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ORIGINAL ARTICLE

Cross-Addiction Risk Profile Associations with COVID-19 Anxiety: a Preliminary Exploratory Study

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Abstract

"Cross-addiction" involves a person substituting one form of addictive behaviour for another. Indeed, cross-additive presentations have been frequently described (e.g. from drugs to alcohol, gambling to sex), and risk profiles have been assumed. Nevertheless, there has been a dearth of evidence considering the occurrence of cross-addiction risk profiles in the community. This research is imperative for informing effective prevention/intervention policies, especially under anxiety-provoking conditions, such as the current coronavirus pandemic. To address this need, a cross-sectional exploratory research design was utilized, with quantitative survey data obtained from 968 respondents (18–64; $M_{age}=29.5$ years, $SD=9.36$), who completed an online survey regarding a range of addictive behaviours (i.e. abuse of alcohol, drug, smoking, online gaming, shopping, internet, exercise, online gambling, sex, and social media) and their anxiety about the coronavirus. Latent class/profiling analyses were implemented to (a) explore profiles of cross-addiction risk, (b) describe the characteristics and the proportions of these profiles, and (c) identify their differential associations with the pandemic precipitated anxiety. Findings revealed two distinct profiles/types, the "cross-addiction low risk" (57.4%) and the "cross-addiction high risk" (42.6%). Those in the latter scored consistently higher across all behaviours assessed, were more likely to suffer from concurrent addictive problems, and reported significantly higher levels of pandemic-related anxiety. Implications for prevention, assessment, and treatment and future research are discussed.

Keywords Addictive behaviours · Latent class analysis · COVID-19 · Cross-addiction

Over the past 30 years, research in a variety of addictive behaviours including the abuse of alcohol, drugs, gambling, smoking, videogames, social media use, shopping, exercise, internet, pornography, and sex has increased (Burleigh et al., 2019; Sussman, 2020; Zarate

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et al., 2022). This has expanded the knowledge considering the prevalence and risk factors of different addictive behaviours, the similarities between substance and behavioural (i.e. non-substance related) addictions, and the impact of these addictive behaviours on individuals (e.g. reduced well-being and functioning) as well as on their family and friends (e.g. increased stress and anxiety; Abdo et al., 2020; Esparza-Reig et al., 2022; Grubbs et al., 2019). The coronavirus (COVID-19) pandemic has prompted researchers to explore COVID-19-related psychological factors that are associated with increases in addictive behaviours (e.g. anxiety about COVID-19; Panno et al., 2020; Salerno & Pallanti, 2021). Despite the progress recorded, research to understand the complex processes generating addiction(s), as well as inter-addiction links is lacking (Kardefelt-Winther et al., 2017; Starcevic, 2016). Researchers have identified the phenomenon of cross-addiction where an individual transitions from one addiction to another, often via replacement, as an area requiring further investigation (Sinclair et al., 2021a,b; Zarate et al., 2022). To date, various cross-addiction exhibitions (e.g. drugs to alcohol, alcohol to eating, gambling to videogames) and risk profiles have been suggested (Burleigh et al., 2019; Zarate et al., 2022). However, distinct cross-addiction risk types/profiles that may explain why people transition to certain addictive behaviours have been relatively unexplored (e.g. substance type, interactive type; Sinclair et al., 2021a,b). Thus, this study aims to address this gap, while concurrently investigating the associations of cross-addiction risk profiles with COVID-19-related anxiety.

Defining Addiction(s)

Addiction(s) initially are referred exclusively to the excessive/problematic consumption of alcohol and/or drugs, characterized by the presence of physical dependence, tolerance, and withdrawal symptoms (Alexander & Schweighofer, 1988; West & Brown, 2013). Nonetheless, there has been growing support for the definition to be broadened to host different categories: (a) substance addictions, which involve the ingestion of products that directly manipulate the experience of pleasure and provide mood-altering effects (e.g. alcohol, drugs, cigarettes), (b) and behavioural addictions, which consist of non-substance-use behaviours that have the potential to be addictive through exposing people to events that elicit pleasure and alter mood (e.g. gambling, internet use, playing videogames; Griffiths, 2019; Pontes et al., 2019; Stavropoulos et al., 2019; Sussman, 2017). Based on this broader conceptualization, addiction can be defined as the persistent preoccupation with and/or use of a substance or activity, which continues despite substantial biological, psychological, and/or social consequences, and can result in the development of tolerance through repeated use and withdrawal symptoms when discontinued or suddenly reduced (Kurniasanti et al., 2019; Pan et al., 2020). In that context, all substance and behavioural addictions have been suggested to consist of six distinct common components (Griffiths, 2005): (a) "salience", where the activity dominates the individual's life through their thoughts, feelings, and behaviours; (b) "mood modification", where the activity provides mood-altering effects that the individual desires and repeatedly uses to "self-medicate"; (c) "tolerance", where the individual needs to engage in increasing amounts of the activity overtime in order to obtain the same mood altering effects; (d) "withdrawal symptoms", where the individual experiences psychological symptoms and/or physiological symptoms when the activity is discontinued or drastically reduced; (e) "conflict", where the person experiences interpersonal/intrapsychic conflicts relating to the activity; and (f) "relapse", where one re-engages in previous patterns of the activity after they failed to stop or control it (Griffiths, 2005).

