) met the study's definition for gaming disorder (Slack et al., 2022). In comparing those highly engaged gamers who qualified for gaming disorder to those who did not, the gaming disorder group was significantly lower in reported quality of life and had worse sleep. Thus, we do not claim that any particular media use is inherently problematic; rather, for some people, the use of any medium can *become* problematic the more it meets the aforementioned symptomology. This is similar to alcohol use; some people can be heavy drinkers and not experience impairment in functioning to qualify as having alcohol use disorder, while others do meet the disorder criteria (King et al., 2016). While much of this debate has centered on clinical levels of problematic media use, measures can identify problematic use that does not necessarily meet the threshold for a mental health diagnosis but is nonetheless concerning (Tham et al., 2020; van Holst et al., 2012). Given that clinical thresholds for problematic use vary a great deal depending on the domain (and some domains have no clearly established threshold), but are somewhere between 3% and 19% of users (Mentzoni et al., 2011; Wittek et al., 2016), in the present study we treat problematic use as a continuum rather than designate a cutoff point.

Problematic Media and Technology Use and Associations With Other Addictive Behaviors

Research has revealed similar symptomology, neurobiology, physiology, genetics, cognition, comorbidity, outcomes, and response to treatment for behavioral addictive disorders and substance use disorders (Rosenberg & Feder, 2014; Sussman, 2017). Indeed, the current director of the U.S. National Institute of Drug Abuse has argued for the parallel between behavioral and substance use disorders (Volkow et al., 2016). This overlap is so significant that some have proposed that addiction should be considered as a general syndrome, regardless if stemming from the consumption of a psychoactive drug or engagement of a non-substance-consuming behavior (Griffiths, 2005; Shaffer et al., 2004).

Much of the research on problematic media use likens the phenomenon to other behavioral addictive disorders, such as gambling disorder, as well as in some extreme cases to substance use disorders (Griffiths et al., 2017). In fact, research has found that addictive behaviors are likely to co-occur. For example, a study of adolescents found an association between problem gaming behaviors and use of alcohol, nicotine, and cannabis, especially for boys (Van Rooij et al., 2014). Another study found an association between problematic gaming and gambling, and between problematic gaming and cannabis use (Walther et al., 2012). Still, another found an association between playing video games with simulated gambling (e.g., loot boxes) and real-world gambling behaviors (Hing et al., 2022), which a review suggests also can include speculative trading in cryptocurrency (Delfabbro & King, 2023). Clearly, there is some overlap between problematic media and technology use and other domains of addiction. However, thus far, most of the research in this vein has included only one media domain (e.g., video gaming) without considering the potential for multiple media domains to be simultaneously problematic with multiple other addictive domains. The present study will evaluate many media domains in conjunction with other addictive categories (behavioral and substance-based).

Disentangling Addictive Domain Categories and Their Relationships

Many hesitate to classify problematic media use on the same level as the categories of substance use and other behavioral addictive disorders (Aarseth et al., 2017). However, it remains clear that there are overlaps in antecedents and consequents of problematic media use, other addictive behaviors, and substance addictions that should not be ignored (Griffiths et al., 2017). There is still a great deal unknown about the relative risks for developing problematic media use behaviors for different types of media, as well as how those behaviors relate to other behavioral addictive disorders, such as gambling disorder, or to substance use disorders. As previously mentioned, most research tends to focus on a single medium (e.g., social media) or a single type of disorder (e.g., gambling) without direct comparisons between categories, despite the likely overlap in problematic uses within domains. Although the idea of an "addictive personality" has been vehemently debated (Griffiths, 2017; Szalavitz, 2015), it remains true that there are individual difference factors (e.g., impulsivity) that make problematic behaviors and disorders more likely (Walther et al., 2012), and also that many problematic behaviors and addictive disorders do co-occur (Coëffec et al., 2015; Delfabbro & King, 2023; Hing et al., 2022; Van Rooij et al., 2014; Walther et al., 2012). Therefore, a major contribution of the present study is to simultaneously measure multiple domains (e.g., video games, gambling) within multiple categories (i.e., media, nonmedia behavior, substance use). This will allow a more thorough understanding of the individual difference and the health and well-being variables most associated with each domain, and ways that the domains might cluster.

Problematic Domains of Interest

To better conceptualize the cross-domain aspects of problematic behaviors emerging from media and technology use, as well as substance use and other behavioral addictive disorders, we identify three key categories: media use domains, other behavioral domains, and substance use domains.

Media Use Domains

It is already well-known that problematic media use is associated with health and well-being outcomes including mental health, sleep, dietary behavior, and sedentary activity in the domains of video gaming (Griffiths et al., 2017; Männikkö et al., 2015; Tham et al., 2020; Wolfe et al., 2014), social media use (Lee et al., 2017; Marino et al., 2018; Meshi & Ellithorpe, 2021; Van den Eijnden et al., 2016), internet use (Derbyshire et al., 2013; El Asam et al., 2019; Kelley & Gruber, 2013), and television use (Eden et al., 2021; Ellithorpe et al., 2022; Flayelle et al., 2022; Rubenking et al., 2018). However, as technologies evolve and proliferate, there are constant changes to their propensity for addictive behaviors (Flayelle et al., 2023).

Additionally, emerging technologies have combined media domains with other behavioral domains such as gambling, in the contexts of cryptoassets, loot box gaming, and play-to-earn gaming. Much less is known about these domains, and how they relate to antecedents and consequents of problematic use, nor how they might relate to the other domains of interest. Cryptoassets utilize blockchain technology, and people can invest in these assets by purchasing them on various exchanges. The act of cryptoasset investing combines the potential to develop a problematic focus on monetary rewards, similar to gambling disorder, with the social rewards obtained on social media platforms such as Reddit and Twitter when discussing cryptoassets (Delfabbro et al., 2021; Delfabbro & King, 2023; Menteş et al., 2021).

Loot boxes and play-to-earn gaming represent two facets of gambling characteristics in media use. Loot boxes are in-game purchases with a chance-based outcome (Spicer et al., 2022), while play-to-earn games are a combination of video games and cryptoassets, in which players can earn cryptocurrency by playing, and often sell those earned cryptocurrencies for real-world money to other players (De Jesus et al., 2022). The risks of play-to-earn and loot box gaming are akin to those in gambling, including the potential for monetary exploitation of gamers (Delfabbro et al., 2022), as well as some mixed associations with mental health (Johnson et al., 2023).

Other Behavioral Domains

The nonmedia behavioral addictive domains of interest in the present study are gambling and shopping. Gambling disorder is associated with poor mental health, increased substance use, and financial harm (Muggleton et al., 2021; Scholes-Balog & Hemphill, 2012). There have been calls to consider gambling a major public health problem and enact policy concomitant with the level of health problems it causes (Abbott, 2020; Price et al., 2021; Wardle et al., 2019). Similarly, problematic shopping is associated with poorer mental health, lower life satisfaction, and financial problems (Black, 2022; Lawrence et al., 2014; Maraz & Costa, 2022; Müller et al., 2019). Problematic gambling and shopping also tend to be comorbid with each other (Ford & Håkansson, 2020; Maraz & Costa, 2022). Additionally, the technological affordances of the internet have been implicated in the furthering of both problematic gambling and shopping, as the internet provides new, immediate, and easily accessible platforms for such behaviors (Abbott, 2020; Maraz & Costa, 2022; Wardle et al., 2021).

Substance Use Domains

Substance use disorder is a public health crisis that is arguably on a different level from behavioral addictive disorders due to the potential for more acute health consequences, such as cancer risks (Rumgay et al., 2021; Zhang et al., 2020) and death and injury due to impaired driving (Simmons et al., 2022). In addition, there are known relationships between substance uses such as alcohol, tobacco, cannabis, and caffeine, and the health factors most associated with media and behavioral domains, especially mental health (Paz-Graniel et al., 2022; Scheier & Griffin, 2021; Taylor et al., 2021) and sleep (Catoire et al., 2021; Gardiner et al., 2023; He et al., 2019). As previously noted, substance use often co-occurs with problematic behaviors, including media use. Of interest in the present study is whether problematic substance use is distinct from problematic behaviors in media use and other behavioral domains in terms of how they cluster and their relationships with other variables (individual differences and health and well-being), or if they are as comorbid as their co-occurrence appears to be.