Impacts of Addiction

Solid evidence illustrates a range of negative consequences for addicted individuals including low mood, sleep problems, increased anxiety and distress, reduced functioning and performance at school/work, problems with interpersonal relationships, stigma, and reduced self-esteem and self-worth (Kuss et al., 2020; Sahu et al., 2019; Sussman, 2020). Indicatively, alcohol, drug, and gambling addictions have been associated with financial and legal problems, the development and exacerbation of physical and psychological conditions, and increased risks of suicidal behaviour and death (McCradden et al., 2019; Sussman, 2020; Tabri et al., 2021). Research has also shown that family and friends of addicted individuals tend to experience increased stress and anxiety and reduced well-being and quality of life (Arlappa et al., 2019; Esparza-Reig et al., 2022; Kennett et al., 2018). Thus, one could assume that the magnitude of addiction(s)' impact may be multiplied when experienced by the same individual either successively or concurrently, underlining the importance of developing a better understanding about inter-addiction links, such as cross-addictive behaviours.

Defining Cross-Addiction

Cross-addiction, also known as substitute addiction or addiction hopping, is when a person presenting with one form of addiction proceeds to substitute it with another addictive behaviour (Burleigh et al., 2019; Sinclair et al., 2021a,b). Cross-addiction is often discussed in the context of addiction recovery and in support groups such as Alcoholics Anonymous (AA) and Smart Recovery (Barnett et al., 2018). There are a few reasons why people engage in cross-addiction including (a) forced abstinence, where a person cannot access their original addiction and seeks an immediate alternative (e.g. alcohol/drugs being substituted with smoking in detoxification/rehabilitation programs); (b) harm reduction, where a person decides to stop their original addiction and finds an alternative behaviour that provides similar effects without as many harms (e.g. substituting gambling for videogames to reduce financial harms); and (c) relapse prevention, where a person adopts a new behaviour to reduce their risk of relapsing with their original addiction. While short-term substitution can facilitate early recovery by providing a distraction from the original addiction, there have been suggestions that long-term substitution may lead to harms related to the development of a new addiction and/or relapse with the original addiction (Kim et al., 2021; Sinclair et al., 2021a,b). The experience of cross-addiction can also prevent individuals from properly acknowledging and dealing with the underlying psychological issues related to the development and maintenance of their original addiction, thus preventing them from being able to fully recover.

Numerous examples of cross-addiction have been presented throughout the literature. Vaillant and Milofsky (1982) investigated the natural recovery processes of alcohol misuse among men and found that 47% of participants, who abstained from alcohol for over a year, reported transitioning to other addictive behaviours. These findings were supported by recent studies which found that a proportion of people who abstained from alcohol engaged in alternative behaviours as a substitute including gambling, shopping, sex, work, exercise, smoking, cannabis use, and pornography use (Kim et al., 2021; Sinclair et al. 2021a,b; Tadpatrikar & Sharma, 2018; Xuereb et al., 2021). There has also been extensive evidence of alcohol being used as a substitute for drug addictions involving heroin, opioids, cannabis, and cocaine (Buga et al., 2017; Kim et al., 2021; Sinclair et al., 2021b). Finally, research has supported different substitute behaviours being used after a period of abstinence from gambling, such as compulsive sexual behaviour, playing social casino videogames, alcohol use, internet use, and drug use (Black et al., 2021; Gainsbury et al., 2015; Xuereb et al., 2021). As such, it has been hypothesized that cross-addiction risk increases for more vulnerable individuals during distressing conditions such as the current pandemic (Zarate et al., 2022).

There are two main theories explaining cross-addiction. Firstly, "substitution hypothesis" suggests that people substitute one addiction for another, if the new addiction serves at least one function provided by the original addiction (e.g. providing mood-altering effect; Sussman & Black, 2008). The second is the "typology hypothesis", which suggests that different addictive behaviours are linked and can be categorized together through common characteristics and functions (e.g. nature of behaviour, type of mood-altering effect) and that people move towards certain types of addictive behaviours based on individual characteristics and other environmental factors (e.g. personality traits, mental health issues, coping style, exposure to and experience with substance/activity; Haylett et al., 2004). In that line, Haylett et al. (2004) identified two addiction groups that each contains two sub-types. The first group was classified "hedonistic addictions", relating to activities that involved eliciting pleasure and reducing pain, with the sub-types of "sensation-seeking hedonism" (i.e. activities that involved striving for excitement such as recreational drug use, alcohol use, and smoking), and "dominance-related hedonism" (i.e. activities that related to the exploitation and domination of other people such as sex and gambling; Haylett et al., 2004). The second group was classified "nurturant addictions", relating to activities of providing nourishment and care to self or others, with the sub-types of "self-regarding nurturance" (i.e. activities related to controlling body image and consumption such as food starving/binging and shopping), and "other-regarding nurturance" (i.e. activities considered praiseworthy such as excessive work and exercise; Haylett et al., 2004).

Individuals with cross-addiction can present in a variety of ways due to the many types of addictive behaviours and substances coupled with risk factors involved in developing an addiction (e.g. stress and genetics; Griffiths, 2005). Researchers may follow differing hypotheses on how to understand cross-addiction. One approach tends to separate substance addiction(s) from behavioural addictions by indicating that individuals who substitute one addiction for another will generally stay within the same category (e.g. switching a drug addiction for alcohol; Sinclair et al., 2021a, b). A different approach could suggest that there may be differing severity of addiction profiles. Thus, individuals at high risk can transition from any type of addiction to another equally (and independent of the nature of the addictive behaviour), and what they gravitate to is based on what is accessible and their personal factors; Sinclair et al., 2021a,b). With a greater understanding in how cross-addictions function, prevention and treatment efforts can be better equipped to help individuals at risk of substituting one addiction for another.

Cross-Addiction and COVID-19 Anxiety

Research during the early stages of the COVID-19 pandemic found that feelings of anxiety and distress related to COVID-19 were associated with increased rates of internet use, alcohol consumption, videogame use, online gambling, social media use, pornography use, and food consumption (Albertella et al., 2021; Håkansson & Widinghoff, 2021; Panno et al., 2020; Siste et al., 2020; Yazdi et al., 2020). Additionally, pandemic-related lifestyle changes, such as quarantining and lockdown isolation, have been assumed to increase the risk of addictions (e.g. developing an addiction and/or relapsing), due to restricting individuals' capacity to moderate their feelings via socialization and face-to-face support (Panno et al., 2020; Sinclair et al., 2020; Yazdi et al., 2020). There were also concerns about the potential for cross-addiction manifestations, as quarantine measures made some addictions difficult or impossible to access (e.g. casinos, drugs), likely leading individuals to engage in easily accessible behaviours when needing to cope with stress and/or anxiety related to the COVID-19 pandemic (e.g. videogames, internet, pornography, online gambling; King et al., 2020; Sinclair et al., 2020). Thus, Sinclair et al. (2020) proposed that further research exploring the impacts of COVID-19 on cross-addiction was needed.

Present Study

To address the dearth of evidence examining the occurrence of cross-addiction risk profiles, the present study innovatively examined a large community sample across a range of concurrent addictive behaviours (i.e. abuse of alcohol, drug, smoking, online gaming, shopping, internet, exercise, online gambling, sex, and social media). A sequence of advanced Latent Class Profile models (i.e. data-driven modelling, which allows identifying naturally homogenous/distinctive sub-groups within a broader population, based on selected indicators; in this case addictive measures Jason & Glenwick, 2015; Rosenberg, 2020) were employed to (a) explore profiles of cross-addiction risk, (b) describe the characteristics and the proportions of these profiles, (c) identify differential associations with COVID-19 pandemic precipitated anxiety, and (d) explore potential differences between the profiles proposed and the proportion of those who met criteria for diagnosable behaviours (i.e. exceeding suggested cut-off scores). Findings aim to inform more effective cross-addiction prevention and/or intervention practices, especially under anxiety-provoking conditions, such as the COVID-19 pandemic.

Methodology

Participants

The sample consisted of 968 participants[1] between the ages of 18 and 64 years old ($M = 29.5$ years, $SD = 9.36$). The random sampling error for 968 participants at the 95% confidence interval was found to be 3%. This satisfied Hill's (1998) recommendation of a maximum sampling error of ± 3.2% for a sample of 1000 participants. An a priori analysis using the G-power software was also conducted suggesting a minimum sample size of 178 participants (well exceeded by the number of respondents), based on a linear multiple

[1] The final sample was obtained from a larger sample of 1097 participants, who were recruited online. Of those, 129 participant results were excluded for being younger than 18, older than 65, or having completed less than 75% of the survey. Removing these left a final sample of 968 participants.

regression R^2 deviation from 0, an effect size F^2 of 0.15, an (α) error probability of 0.05 and power (1β) of 95%, a non-centrality parameter λ of 26.7, a critical F of 1.85, and an actual power of 0.9504. The sociodemographic characteristics for the sample are presented in Table 1.

Materials

A sequence of 14 demographic questions (e.g. age, gender, race/ethnicity, sexual orientation, relationship and marital status, education level, current employment), one scale assessing anxiety about COVID-19, and 11 scales assessing addictive behaviours experiences were analysed (see Table 2).