Cross-Domain Comparisons and Clusters

With the above in mind, the present study investigates specific problematic behaviors and substance use in the three categories of media use, other behaviors, and substance use. We do this simultaneously in a single sample, in order to better understand the ways these domains and categories converge and diverge. We accomplish this in two ways—first, by comparing the relative relationships between all constructs simultaneously and known health and well-being comorbidities (i.e., mental health, sleep quality, dietary behavior, sedentary behavior), and second by using a cluster analysis to determine whether dimension reduction finds the domain categories are distinct from one another or if they cluster together in ways that blend across media and technology, nonmedia behaviors, and substance uses. Because this is an exploratory study, we present two research questions:

> *Research Question 1:* Are there certain problematic behavior domains in the categories of media technology use, nonmedia problematic behaviors, or substance use that are more strongly associated with mental and physical health outcomes than others?

> *Research Question 2:* Will domains within problematic media technology use, nonmedia problematic behaviors, and substance use cluster in systematic ways?

Differential Susceptibility

A final component of problematic behaviors and substance use is the risk profile of an individual for developing these conditions, especially as compared to those who engage in the behavior or substance use but do not score highly on problematic measures. The differential susceptibility to media model (Valkenburg & Peter, 2013) specifies that there are crucial individual differences, classified into the categories of dispositional, developmental, and social susceptibility, that both predict media use and moderate the relationship between media use and outcomes. In the present study, we measure variables relevant to all three categories of susceptibility to understand what kinds of individual susceptibilities are associated with the clusters of problematic behaviors and substance use. We will also look to these individual susceptibilities as potential influences on health and well-being as known predictors of such outcomes from public health research. In line with this, we offer a third research question:

> *Research Question 3:* Will certain clusters of problematic media and technology use, nonmedia problematic behaviors, or substance use be differentially associated with (a) individual differential susceptibility and/or (b) health and well-being?

Method

Participants

Participants were 1,227 English-speaking adults (M_{age} = 44.81 years, *SD* = 16.18, ranging 18–93 years) residing in the United States recruited through Prolific. Gender identities were 597 (48.66%) women, 595 (48.49%) men, 28 (2.28%) other, and seven (0.57%) no response. Racial and ethnic identities included 898 (73.19%) White, 151 (12.31%) Black/African American, 76 (6.19%) Asian/Asian American, 55 (4.48%) multiracial, 32 (2.61%) Hispanic/Latino, four (0.33%) Arab/Middle Eastern, two (0.16%) Indigenous/Native American, seven (0.57%) other, and two (0.16%) no response. Education levels included 11 (0.90%) less than high school, 183 (14.91%) high school degree or general education development test, 277 (22.58%) some college, 127 (10.35%) trade or associate's degree, 433 (35.29%) bachelor's or other 4-year degree, 191 (15.57%) graduate degree, and five (0.41%) no response.

Procedure

An online survey was conducted using the Qualtrics survey platform. The sample size goal was at least 1,219 respondents based on an a priori power analysis of the planned regressions with power = .80, α = .05, and an expected effect size of *r* = .08, using the program G*Power. This expected effect size was obtained from a recent meta-analysis of the relationship between problematic social media use and mental health (Huang, 2022), using the smallest correlation reported in the meta-analysis. Participants were paid $4.00 USD for completing the 20-min survey, and all procedures were determined exempt by the institutional review board at the University of Delaware.

Measures

Problematic Behaviors and Substance Use

Participants were asked if they engaged in each target behavior or substance use within the past 12 months. For each domain, they indicated yes (Table 1), they then filled out a pair of scales (the Bergen scale and an additional scale) that assess that specific problematic behavior or substance use. Number of domains reported per participant ranged from 2 to 13 (*M* = 7.48, *SD* = 1.84).

Bergen Scales. As highlighted by Griffiths (2005), the phenomenon of addiction—whether resulting from a psychoactive substance or a compulsive behavior—consists of six components within a biopsychosocial framework: preoccupation, mood modification, tolerance, conflict, withdrawal, and relapse. Researchers have built on this concept, creating scales to measure problematic behaviors that assess each of these six components. For example, the Bergen Facebook Addiction Scale (Andreassen et al., 2012), was later adapted to capture all social media use, rather than just use of Facebook (Schou Andreassen et al., 2016). We capitalize on these six common components, as this scale has already been validated for use across multiple domains. We adapted this scale to assess all domains measured, as a consistent measurement is important for the cluster analysis that we conduct (Ferreira & Hitchcock, 2009). The Bergen scale is six items measured on a scale from 1 (*never or very rarely*) to 5 (*very often*), and the scores are traditionally summed for a possible score from 6 to 30 (Andreassen et al., 2012; Schou Andreassen et al., 2016). See Table 1 for central tendency information.

Other Addictive Behavior and Substance Use Measures. Despite its previous adaptation across domains and its face validity in assessing the core components of addiction, adapting the Bergen measure to all measured behaviors and substance uses has not been fully validated. Therefore, to check our use of this scale in place of other measures for each behavior and substance use, we also asked participants to complete previously validated assessments for each problematic behavior or substance use that they reported engaging in. When there were multiple addiction scales to choose from for a domain, we selected the most-cited and/or one that was independently validated separately from the original validation.

These include The Television Addiction Scale (20 items, 1 = *strongly disagree* to 7 = *strongly agree*; Horvath, 2004), Internet Gaming Disorder scale (nine items, 1 = *never* to 6 = *every day or almost every day*; Lemmens et al., 2015), Social Media Use Disorder scale (nine items, dichotomous yes/no—scale is summed to a count; Van den Eijnden et al., 2016), Internet Addiction Scale (eight items, dichotomous yes/no—scale is summed to a count; Young, 1998), The South Oaks Gambling Screen (30 items, scored according to the original article with range 0–16; Lesieur & Blume, 1987), Shopping Addiction Scale (seven items, 1 = *completely disagree* to 5 = *completely agree*; Andreassen et al., 2015), Problematic Cryptocurrency Trading Scale (15 items, 1 = *never* to 5 = *always*; Menteş et al., 2021), Risky Loot Box Index (five items, 1 = *strongly disagree* to 5 = *strongly agree*; Brooks & Clark, 2019), Alcohol Use Disorders Identification Test (10 items, scored according to the original article with range 0–29; Reinert & Allen, 2002), Caffeine Addiction Scale (11 items, dichotomous

Table 1

Frequencies for Behaviors and Substance Use, in Descending Order of Prevalence, and Descriptive Statistics for the Bergen and Non-Bergen Scale Versions of Their Measurement for Only Those Participants Who Indicated Performing the Behavior