Procedure

The current study was approved by the Victoria University Human Research Ethics Committee on 07/10/2020 (HRE20-169). Individuals interested in participating clicked on a Qualtrics link that took them to the plain language information statement (PLIS), which provided information about (a) the study's background, purpose, and subjects assessed; (b) the expected time commitment; (c) one's eligibility to participate (i.e. be at least 18 years old, have no current untreated severe mental illness); (d) the use of anonymized data; and (e) one's right to withdraw without consequences. Subsequently, those interested in participating were directed to click a button indicating their informed consent, before completing the survey.

Statistical Analyses

To identify whether different types of cross-addiction risk exist, latent class/profiling analyses (LCA) was conducted in R Studio software using the tidyLPA package (Rosenberg et al., 2018). Calculations allowed for the means, variances, and covariances of the profile indicators to be estimated and compared concurrently as (a) freely estimated across classes, (b) fixed as equal across classes, or (c) constrained to zero (Table 3) (Rosenberg, 2020).

Firstly, to determine the model with the optimal fit, several fit indices (all advocating for the model with the lowest value) were considered including (a) Akaike's information criterion (AIC), (b) approximate weight of evidence (AWE), (c) Bayesian information criterion (BIC), (d) classification likelihood criterion (CLC), and (e) Kullback information criterion (KIC). These indices were evaluated following a hierarchy of significance of AIC, AWE, BIC, CLC, KIC, and a model's entropy, which was based on the recommendations of Akogul and Erisoglu (2017). Secondly, entropy, which is recommended to exceed 0.64, was observed (Akaike, 1974; Banfield & Raftery, 1993; Biernacki & Govaert, 1997; Brown et al., 2021; Cavanaugh, 1999; Celeux & Soromenho, 1996; Rosenberg, 2020; Schwarz, 1978). In addition, to determine whether the identified cross-addiction risk profiles were differently associated with COVID-19 anxiety, a Welch's independent samples t-test was performed using the Jamovi software (Navarro & Foxcroft, 2018). Finally, the proportions of those exceeding the cut-off score suggested regarding the instruments used, across all the addictive behaviours examined, were compared via chi-square analyses.

Table 1 Participants' demographic data

	Frequency ($N=968$)	Percentage (%)
Demographics		
Gender		
Female	315	32.5%
Male	622	64.3%
Trans/non-binary gender identification	26	2.7%
Genderqueer	1	0.1%
Other	1	0.1%
Prefer not to say	3	0.3%
Marital status		
Single	592	61.2%
Living with another	137	14.2%
Married	188	19.4%
Separated	6	0.6%
Divorced	20	2.1%
Widowed	3	0.3%
Prefer not to say	15	1.5%
Other	7	0.7%
Employment status		
Full-time	331	34.2%
Part-time	111	11.5%
Casual	23	2.4%
Self-employed	67	6.9%
Retired	5	0.5%
Unemployed	187	19.3%
Full-time student	141	14.6%
Other	103	10.6%
Highest level of education completed		
Elementary or Middle School	12	1.2%
High School or Equivalent	251	25.9%
Vocational/Technical School/TAFE (2 years)	85	8.8%
Some Tertiary Education	185	19.1%
Bachelor's Degree (3 years)	218	22.5%
Honours Degree or Equivalent (4 years)	109	11.3%
Master's Degree (MS)	68	7.0%
Doctoral Degree (PhD)	9	0.9%
Professional Degree (MD, JD)	14	1.4%
Other	12	1.2%
Prefer not to say	5	0.5%
Race/ethnicity		
Black/African-American	55	5.7%
White/Caucasian	595	61.5%
Asian	184	19.0%
Hispanic/Latino	46	4.8%
Aboriginal/Torres Strait islander	1	0.1%

Table 1 (continued)

	Frequency ($N=968$)	Percentage (%)
Indigenous	3	0.3%
Indian	5	0.5%
Pacific Islander	4	0.4%
Middle-Eastern	4	0.4%
Mixed	68	7.0%
Other	3	0.3%
Sexual orientation		
Heterosexual/straight	743	76.8%
Homosexual/gay	50	5.2%
Bisexual	125	12.9%
Unidentified/other	50	5.2%

Results

Missing Values

An insignificant missing completely at random test (MCAR; $\chi^2=3733.672$, $df=3803$, $p=0.786$) indicated that the missing values did not present to be systematic. No imputation was applied as missing values did not exceed 2% for each scale used (Field, 2017).

Number of Classes

To determine the model with optimal fit, 20 models (the four parameterizations multiplied by a sequence of 1 to 5 classes) were compared based on the fit indices' hierarchy of significance (i.e. AIC, AWE, BIC, CLC, KIC; Akogul & Erisoglu, 2017). The CVUP model with 2 classes/profiles was deemed as the best solution (see Table 4 for summary of model comparison).

As seen in Table 5, the CVUP two-class structure was found to have an entropy score of 0.92, which indicated high classification accuracy of participants across the two classes (e.g. low possibilities of a participant being classified in the wrong class).

Size of Classes

A descriptive analysis was completed to determine the size of each class of the model with the optimum fit (e.g. CVUP, 2 classes), in terms of both their frequency and their percentages/proportions (see Table 6).