Behaviors and substances	*n*	%	Bergen scale (*M*, *SD*) Cronbach α	Non-Bergen scale (*M*, *SD*) KR20 or Cronbach α[a]	*r*
Browsing the internet, not including social media websites	1,205	98.21	11.69, 5.73 .89	2.11, 1.90 .77[b]	.78
Shopping, including online or physically in a store	1,197	97.56	9.24, 4.55 .88	1.60, 0.75 .89	.86
Watching television including traditional television as well as streaming online (e.g., Netflix) and watching YouTube videos (but not time spent engaging with comments)	1,190	96.98	10.51, 4.82 .86	1.93, 1.07 .96	.79
Using social media including platforms such as Instagram, TikTok, Twitter, Facebook, Snapchat, and comments on YouTube, and can include things like browsing, posting, liking, and commenting	1,169	95.27	11.21, 5.89 .92	1.37, 1.89 .80[b]	.79
Caffeine	1,054	85.90	9.50, 4.43 .84	5.48, 2.11 .64[b]	.41
Playing video games including games on PC, console (e.g., Xbox), or smartphone	914	74.49	11.48, 5.83 .90	1.63, 0.89 .92	.83
Alcohol	818	66.67	9.55, 5.03 .91	5.13, 5.06 .87	.79
Cannabis/THC	370	30.15	11.26, 6.03 .91	1.31, 0.54 .89	.80
Tobacco/nicotine including vaping/e-cigarettes	321	26.16	14.22, 6.78 .89	3.66, 2.85	.55
Buying, staking, selling, or otherwise following cryptoassets including cryptocurrencies (e.g., Bitcoin), NFTs, security tokens, and the like	305	24.86	9.05, 4.38 .87	1.29, 0.51 .94	.83
Gambling including casino games, in a sports setting, and/or casual card games for money, and can be in person or online	292	23.80	10.07, 6.25 .95	0.63, 2.14 .90[b]	.79
Playing play-to-earn games including earning potentially valuable in-game assets like skins or cards or cryptocurrency that have real-world value	181	14.75	11.29, 5.92 .91	1.64, 0.94 .93	.84
Buying or interacting with loot boxes *in* gaming including any in-game reward that costs money or cryptoassets to purchase, and it is unknown exactly what will be received until after purchase	167	13.61	8.80, 4.27 .89	2.45, 1.04 .84	.56
Stimulants including amphetamines such as meth, Ritalin, Adderall, and so forth[c]	89	7.25	11.80, 6.78 .91	2.25, 1.02 .75	.83

Note. Pairwise bivariate Pearson's correlations between the Bergen version and non-Bergen version of each scale are included all $p < .001$.
[a] Because of the nature of the tobacco addiction measure calculation, it was not appropriate to use Cronbach α or KR20. [b] Scale used KR20 in place of Cronbach α due to dichotomous items. [c] As a participant pointed out in a message to the researchers on Prolific, we failed to specify that we intended unprescribed use of stimulant medications and not the use as prescribed to treat a known medical condition. Given this definitional oversight, we dropped the stimulant category from analysis.

yes/no—scale is summed to a count; Samaha et al., 2020), Fagerstrom Test for Nicotine Dependence (six items, scored according to the original article with range 0–10; Heatherton et al., 1991), Severity of Dependence Scale for Cannabis (five items, four on a 1 = *never* to 4 = *always/nearly always* scale, one on a 1 = *not difficult* to 4 = *impossible* scale; van der Pol et al., 2013), and World Health Organization-Assist v3.0 amphetamines subscale (four items, 1 = *never* to 5 = *daily or almost daily*; Humeniuk et al., 2006). We were unable to find a satisfactory measure of addiction to play-to-earn gaming, so we repeated the Internet Gaming Disorder scale (nine items, 1 = *never* to 6 = *every day or almost every day*; Lemmens et al., 2015) with the specification that it be answered regarding play-to-earn games only. See Table 1 for central tendency information.

Health Outcomes

Depression, Anxiety, and Well-Being. We used the PROMIS four-item scales (1 = *never* to 5 = *always*) to measure depression (M = 1.95, SD = 0.80, Cronbach α = .94) and anxiety (M = 2.05, SD = 1.04, Cronbach α = .92) as measures of mental health (Hahn et al., 2014; Pilkonis et al., 2011). Depression and anxiety were correlated very highly at $r = 0.87$, $p < .001$, which indicated they should be combined to reduce multicollinearity (M = 2.00, SD = 1.02, Cronbach α = .93). We captured participants' well-being using the five-item satisfaction with life scale (1 = *strongly disagree* to 7 = *strongly agree*, M = 4.09, SD = 1.65, Cronbach α = .93; Diener et al., 1985).

Sleep Health. The 19-item Pittsburgh Sleep Quality Index was used to assess participants' sleep quality over the past month (Buysse et al., 1989). This index includes seven components (sleep duration, sleep quality, sleep efficiency, sleep latency, sleep disturbances, daytime dysfunction, and use of sleep medication). It should be noted that higher scores indicate *worse* sleep quality, which is the convention for the calculation of this measure (M = 5.98, SD = 3.22, range: 1–17).

Dietary Behavior. The Three-Factor Eating Questionnaire–R18 (Karlsson et al., 2000) assesses eating behavior associated with obesity with 18 items on a 4-point response scale from 1 (*definitely false*) to 4 (*definitely true*). Responses are summed to create scores for three factors: cognitive restraint, uncontrolled eating, and emotional eating. However, the subscales for uncontrolled and emotional eating were highly correlated at $r = 0.72$, so these items were combined into a single subscale ($M = 1.87$, $SD = 0.71$), plus the cognitive restraint subscale ($M = 2.46$, $SD = 0.77$).

Sedentary Activity. Sedentary activity was measured by asking participants how many days in the past week they would say they spent at least 10 min sitting, and on those days that they sat for at least 10 min, approximately how many hours were spent sitting on average. The responses to these two questions were multiplied together to get a measure of sedentary activity in the past week ($M = 45.60$, $SD = 26.17$).

Individual Susceptibilities

As per the differential susceptibility to media model, we measured attributes that are known or expected to relate to addictive behaviors under the domains of dispositional (impulsivity, gender), developmental (age), and social (social support, education) susceptibilities. We assessed impulsivity with the 20-item short version of the UPPS impulsive behavior scale (Cyders et al., 2014), which captures components on a 1 = *strongly disagree* to 7 = *strongly agree* scale ($M = 2.73$, $SD = 0.80$, Cronbach $\alpha = .86$). We also asked participants to complete a 27-item delay discounting questionnaire (Kirby et al., 1999; Richards et al., 1999). In this questionnaire, participants must decide between smaller, immediate monetary rewards and larger, delayed monetary rewards that vary on value and time of delivery. Using each participant's response, we calculated a discount rate (k) to be used in analyses ($M = 0.03$, $SD = 0.05$). Previous research found that impulsivity was the only individual difference variable that was predictive of problematic gaming, gambling, alcohol use, tobacco use, and cannabis use (Walther et al., 2012), and reviews found consistent correlations with impulsivity and problematic behaviors (Gentile et al., 2017; Király et al., 2023). Social support was assessed using the 12-item multidimensional scale of perceived social support (Zimet et al., 1988). Real-world (nonmediated) social support has been demonstrated to be a protective factor in problematic behaviors, particularly for media technologies (Meshi & Ellithorpe, 2021; Tham et al., 2020; Tudorel & Vintilă, 2018; Wang & Wang, 2013).

Statistical Analysis

We tested our research questions in a multistep process using Stata 17 and SPSS 26. First, the concurrent validity of the Bergen scales was assessed using the other, non-Bergen measures for each domain using a combination of bivariate correlation and exploratory factor analysis (EFA). Then, the individual domains were tested for their relationships with health variables using seemingly unrelated estimation (SUEST). Wald tests were used to compare the magnitude of the unstandardized regression coefficients from the SUEST analysis in order to test whether any domains are more strongly related to outcomes than others (Klopp, 2019). Finally, cluster analysis (Ferreira & Hitchcock, 2009) was used to determine whether the underlying communality of the domains was captured by a smaller number of factors. These factors were used in a path model with differential susceptibility precursors as the exogenous precursor variables, cluster factors as mediators, and health variables as the outcomes.

Results

Bergen Scales Validation

Correlation Analyses

We ran bivariate Pearson's correlations (Table 1) as a first step in testing whether the Bergen version of each domain measure was appropriate to use as a substitute for previously established measures in each domain. The a priori threshold was $r > 0.70$ to be considered highly intercorrelated. All domains were correlated $r > 0.70$ except for three: loot box gaming ($r = 0.56$), tobacco/nicotine ($r = 0.55$), and caffeine ($r = 0.41$). Face validity checks make it relatively clear why this is—these three measures do not ask about the social dimensions of substance use and behavioral addictive disorders (e.g., people in your life have expressed concern), but instead mostly focus on the tolerance and withdrawal components of addictive disorders. Therefore, the Bergen scales comprehensively cover more aspects of addictive disorders (Griffiths, 2005) than the non-Bergen version of these scales. As a result, the Bergen adaptations may be conceptually superior for the goals of this project.

Exploratory Factor Analyses

We ran EFA with all items together from each pair of scales—the Bergen scale and the non-Bergen scale—for each addictive domain (e.g., alcohol). We did this by first allowing any number of factors to be freely estimated and then constraining the number of factors to one. Promax oblique rotation was used given the known correlations between the measures.[1] It was determined a priori that indications of the suitability to replace the non-Bergen measures with the Bergen versions for each domain would be meeting at least one of the following conditions: (a) if unconstrained EFA finds only a single viable factor (defined by eigenvalues >1.00) where most to all items from both scales load at >.30; and/or (b) if unconstrained EFA finds more than one viable factor, but the items from the Bergen and non-Bergen scales cross-load together at >.30 without clearly distinguishing (e.g., some items from Bergen and some from non-Bergen load >.30 on Factor 1, and other items from both scales load >.30 on Factor 2); and/or (c) if EFA constrained to one factor finds that most or all items from both scales load on that single factor at >.30. Whether each domain meets these qualifications is specified in Table 2. Full output can be found on the Open Science Framework.[2]

All domains met at least one of these criteria except caffeine. The domains that meet all three criteria are shopping, play-to-earn gaming, cannabis/THC, social media, and internet. The domains that meet two criteria are cryptoassets, video games, gambling, alcohol, and television. Two more domains clearly meet one criterion and somewhat meet a second criterion: loot box gaming

[1] The EFA was also run with varimax orthogonal rotation, and while some small changes occurred to specific factor loadings, the substantive interpretation for the purposes of the study was essentially unchanged for all measures, with the exception that alcohol changed categories from "medium" to "yes" for the initial two-factor solution (Criterion 2 in Table 2) when using varimax rotation.

[2] https://doi.org/10.17605/OSF.IO/VKDW4.

Table 2
Exploratory Factor Analysis Simplified Results

Domain	1	2	3
Shopping	Yes One factor: eigenvalue 7.37 (Factor 2 = 0.75)	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.68
Play-to-earn gaming	Yes One factor: eigenvalue 9.01 (Factor 2 = 0.87)	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.67
Cryptoassets	No Two factors: eigenvalues 10.96 and 1.33	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.51
Video games	No Two factors: eigenvalues 8.56 and 1.11	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.65
Cannabis/THC	Yes One factor: eigenvalue 6.68 (Factor 2 = 0.75)	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.68
Social media	Yes One factor: eigenvalue 6.64 (Factor 2 = 0.83)	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.32
Gambling	No Two factors: eigenvalues 6.79 and 2.55	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.41
Television	No Two factors: eigenvalues 13.49 and 1.35	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.54
Internet	Yes One factor: eigenvalue 5.84 (Factor 2 = 0.68)	Yes Items cross-load with no clear pattern separating versions	Yes All factor loadings >.37
Alcohol	Yes One factor: eigenvalue 7.85 (Factor 2 = 0.70)	Medium A few items cross-load but Bergen items mostly load on Factor 1 and addict items mostly load on Factor 2	Yes All factor loadings >.33
Loot box gaming	No Two factors: eigenvalues 5.15 and 1.36	Medium A few items cross-load but Bergen items mostly load on Factor 1 and all but one addict item load on Factor 2	Yes All factor loadings >.57
Tobacco/ nicotine	No Two factors: eigenvalues 4.89 and 1.02	Medium A few items cross-load but Bergen items mostly load on Factor 1 and all but one addict item load on Factor 2	Yes All factor loadings >.36
Caffeine	No Two factors: eigenvalues 3.65 and 1.17	No Bergen items all load on Factor 1 and addict items mostly load on Factor 2 or alone on other factors	Medium Bergen items and most addict items will load together >.30 on one factor when constrained, but some addict items remain <.30

Note. (1) If unconstrained EFA finds only a single viable factor (defined by eigenvalues >1.00) where most to all items from both scales load at >.30; and/or (2) if unconstrained EFA finds more than one viable factor, but the items from the Bergen and non-Bergen scales cross-load together at >.30 without clearly distinguishing with Bergen items on one factor and non-Bergen items on the other (e.g., some items from Bergen and some from non-Bergen load >.30 on Factor 1, and the rest of the items from both scales load >.30 on Factor 2); and/or (3) if EFA constrained to one factor finds that all items from both scales load on that single factor at >.30. EFA = exploratory factor analysis.

and tobacco/nicotine. Based on these results, we conclude that the Bergen version of the scales can be used for all domains except possibly caffeine. However, we include the Bergen version of the caffeine measure in the cluster analysis in order to meet the best practice that the scales be similar for such an analysis (Jurowski & Reich, 2000) and include this version in the SUEST for coefficient comparison for the same reason; however, conclusions regarding caffeine should be made with caution.

Domain-Specific Analyses

SUEST was used to simultaneously test the unstandardized regression coefficients of all domains (Bergen scales) on each of the outcome variables of depression and anxiety, life satisfaction, sleep quality, cognitive restraint, emotional and uncontrolled eating, and sedentary activity. SUEST provides the more conservative robust standard errors of the regression coefficients and allows for postestimation of the cross-model comparison null hypothesis that $b_1 - b_2 = 0$ for each pair of predictors using Wald tests, without the models needing to be nested. Given the patterns of missing data in this sample (e.g., that not every person engaged in every activity), this was a necessary aspect to the comparison testing. All variables were significantly positively associated with depression and anxiety. Most variables were significantly negatively associated with life satisfaction, except for loot box gaming, cryptoassets, and play-to-earn gaming. Most variables were significantly associated with poorer sleep, except for loot box gaming and cryptoassets. Most variables were significantly associated with cognitive dietary restraint, except for television, gambling, alcohol, caffeine, and cannabis/THC. Most variables were significantly positively associated with uncontrolled and emotional eating, except for cryptoassets. Finally, most variables were *not* significantly associated with sedentary behavior, except for video games and internet. See Table 3 for statistical details and see full output on the Open Science Framework.

Coefficient Comparisons

Depression and Anxiety. Television was the strongest predictor of higher depression and anxiety while loot box gaming was the weakest. Television, social media, and internet were all significantly more strongly associated with higher depression and anxiety compared to gambling, cryptoassets, loot box gaming, caffeine, tobacco, and cannabis/THC. Video games were more strongly associated with higher depression and anxiety compared to loot box gaming. No other comparisons were significantly different for their association with depression and anxiety. Interestingly, these results suggest that the media behavioral addictions may be more strongly associated with higher depression and anxiety compared to some other commonly accepted behavioral addictions (e.g., gambling) and some substance addictions (e.g., caffeine, tobacco, cannabis). It also suggests that cryptoassets and loot box gaming may be less concerning behaviors.

Life Satisfaction. Internet was the strongest predictor of lower life satisfaction, while play-to-earn gaming was the weakest. Internet and video games were both more strongly associated with lower life satisfaction compared to shopping, cryptoassets, loot box gaming, play-to-earn gaming, caffeine, and tobacco. Internet was also significantly stronger than social media. Television was more strongly associated with lower life satisfaction compared to social media, shopping, loot box gaming, caffeine, and tobacco. Social media was more strongly associated with loot box gaming. Gambling, alcohol, and cannabis/THC were more strongly associated with lower life satisfaction compared to loot box gaming, and alcohol and cannabis/THC were also more strongly associated than play-to-earn games. Alcohol and cannabis/THC were both more strongly associated with lower life satisfaction compared to caffeine and tobacco. No other comparisons were significantly different for their association with life satisfaction. These results were a bit less clear than those for depression and anxiety, but in general also suggest that some of the media domains were more strongly associated with lower life satisfaction than some other commonly accepted behavioral addictions (e.g., shopping) and some substance addictions (e.g., caffeine, tobacco). It also again suggests that cryptoassets and loot box gaming may be less concerning behaviors.