Classes and Addictive Behaviours

Class 1 had higher standardized averages across all addictive behaviours, particularly for alcohol use, drug use, gambling, and smoking (see Table 7, Fig. 1 for standardized averages). Class 1 was consistently higher across all addiction forms/behaviours compared to class 2. Interestingly, the difference between the two classes hiked across substance-related

Table 2 Questionnaire descriptions and reliability

Scale	Description	Reliability (Cronbach's alpha and McDonald's Omega)	Scale cut-off scores to distinguish between disordered and non-disordered behaviours
Internet Gaming Disorder Scale Short-Form (IGDS9-SF; Pontes & Griffiths, 2016)	A nine-item psychometric measure designed to assess the proposed nine core criteria of Internet Gaming Disorder. Scored on a 5-point Likert scale (1 = *never* to 5 = *very often*)	$\alpha = 0.885$ $\omega = 0.892$	Cut-off score of 32 to distinguish between disordered and non-disordered gaming (Arıcak et al., 2019; Pontes & Griffiths, 2016; Pontes et al., 2017)
Alcohol Use Disorder Identification Test (AUDIT; Saunders et al., 1993)	A 10-item screening tool designed to assess risky and harmful alcohol use patterns during the past year across three domains: alcohol use (3 items), dependence symptoms (3 items), and experience of alcohol-related harms (4 items). Eight of the items are rated on a 5-point Likert scale (0 = *never* to 4 = *daily or almost daily*), and the remaining two items are rated on a 3-point Likert scale (0 = *no*, 2 = *Yes, but not in the last year*, 4 = *Yes, during the last year*)	$\alpha = 0.893$ $\omega = 0.907$	Cut-off score of 16 suggests high-risk/harmful level of alcohol use (Saunders et al., 1993)
Drug Abuse Screening Test (DAST-10; Skinner, 1982)	10 items were used to assess drug use behaviours during the past 12 months. Items are rated on a dichotomous scale with either a "yes" or "no" response that is allocated a score of 0 or 1	$\alpha = 0.864$ $\omega = 0.879$	Cut-off score of 6 indicating a substantial degree of drug abuse problems (Skinner, 1982)

Table 2 (continued)

Scale	Description	Reliability (Cronbach's alpha and McDonald's Omega)	Scale cut-off scores to distinguish between disordered and non-disordered behaviours
Cigarette Dependence Scale (CDS-5; Etter et al., 2003)	This scale uses 5 items to measure participants' dependency to nicotine. Items were scored differently to one another; one is rated on a 5-point Likert-type scale (1 = *totally disagree* to 5 = *fully agree*); one is rated on a unipolar scale (1 = *very easy* to 5 = *impossible*); one is rated from 0 to 100; and two ask about cigarette use habits. The three non-scale items are recoded with a score from 1 to 5, and all item responses are combined to make a total score, with higher scores indicating higher dependence on cigarettes	$\alpha = 0.683$ $\omega = 0.869$	No cut-off score identified in previous papers
Bergen Shopping Addiction Scale (BSAS; Andreassen et al., 2015)	Measures how much statements related to participants' thoughts, feelings, and actions towards shopping over the past 12 months Items are rated on a 5-point Likert scale (1 = completely disagree to 5 = completely agree)	$\alpha = 0.880$ $\omega = 0.888$	Providing at least four *agree* or *completely agree* responses was an indication of shopping addiction (Andreassen et al., 2015)
Exercise Addiction Inventory-Revised (EAI-R; Szabo et al., 2019)	The scale contains 6 items rating participants' exercise addiction behaviours. It is rated using a 6-point Likert scale (1 = *strongly disagree* to 6 = *strongly agree*)	$\alpha = 0.837$ $\omega = 0.843$	Cut-off score of 30 indicating exercise addiction (Szabo et al., 2019)
Online Gambling Disorder Questionnaire (OGD-Q; González-Cabrera et al., 2020)	Online gambling behaviours were assessed using 11 items. Items are rated on a 5-point Likert-type scale, ranging from 1 (*never*) to 5 (*every day*)	$\alpha = 0.946$ $\omega = 0.949$	Providing at least four *very often* or *every day* responses was an indication of online gambling addiction (González-Cabrera et al., 2020)

Table 2 (continued)