Sleep Quality. Television was the strongest predictor and cryptoassets was the weakest predictor of sleep. Television was significantly more strongly associated with worse sleep quality compared to video games, social media, gambling, shopping, cryptoassets, loot box gaming, tobacco, and cannabis/THC. Cryptoassets were significantly more weakly associated with sleep quality compared to television, video games, social media, internet, shopping, alcohol, caffeine, and tobacco. Internet was significantly more strongly associated with sleep quality compared to gambling and cannabis/THC. Caffeine was more strongly associated compared to gambling and cannabis/THC, and alcohol was more strongly associated compared to cannabis/THC. No other comparisons were significantly different for their association with sleep quality. Again, the media domains were either more strongly associated with poorer sleep or no different in their association even when compared to other previously accepted sleep-disrupting behaviors or substance uses such as caffeine and alcohol. Cryptoassets again appear to be less problematic in this context compared to the other domains.

Dietary Outcomes. In terms of cognitive restraint, loot box gaming and play-to-earn gaming were the strongest predictors, while gambling was the weakest. Loot box gaming and play-to-earn gaming were both significantly more strongly associated with cognitive restraint compared to all other domains except for tobacco. Tobacco was significantly more strongly related to cognitive restraint compared to television, social media, internet, gambling, alcohol, and cannabis/THC. No other comparisons were significantly different for their association with dietary restraint. In this case, two media domains and a substance domain were the top variables most strongly related to cognitive restraint.

In terms of uncontrolled and emotional eating, shopping and television were the strongest predictors, while cryptoassets were the weakest. Shopping was significantly more strongly associated with uncontrolled and emotional eating compared to video games, gambling, cryptoassets, loot box gaming, play-to-earn gaming, alcohol, tobacco, and cannabis/THC. Television was significantly more strongly associated with uncontrolled and emotional eating compared to video games, internet, cryptoassets, play-to-earn gaming, alcohol, tobacco, and cannabis/THC. Social media use was significantly more strongly associated with uncontrolled and emotional eating compared to video games, cryptoassets, play-to-earn gaming, alcohol, and cannabis/THC. Internet use was significantly more strongly associated with uncontrolled and emotional eating compared to cryptoassets, play-to-earn gaming, alcohol, and cannabis/THC. Gambling was significantly more strongly associated with uncontrolled and emotional eating compared to cryptoassets, play-to-earn gaming, alcohol, and cannabis/THC. Caffeine use was significantly more strongly associated with uncontrolled and emotional eating compared to crytpoassets, play-to-earn gaming, alcohol, and cannabis/THC. Video games were significantly more strongly associated compared to cryptoassets. All other comparisons were not significant. In this case, the strongest predictors were a mix of media, behavioral, and substance domains.

Sedentary Behavior. Video game use was the strongest predictor and internet was the next strongest, and they were not significantly different from each other; no other variables were significantly associated with sedentary behavior. Video games were significantly more strongly associated with sedentary behavior compared to social media, shopping, loot box gaming, alcohol, caffeine, and tobacco. Internet was significantly more strongly associated with sedentary behavior compared to shopping, loot box gaming, alcohol, caffeine, and tobacco. Television was significantly more strongly associated with sedentary activity compared to shopping, loot box gaming, alcohol, caffeine, and tobacco, even though its relationship with behavior was not significant. No other

Table 3

Regression Analysis Results for Each Domain's Association With Outcomes of Mental Health, Life Satisfaction, Sleep Quality, Cognitive Restraint, Uncontrolled and Emotional Eating, and Sedentary Behavior

Domain	*b*	β	1 *p*	2 *p*	3 *p*	4 *p*	5 *p*	6 *p*	7 *p*	8 *p*	9 *p*	10 *p*	11 *p*	12 *p*	13 *p*
Depression and anxiety as the outcome															
1. Television	.08	.35	—												
2. Video games	.07	.37	.16	—											
3. Social media	.07	.40	.27	.53	—										
4. Internet	.07	.42	.90	.12	.28	—									
5. Gambling	.05	.31	**.01**	.10	**.04**	**.01**	—								
6. Shopping	.06	.29	.13	.89	.49	.13	.11	—							
7. Cryptoassets	.04	.19	**.02**	.09	**.05**	**.02**	.69	.11	—						
8. Loot box gaming	.03	.14	**.01**	**.04**	**.02**	**.01**	.38	.06	.62	—					
9. Play-to-earn gaming	.05	.28	.10	.30	.21	.07	.75	.37	.52	.27	—				
10. Alcohol	.06	.31	.13	.67	.38	.09	.23	.78	.20	.09	.50	—			
11. Caffeine	.06	.25	**.04**	.40	.16	**.03**	.31	.51	.25	.12	.64	.77	—		
12. Tobacco	.06	.35	**.04**	.28	.15	**.04**	.51	.39	.38	.17	.81	.55	.75	—	
13. Cannabis/THC	.05	.29	**.03**	.18	.08	**.02**	.75	.25	.54	.28	.98	.36	.51	.71	—
All individual coefficients are significant at $p < .05$ except for loot box gaming, $p = .06$.															
Life satisfaction as the outcome															
1. Television	−0.06	−0.18	—												
2. Video games	−0.06	−0.22	.74	—											
3. Social media	−0.04	−0.14	**.03**	**.01**	—										
4. Internet	−0.07	−0.23	.48	.75	**.001**	—									
5. Gambling	−0.04	−0.17	.31	.19	.77	.13	—								
6. Shopping	−0.03	−0.09	**.01**	**.01**	.47	**.002**	.45	—							
7. Cryptoassets	−0.02	−0.06	.06	**.04**	.36	**.03**	.30	.61	—						
8. Loot box gaming	0.02	0.06	**<.01**	**<.01**	**.02**	**.001**	**.02**	.05	.14	—					
9. Play-to-earn gaming	−0.01	−0.04	**.03**	**.01**	.18	**.01**	.17	.34	.66	.23	—				
10. Alcohol	−0.06	−0.19	.99	.78	.10	.58	.34	.05	.08	**<.01**	**.03**	—			
11. Caffeine	−0.02	−0.07	**<.01**	**.001**	.14	**<.001**	.19	.46	.95	.09	.58	**.01**	—		
12. Tobacco	−0.03	−0.11	**.03**	**.01**	.34	**.01**	.31	.68	.86	.08	.52	**.03**	.87	—	
13. Cannabis/THC	−0.06	−0.23	.84	.99	.13	.83	.61	.07	.08	**<.01**	**.04**	.84	**.02**	**.04**	—
All individual coefficients are significant at $p < .05$ except for cryptoassets, $p = .24$, loot box gaming, $p = .40$, and play-to-earn gaming, $p = .58$.															
Sleep quality as the outcome (higher means worse sleep quality)															
1. Television	.19	.29	—												
2. Video games	.13	.23	**<.01**	—											
3. Social media	.14	.26	**<.01**	.41	—										
4. Internet	.16	.28	.05	.08	.30	—									
5. Gambling	.09	.19	**<.01**	.27	.09	**.03**	—								
6. Shopping	.12	.17	**<.01**	.77	.27	.06	.33	—							
7. Cryptoassets	.03	.04	**<.001**	**.01**	**<.01**	**<.01**	.11	**.02**	—						
8. Loot box gaming	.08	.11	**.03**	.32	.20	.12	.75	.39	.43	—					
9. Play-to-earn gaming	.12	.21	.05	.76	.49	.25	.59	.91	.06	.46	—				
10. Alcohol	.15	.24	.10	.38	.73	.77	.10	.26	**<.01**	.17	.38	—			
11. Caffeine	.16	.22	.18	.14	.35	.85	**.03**	.09	**<.01**	.10	.26	.70	—		
12. Tobacco	.12	.24	**.02**	.82	.44	.19	.44	1.00	**.04**	.42	.92	.34	.17	—	
13. Cannabis/THC	.08	.15	**<.001**	.15	**.04**	**.01**	.78	.22	.22	.89	.43	**.04**	**.01**	.26	—
All individual coefficients are significant at $p < .05$ except for cryptoassets, $p = .53$, and loot box gaming, $p = .16$.															
Cognitive restraint as the outcome															
1. Television	.01	0.06	—												
2. Video games	.01	0.11	.31	—											
3. Social media	.01	0.10	.34	.84	—										
4. Internet	.01	0.07	.92	.29	.30	—									
5. Gambling	−.00	−0.00	.30	.10	.12	.26	—								
6. Shopping	.01	0.07	.59	.72	.79	.61	.16	—							
7. Cryptoassets	.02	0.15	.12	.29	.24	.12	**.03**	.22	—						
8. Loot box gaming	.04	0.22	**.01**	**.04**	**.02**	**.01**	**<.01**	**.03**	.38	—					
9. Play-to-earn gaming	.03	0.25	**.01**	**.02**	**.02**	**.01**	**<.01**	**.02**	.50	.72	—				
10. Alcohol	.01	0.05	.91	.38	.41	.85	.34	.60	.14	**.01**	**.01**	—			
11. Caffeine	.01	0.06	.94	.42	.48	.99	.27	.68	.14	**.01**	**.01**	.86	—		

(*table continues*)

Table 3 (*continued*)

Domain	*b*	β	1 *p*	2 *p*	3 *p*	4 *p*	5 *p*	6 *p*	7 *p*	8 *p*	9 *p*	10 *p*	11 *p*	12 *p*	13 *p*
12. Tobacco	.03	0.22	**.02**	.53	**.05**	**.01**	**<.01**	**.05**	.88	.39	.54	**.01**	**.02**	—	
13. Cannabis/THC	.01	0.07	.98	.53	.60	.97	.35	.74	.19	**.03**	**.03**	.90	.97	**.05**	—

All individual coefficients are significant at $p < .05$ except for television, $p = .053$, gambling, $p = .98$, alcohol, $p = .14$, caffeine, $p = .07$, and cannabis/THC, $p = .18$.

Uncontrolled and emotional eating as the outcome

Domain	*b*	β	1 *p*	2 *p*	3 *p*	4 *p*	5 *p*	6 *p*	7 *p*	8 *p*	9 *p*	10 *p*	11 *p*	12 *p*	13 *p*
1. Television	.06	0.38	—												
2. Video games	.04	0.35	**<.01**	—											
3. Social media	.05	0.42	.16	**.04**	—										
4. Internet	.05	0.38	**.02**	.25	.22	—									
5. Gambling	.05	0.41	.20	.52	.56	.99	—								
6. Shopping	.06	0.37	.82	**<.01**	.13	**.02**	.14	—							
7. Cryptoassets	.02	0.10	**<.001**	**<.01**	**<.001**	**<.01**	**.01**	**<.001**	—						
8. Loot box gaming	.03	0.20	.06	.48	.14	.27	.33	**.05**	.17	—					
9. Play-to-earn gaming	.03	0.24	**<.001**	.08	**<.01**	**.02**	**.04**	**<.001**	.20	.62	—				
10. Alcohol	.03	0.23	**<.001**	.07	**<.001**	**.01**	**.03**	**<.001**	.11	.80	.75	—			
11. Caffeine	.05	0.33	.48	.07	.78	.28	.47	.38	**<.001**	.13	**.01**	**<.01**	—		
12. Tobacco	.04	0.37	**.03**	.84	.11	.37	.45	**.02**	**.01**	.57	.18	.16	.09	—	
13. Cannabis/THC	.03	0.25	**<.001**	.06	**<.01**	**.01**	**.04**	**<.001**	.17	.72	.89	.85	**<.01**	.13	—

All individual coefficients are significant at $p < .05$ except for cryptoassets, $p = .06$.

Sedentary behavior as the outcome

Domain	*b*	β	1 *p*	2 *p*	3 *p*	4 *p*	5 *p*	6 *p*	7 *p*	8 *p*	9 *p*	10 *p*	11 *p*	12 *p*	13 *p*
1. Television	.28	0.05	—												
2. Video games	.54	0.12	.19	—											
3. Social media	.05	0.01	.12	**<.01**	—										
4. Internet	.33	0.07	.76	.16	**.02**	—									
5. Gambling	.04	0.01	.40	.06	.97	.26	—								
6. Shopping	−.13	−0.02	**.04**	**<.001**	.30	**.01**	.53	—							
7. Cryptoassets	−.21	−0.03	.23	.06	.51	.16	.53	.83	—						
8. Loot box gaming	−.70	−0.11	**.03**	**<.01**	.09	**.02**	.12	.20	.39	—					
9. Play-to-earn gaming	.28	0.05	.99	.47	.53	.89	.55	.27	.30	.06	—				
10. Alcohol	−.22	−0.04	**.03**	**<.001**	.19	**.01**	.38	.66	.97	.31	.20	—			
11. Caffeine	−.27	−0.05	**.01**	**<.001**	.08	**<.01**	.28	.47	.88	.31	.17	.83	—		
12. Tobacco	−.33	−0.08	**.02**	**<.001**	.11	**.01**	.22	.43	.77	.43	.13	.71	.84	—	
13. Cannabis/THC	.06	0.01	.42	.06	.95	.28	.94	.47	.54	.13	.60	.29	.21	.22	—

In this case, all individual coefficients are *not* significant at $p < .05$, except for video games, $p < .001$ and internet, $p = .02$.

Note. Coefficients reported below include both standardized and unstandardized, and statistical comparisons in the numbered columns are Wald tests using seemingly unrelated estimation using the unstandardized coefficients. For ease of interpretation, all Wald tests that are significant for a difference in coefficient at $p < .05$ are bolded ($p = .05$ but bolded means they rounded up to .05 but were less than, e.g., .047).

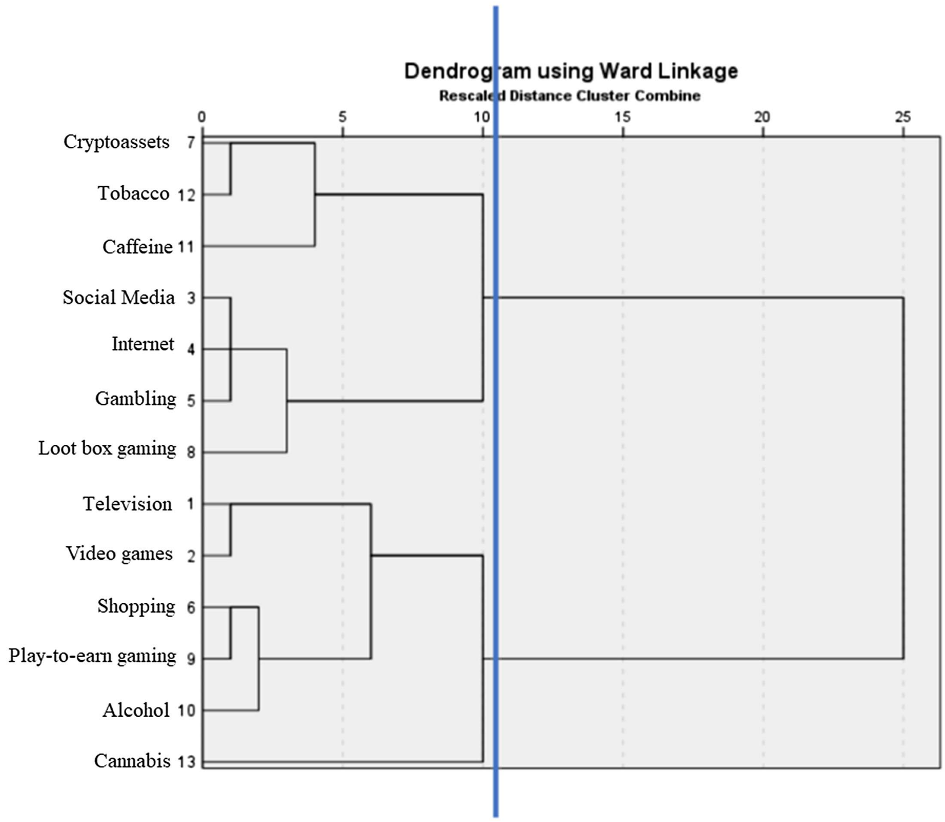
comparisons were significantly different for their relationship with sedentary behavior. In this case, most problematic behaviors were not associated with sedentary behavior except for video games and internet use.