Scale	Description	Reliability (Cronbach's alpha and McDonald's Omega)	Scale cut-off scores to distinguish between disordered and non-disordered behaviours
Bergen-Yale Sex Addiction Scale (BYSAS; Andreassen et al., 2018)	Contains six items measuring sex addiction behaviours. Items are rated using a 5-point Likert scale (0 = *very rarely* to 4 = *very often*)	$\alpha = 0.837$ $\omega = 0.838$	Providing at least four *often* or *very often* responses was an indication of sex addiction (Andreassen et al., 2018)
Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016)	Social media addiction behaviours were assessed with six items rated on a 5-point Likert scale (1 = *very rarely* to 5 = *very often*)	$\alpha = 0.882$ $\omega = 0.885$	Cut-off score of 24 indicating social media addiction (Andreassen et al., 2016; Luo et al., 2021)
Internet Disorder Scale–Short Form (IDS9-SF; Pontes & Griffiths, 2016)	Internet addiction behaviours were assessed using nine items that are rated using a 5-point Likert scale, ranging from 1 (*never*) to 5 (*very often*)	$\alpha = 0.895$ $\omega = 0.897$	Providing at least five *very often* responses was an indication of internet addiction (Pontes & Griffiths, 2016)
Coronavirus Anxiety Scale (CAS; S. A. Lee, 2020)	Measures participants' anxiety about COVID-19. Using five items, participants rated how often they experienced symptoms over the past 2 weeks using a 5-point time anchored scale, with scores ranging from 0 (*not at all*) to 4 (*nearly every day over the last 2 weeks*)	$\alpha = 0.868$ $\omega = 0.872$	NA

Table 3 Summary of tidyLPA model combinations

Model	Variance	Covariance	Description
A	Equal	Zero	Model A (also known as class-invariant parameterization [CIP]) assumes the variance of class indicators to be equal and covariance to be zero. Within the current analysis, where addictive behaviours are used as class indicators, equal variance suggests that the highest and lowest addictive behaviour score of participants from one class is equal to that of all other classes. Covariance constrained to zero suggests that the different addictive behaviour scores do not correlate within the various classes (e.g. higher online gambling scores do not correlate with other addictive behaviours within the classes)
B	Varying	Zero	Model B (also known as class-varying diagonal parameterization [CVPD]) assumes the variance of class indicators to be varying and covariance to be zero. For the current analysis, variance varying suggests that the correlations and differences between the highest and lowest addiction score of participants within a class vary with all other classes. Covariance constrained to zero suggests that the different addictive behaviour scores do not correlate within the various classes
C	Equal	Equal	Model C (also known as class-invariant unrestricted parameterization [CIUP]) assumes the variance and covariance of class indicators to be equal. For the current analysis, variance equal suggests that the highest and lowest addictive behaviour score of participants from one class is equal across and within all other classes
D	Varying	Varying	Model D (also known as class-varying unrestricted parameterization [CVUP]) assumes the variance and covariance of class indicators to be varying. For the current analysis, this suggests that correlations and differences between the highest and lowest addiction score of participants within a class vary with all other classes. Covariance varying suggests that the correlation between different addictive behaviour scores may vary within the different classes

Table 4 Summary of model comparison

Model	Number of classes	AIC	AWE	BIC	CLC	KIC
CIP	1	59361.62	59654.63	59459.13	59323.62	59384.62
CIP	2	58089.89	58545.45	58241.02	58029.6	58123.89
CIP	3	57298.95	57916.73	57503.71	57216.68	57343.95
CIP	4	56688.27	57468.25	56946.65	56584.05	56744.27
CIP	5	56565.13	57507.47	56877.14	56438.82	56632.13
CVDP	1	59361.62	59654.63	59459.13	59323.62	59384.62
CVDP	2	55159.09	55762.03	55358.97	55078.91	55203.09
CIUP	1	57452.27	58409.05	57769.16	57324.27	57520.27
CIUP [a]	3	56641.21	57923.36	57065.36	56468.36	56731.21
CIUP [a]	4	56162.98	57607.22	56640.76	55968.3	56263.98
CIUP [a]	5	56148.37	57755.01	56679.78	55931.54	56260.37
CVUP	1	57452.27	58409.05	57769.16	57324.27	57520.27
CVUP	2	53979.8	55910.27	54618.46	53719.64	54113.8

CVDP and CIP models with three, four, and five classes could not be estimated/did not converge

[a]CIUP models with three, four, and five classes produced warning messages from the analysis but were still produced/converged and included in the table of results

Table 5 Summary of the CVUP two-class model

LogLik[a]	ICL[b]	Entropy[c]	Prob_min[d]	Prob_max[e]	N_min[f]	N_max[g]	BLRT_p[h]
– 26864	– 54671	0.92	0.966	0.992	0.425	0.575	0.0099

[a]LogLik is the log-likelihood of the data which estimates goodness of fit

[b]ICL is the integrated completed likelihood which chooses the number of clusters in a model

[c]Entropy is a score for the measure of classification uncertainty (Rosenberg, 2020)

[d]Prob_min is the minimum of the diagonal of the average latent class probabilities for most likely class membership (Jung & Wickrama, 2008)

[e]Prob_max is the maximum of the diagonal of the average latent class probabilities for most likely class membership (Jung & Wickrama, 2008)

[f]N_min is the sample proportion allocated to the smallest class (Rosenberg, 2020)

[g]N_max is the sample proportion allocated to the largest class (Rosenberg, 2020)

[h]BLRT_p is the bootstrapped likelihood ratio test's *p*-value (Rosenberg, 2020)