Overall Conclusion. The total sum of these tests indicates that while most of the domains are significantly associated with depression and anxiety, life satisfaction, and sleep quality, some are more strongly associated than others. Interestingly, it is generally the media domains that are the most strongly associated with higher depression and anxiety, lower life satisfaction, and poorer sleep quality, even when compared to problematic substance use and problematic behaviors (e.g., gambling) that have more commonly accepted negative consequences. In addition, there are many cases where the media domains and the other domains do not meaningfully differ, indicating that the underlying dimensions of these domains may not be media use versus other problematic behaviors versus substance use, which is how these domains have often been sequestered in previous research. The cluster analysis in the following section will shed more light on the dimensions identified in these data.

Cluster Analysis

Cluster analysis is a data reduction technique similar to principal component analysis. It looks for item-to-item similarities and assigns them a location in a matrix space. This will allow us to test and visualize the ways that certain kinds of problematic behaviors and substance use may cluster together in our sample. For the present study, we utilized hierarchical cluster analysis and the Ward method (Figure 1) for determining how many clusters to retain (Ferreira & Hitchcock, 2009). Cluster variables were created by replacing the missing values for each Bergen scale with zero (so that each domain had the same sample size and so a single high domain score would not artificially inflate the cluster score) and averaging the scores within the identified cluster combinations: Cluster 1 (social media, internet, gambling, cryptoassets, loot box gaming, caffeine, tobacco/nicotine; $M = 0.95$, $SD = 0.51$); and Cluster 2 (television, video games, play-to-earn gaming, shopping, alcohol, cannabis/THC; $M = 1.09$, $SD = 0.53$). Crucially, these clusters indicate that the media domains do not separate from other broadly accepted behaviors (e.g., gambling), nor do they distinguish

Figure 1
Depiction of the Determination of Two Clusters Using the Ward Method



from problematic substance use (e.g., alcohol, tobacco/nicotine, cannabis/THC, caffeine).

Differential Susceptibility Analysis

This analysis was conducted using path analysis in Stata 17 to test the relationships between the differential susceptibility precursor variables, the behavior clusters, and the health variables. The error terms of the two clusters were specified to covary, as were the error terms of the health outcomes. The model was estimated with full information maximum likelihood estimation with missing values and robust standard errors. Full statistical results are reported in Table 4, and output is available on the Open Science Framework.

First, we report the relationships between the differential susceptibility measures and the behavior clusters. The dispositional susceptibility measures were gender, impulsivity, and delay discounting. Gender was not significantly associated with either cluster. Impulsivity was significantly positively associated with both clusters, indicating that as impulsivity increases problematic behaviors in both clusters increase. Delay discounting was not significantly associated with either cluster. The development susceptibility measure was age, which was significantly negatively associated with both clusters, indicating that the older someone is, the lower their problematic behaviors in both clusters. The social susceptibility measures were social support and education. Social support was not significantly associated with either cluster. Education level was associated with Cluster 2 at $p = .050$, but the 95% confidence interval contained zero, so we cannot conclude statistical significance. Education was not significantly related to Cluster 1.

Both clusters were significantly associated with higher depression and anxiety, poorer sleep quality, and more uncontrolled and emotional eating. Cluster 2 was significantly associated with decreased life satisfaction and higher cognitive restraint, but Cluster 1 was not. Neither cluster was significantly associated with sedentary behavior. This indicates that, overall, problematic behaviors are associated with mental health, sleep, and diet, but there may be some differences depending on domain category.

Discussion

The study's main interest was whether problematic media use domains are distinct from other, more well-accepted domains of problematic behaviors and substance use. The results suggest that media domains are not particularly distinct from other domains. In terms of the relationships between each domain and the health and well-being measures of depression and anxiety, life satisfaction, sleep quality, dietary behavior, and sedentary activity, there was little distinction between domain categories. In fact, the media domains were in many cases the strongest predictors of the outcomes, and in other cases similarly strong in their relationships as other domains, such as the relationship between alcohol use and mental health (Puddephatt et al., 2022), cannabis use and life

Table 4

Path Analysis for Differential Susceptibility Measures of Gender, Age, Impulsivity, Delay Discounting, Education Level, and Social Support Associated With Two Clusters of Bergen Addiction Measures, and the Bergen Addiction Measures Associations With Outcomes

	Bergen Cluster 1		Bergen Cluster 2		Depression and anxiety		Life satisfaction	
Variable	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Gender	−0.05	[−0.10, 0.00]	−0.02	[−0.07, 0.03]	**0.15**	**[0.11, 0.20]**	−0.01	[−0.06, 0.03]
Age	**−0.19**	**[−0.24, −0.14]**	**−0.27**	**[−0.32, −0.22]**	**−0.14**	**[−0.18, −0.09]**	**0.06**	**[0.01, 0.11]**
Impulsivity	**0.29**	**[0.23, 0.35]**	**0.32**	**[0.26, 0.37]**	**0.15**	**[0.10, 0.24]**	**−0.10**	**[−0.15, −0.04]**
Delay discounting	0.03	[−0.03, 0.09]	0.05	[−0.00, 0.10]	−0.05	[−0.10, 0.00]	0.03	[−0.02, 0.08]
Education level	−0.04	[−0.10, 0.01]	−0.05	[−0.10, 0.00]	**−0.06**	**[−0.11, −0.01]**	**0.13**	**[0.09, 0.18]**
Social support	−0.02	[−0.08, 0.04]	−0.01	[−0.06, 0.05]	**−0.34**	**[−0.39, −0.29]**	**0.48**	**[0.44, 0.53]**
Bergen Cluster 1	—	—	—	—	**0.11**	**[0.05, 0.18]**	0.02	[−0.05, 0.09
Bergen Cluster 2	—	—	—	—	**0.17**	**[0.10, 0.24]**	**−0.08**	**[−0.16, −0.02]**
R^2		.18		.25		.36		.33

	Sleep quality		Cognitive restraint		Uncontrolled and emotional eating		Sedentary behavior	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Gender	**0.20**	**[0.15, 0.25]**	0.04	[−0.02, 0.09]	**0.14**	**[0.09, 0.19]**	−0.01	[−0.07, 0.05]
Age	0.04	[−0.01, 0.09]	**0.12**	**[0.06, 0.18]**	0.01	[−0.04, 0.06]	−0.05	[−0.11, 0.02]
Impulsivity	**0.11**	**[0.05, 0.17]**	**−0.06**	**[−0.13, −0.00]**	**0.18**	**[0.12, 0.27]**	−0.04	[−0.10, 0.03]
Delay discounting	−0.00	[−0.06, 0.05]	−0.01	[−0.07, 0.04]	−0.01	[−0.06, 0.04]	**−0.09**	**[−0.15, −0.03]**
Education level	**−0.11**	**[−0.17, −0.06]**	**0.08**	**[0.02, 0.13]**	0.01	[−0.05, 0.06]	0.00	[−0.05, 0.06]
Social support	**−0.23**	**[−0.29, −0.18]**	−0.03	[−0.09, 0.03]	−0.05	[−0.10, 0.01]	**−0.12**	**[−0.18, −0.06]**
Bergen Cluster 1	**0.11**	**[0.04, 0.18]**	0.04	[−0.04, 0.11]	**0.21**	**[0.13, 0.28]**	−0.07	[−0.15, 0.01]
Bergen Cluster 2	**0.16**	**[0.09, 0.23]**	**0.14**	**[0.06, 0.21]**	**0.20**	**[0.12, 0.27]**	0.08	[−0.00, 0.16]
R^2		.22		.03		.24		.03

Note. Regression coefficients are standardized, and significant coefficients at $p < .05$ are bolded for ease of interpretation. CI = confidence interval.

satisfaction (Tartaglia et al., 2017), and caffeine use and sleep quality (Gardiner et al., 2023). They were also consistently more strongly related to outcomes compared to the oft-studied and maligned behavior of gambling in many of the outcome variables. Interestingly, cryptoasset behaviors and play-to-earn gaming were often unassociated with health and were also often significantly weaker in their relationships with health compared to the other domains. More research is needed to understand when and for whom these domains, which have formerly been associated with problem gaming and gambling (Delfabbro et al., 2022; Delfabbro & King, 2023), may or may not be associated with health.