Table 6 Size of classes

Class	Frequency	Percentage
1	412	42.6%
2	556	57.4%
Total	968	100%

Table 7 Means and standard deviations of addictive behaviour scores across the two classes and total sample

Class		Internet gaming	Alcohol use	Smoking	Drug use	Sex	Social media	Shopping	Exercise	Online gambling	Internet use
Cross-addiction high risk	*Mean*	20.40	7.68	11	2.55	8.05	13.2	15.2	14.8	16.7	22.4
	SD	7.89	7.68	5.13	2.25	5.25	5.97	6.52	6.52	7.93	8.27
Cross-addiction low risk	*Mean*	16.5	2.08	7.94	1.06	5.63	10.6	12.5	14.0	11.3	18.1
	SD	6.02	2.36	2.04	0.39	4.71	4.95	4.95	6.49	0.61	7.14
Total	*Mean*	18.1	4.46	9.23	1.69	6.66	11.7	13.6	14.4	13.6	19.9
	SD	7.14	6.00	3.98	1.67	5.09	5.55	5.82	6.51	5.84	7.94

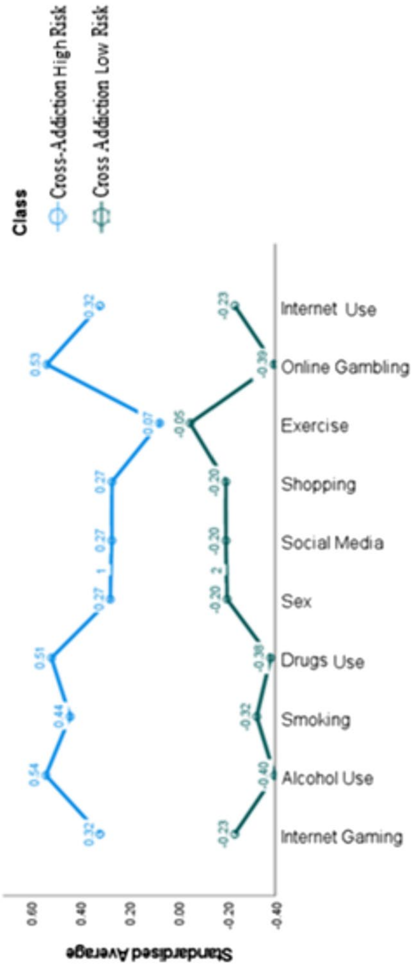

Fig. 1 Standardised addictive behaviours scores across classes

Table 8 Participants that met the addiction cut-off scores across the two classes

	Cross-addiction high risk		Cross-addiction low risk	
	n	Percentage of class	*n*	Percentage of class
Internet gaming	14	3.4%	6	1.1%
Alcohol use	85	20.6%	0	0%
Drug use	57	13.9%	0	0%
Sex	47	11.5%	23	4.2%
Social media	24	5.9%	9	1.6%
Shopping	52	12.7%	21	3.8%
Exercise	49	12%	42	7.7%
Online gambling	24	6%	0	0%
Internet use	17	4.1%	11	2%

addictions and gambling, while reduced for behavioural addictions (e.g. social media, shopping, and sex), with their lowest difference observed in relation to exercise addiction. Examining the addiction cut-off scores, class 1 was found to have more participants who met the cut-off scores for all addictive behaviours (see Table 8 for summary of addiction cut-offs across classes). Class 1 also had more participants who met the cut-off scores for multiple addictions ($n = 77$, percentage of class = 20.2%) compared to class 2 ($n = 20$, percentage of class = 3.8%). Thus, class 1 was named as "cross-addiction high risk", and class 2 was named as "cross-addiction low risk".

Classes and COVID-19 Anxiety

A Welch's independent samples t-test found a significant difference in COVID-19 anxiety between the cross-addiction high risk ($M = 2.24$, $SD = 3.21$) and cross-addiction low risk classes ($M = 1.06$, $SD = 2.22$), $t(689) = 6.40$, $p < 0.001$, $d = 0.427$ (see Table 8). Furthermore, comparisons between the two classes regarding those exceeding the suggested cut-off score for the instruments employed revealed significant higher proportions for the high-risk class/profile across all the addictive behaviours compared.

Discussion

This study investigated addictive behaviours in a large online sample of adults to address (1) different types of cross-addiction risk, (2) how these can be described, (3) what are their proportions in this population, and (4) whether the cross-addiction risk profiles associated differently with anxiety related to the COVID-19 pandemic. A sequence of 20 LCA models of 1 to 5 classes across four different parameterizations were calculated, revealing two distinct cross-addiction risk profiles. These were classified as "cross-addiction high risk" (42.6%) and "cross-addiction low risk" (57.4%). Respondents categorized in the high-risk profile scored consistently higher across all addictive behaviours assessed, presented more likely to suffer from concurrent addictive problems, and reported significantly higher levels of COVID-19 pandemic-related anxiety.