The cluster analysis provided further evidence that media should not be considered a separate area from other behavioral addictions or substance use. Elements from the media domains, and other domains were interspersed to form two clusters. This indicates that the patterns of problematic or addictive behavior within individuals are not limited to media only or to substances only but consistent with the idea of global risk regardless of domain category.

This study also included individual difference variables. Only age and impulsivity were significantly associated with both clusters of behaviors, such that higher trait impulsivity and younger age were both associated with increased addictive behaviors. The other individual differences were often associated directly with the outcomes but were not significantly associated with the problematic behavior clusters. This reflects the findings in an earlier study, where impulsivity was the only individual difference predictive of five addiction domains (Walther et al., 2012).

Finally, a secondary purpose of the present study was to compare the Bergen addiction scales to domain-specific addiction scales in each domain. Our analysis suggested that the Bergen version was an appropriate substitute for nearly all domains, with the possible exception of caffeine. This may help to standardize future comparison across domains, as having all items measured on a similar scale with theoretical composition matching the six components of addiction (Griffiths et al., 2017) can help such comparisons statistically and conceptually.

Implications for Policy and Practice

These results have implications for public health, medical providers, researchers, clinicians, and policymakers. The fact that the domains did not separate in the cluster analysis by category, combined with the fact that the media domains were in many cases more strongly associated with negative health outcomes, supports the argument that researchers and policymakers should be considering media-related problematic behaviors as similar in severity and importance as other behavioral addictive disorders, such as gambling, and substance use disorders (e.g., Griffiths et al., 2017; Vidal & Meshi, 2023). Additionally, while gaming disorder is designated in the *International Classification of Diseases–11*, the other media domains are not included in any commonly used diagnostic manuals (e.g., *Diagnostic and Statistical Manual of Mental Disorders–Fifth Edition*). The present study supports the consideration of internet, social media, and television use to be added with their own disorder designations under a general behavioral addictive disorder section, similar to substance use disorders.

That said, the results of the present study also suggest that the current moral panics regarding the relatively new media technologies of cryptoassets, loot box gaming, and play-to-earn gaming may not deserve the focus they are getting, both in lay writing and in research. There is a long history of the newest media technology becoming the boogeyman of the day (Nicholas & O'Malley, 2013), and today's technologies are no exception. More research is needed in this area, including research that can more clearly establish causal relationships, but based on these findings, it is likely that these current new technologies are receiving more than their fair share of demonization when compared to the generally stronger relationships between more established media technologies (television, etc.) and health outcomes.

The only individual difference variables significantly associated with the behavioral clusters were (younger) age and (higher) impulsivity. This indicates that adolescents and young adults might be most at risk for developing multiple problematic behaviors. Pediatricians can advise parents and caregivers to be vigilant regarding the potential for the development of such addictions, especially for children who are high in trait impulsivity. This is likely already occurring for substance use, but perhaps less so for problematic behaviors (media and nonmedia). It is already known that the risk of negative outcomes of media use can be reduced (and positive outcomes can be increased) when parents employ restrictive and active mediation strategies with their children—more restrictive for younger children and more active/discussion-based for older children and adolescents (Nathanson, 2008).

Relatedly, policymakers have considered regulations on media, especially for young people. For example, the U.S. state of Utah recently banned social media use by youth under the age of 18 without parental consent (Reimann, 2023), while China instituted a policy in 2019 limiting online gaming to less than 90 min per day for children under 18, further limited to 60 min in 2021 (Soo, 2023). However, whether regulation is actually an effective tool for curtailing youth media use is questionable. This is due to parents' low levels of knowledge and attention to rating systems and age restrictions (Funk et al., 2009), as well as the fact that other attempts to limit children's access to potentially harmful and/or addicting content, such as online pornography, have been largely unsuccessful due to the industry's lack of diligence in verifying age (Franklin, 2023). Therefore, regulations are only as useful as their enactment, which history suggests is not particularly effective if relying on industry self-regulation or parents to successfully navigate the rankings and recommendations.

It should be noted that the effects found in the present study are relatively small, with standardized coefficients meeting the threshold of significance ranging from $\beta = 0.07$ to $\beta = 0.42$ for the relationships involving media measures. It has been argued that even tiny effects can be meaningful, especially when they are cumulative over time, as repeated behavior such as media effects tends to be (Abelson, 1985; Lang & Ewoldsen, 2010). This is the view to which we ascribe, but it is in contrast to other arguments that there should be a minimum threshold on the size of an effect that can be considered meaningful (Anvari & Lakens, 2021; Lakens et al., 2018). Researchers should thus interpret our results, with a large sample size for many measures and an at-times quite small effect size, with appropriate caution. More replication is needed in this space to establish the likely range of effects and when to consider them meaningful in terms of practical implications for clinicians and policymakers.

Limitations and Future Research

There are several limitations to the present study. Primarily, this is a cross-sectional survey, which limits the ability to make causal claims. As with most media effects research, the true relationship is likely dynamic (e.g., reinforcing spirals theory; Slater, 2007). For example, individuals with poorer mental health may seek out media, gambling, and/or substance use as a coping mechanism, yet these behaviors might actually exacerbate their depression and anxiety symptoms. It is well-established that many of these relationships are indeed dynamic in nonmedia domains; for example, that poor mental health is a predictor of later alcohol use disorder, which is then associated with worse mental health (Puddephatt et al., 2022). In addition, the differential susceptibility to media model would suggest that the individual difference variables should also be included as moderators of the media–outcome relationships. However, it was beyond the scope of the present study to include all of the interactions necessary to do such an analysis justice. Future research should look for such moderation effects between differential susceptibility variables and outcomes of problematic media use.

It also cannot be ruled out that the relationships found are spurious, with some unmeasured third variable(s) the true causal factor behind both variables in a relationship, or that they are epiphenomenal, with an intercorrelation between X and some other cause of Y, but X and Y are not causally related. Longitudinal data will be needed in this space to clarify the causality of the identified relationships more clearly. Additionally, the sample of this study is derived from a panel, and while approximately representative of adults in the United States, it is a nonprobability sample, limiting our ability to generalize our conclusions and especially to generalize beyond the U.S. context. Finally, the problematic behaviors and substance uses were not exhaustive, and other clusters and relationships may be found with the addition of different domains. Cluster analysis is similar to dimension reduction in that it is data-bound; therefore, changes to the measured domains would result in some changes to how the domains cluster. However, the overall interpretation, which is that the media domains and nonmedia domains are not clearly distinct, is unlikely to change. Future research should consider whether there are domains that were missed in the present study.

Conclusion

Problematic addictive behaviors are often discussed separately for media-related domains, such as social media, video games, and television, compared to other behavioral domains (e.g., gambling) and substance use domains (e.g., alcohol). However, the present study suggests that this separation by category might not be useful and, in fact, may be artificially drawing lines between categories that do not always exist—at least in terms of the health and well-being outcomes investigated in the present study. Our analyses suggest that many domains were significantly associated with health and well-being, and in many cases, the media domains were just as strongly associated, if not more strongly associated, with these health measures compared to the nonmedia behavioral domains and the substance domains. In addition, cluster analysis did not find that dimension reduction required the media domains to be on a separate factor from the other domains, but instead found two domain clusters each with a mix of media and other domains. These results suggest that problematic uses of media perhaps should be studied more firmly in the realm of addiction in general.

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