Cross-Addiction Profiles

Findings suggest two distinct cross-addiction risk profiles, referring to one's symptom severity, occurred within the sample. These presented to differ regarding one's reported levels of experienced addictive behaviours. In other words, profiles uniformly varied in the same direction across both substance and behavioural addictions, while those within the more severe (i.e. high-risk) profile tended to exceed, at significantly higher proportions, the cut-off score for diagnosable behaviours across all measures (except tobacco which lacks a diagnostic threshold). Thus, findings appear to contradict the notion that those more vulnerable to substance-related addictive behaviours are to be considered significantly different to those more at risk for behavioural addictions (Sinclair et al., 2021a, b). In contrast, it is supported that individuals' susceptibility to cross-addiction occurs on the basis of their level of vulnerability to addictive behaviours and may be independent of the nature of these behaviours (i.e. substance or behavioural; Sinclair et al., 2021a,b). This may (to an extent) imply that the underlying personal and surrounding predisposing and precipitating factors (e.g. environmental exposure, awareness, and accessibility) interacting may enforce addictions in a rather similar manner across varying problematic behaviours; or behavioural differences may be overridden by the strong perpetuating role of positive and/or desired mood-altering effects, such as an addiction communality (Starcevic, 2016; Starcevic & Khazaal, 2017; Sussman, 2020).

Consequently, the two profiles were shown to differentiate at around one standard deviation on substance-related behaviours (i.e. abuse of alcohol, drugs, smoking) and online gambling and to converge more on behavioural addictions (i.e. abuse of internet, gaming, sex, social media, shopping, videogames), with excessive exercise showing almost no difference between the two groups. These differences may propose that behavioural addictions' risk tends to be more equally distributed among both higher and lower risk groups in the community, likely due to not possessing as equally strong neurological effects as substance and gambling addictions (Kardefelt-Winther et al., 2017; Najavits et al., 2014; Thege et al., 2015; Zilberman et al., 2018). Lastly, the finding of a limited difference in "exercise addiction" between the two profiles may indirectly reinforce literature arguing against excessive exercise being considered an addictive behaviour (Starcevic, 2016; Thege et al., 2015). Indeed, one could argue that while addictions are pleasure-seeking behaviours that aim to produce immediate gratification, compulsive exercise may target longer-term benefits related to one's appearance and/or physical and mental health (Yücel et al., 2021).

Proportions of Profiles and Diagnosable Behaviours

The cross-addiction low-risk profile appeared to represent a higher proportion of the population examined compared to the cross-addiction high-risk profile. As the study used a community-based sample, this suggests that almost 43% of this sample may be at a higher risk of experiencing some form of cross-addiction based on their engagement patterns with various addictive behaviours. Among the cross-addiction high-risk profile, 20.2% were found to have scores above the addiction and/or high addiction risk cut-off scores for multiple scales. In addition, 3.8% of participants in the cross-addiction low-risk profile were also found to have scores above the cut-off score on multiple scales. This suggests that allocation to each profile, as a data driven process, was not simply restricted to obtaining high scores, but rather to exhibiting signs of several addictive behaviours. Nevertheless, the rates of participants who met the cut-off scores for singular and multiple addictions were relatively consistent with those reported in previous research (Beranuy et al., 2020; Grant & Steinberg, 2005; Luo et al., 2021). Overall, one could conclude that those assessed at higher risk for multiple addictions during the time of the COVID-19 pandemic (in this community online sample) exceeded 40% of the respondents, likely confirming that COVID-19-distress-related effects impact significant increases in addiction presentations (Arora et al., 2021; Rubin, 2021; Stringer et al., 2021).

Cross-Addiction Profiles and COVID-19 Anxiety

Consequently, it may not be surprising that those classified as cross-addiction high risk tended to report significantly higher levels of anxiety related to COVID-19. This is consistent with (a) previous research showing that increased anxiety is associated with increased risk for the abuse of alcohol, drugs, internet, gambling, videogames, social media, and tobacco (Mehroof & Griffiths, 2010; Panno et al., 2020; Siste et al., 2020; Sussman, 2020); (b) the self-medication hypothesis suggesting that those suffering from distressing mental health issues may often aim to moderate how they feel (i.e. either feel better or even feel less worse) via their addiction symptoms (Chopra et al., 2021; Khantzian, 2021; Servidio et al., 2021; Sussman, 2017, 2020); (c) the bi-directional association between distress and addictions may eventually exacerbate pre-existing anxiety (although the latter may initially emerge as the problematic solution of the first; Stathopoulou et al., 2021); and (d) evidence showing that people who experienced anxiety during the COVID-19 pandemic tended to engage in greater levels of substance use, online gambling, and internet-related addictive behaviours (Brailovskaia & Margraf, 2021; Capasso et al., 2021; Håkansson & Widinghoff, 2021; Sharman et al., 2021). In conclusion, it is supported that individuals of a cross-addiction high-risk profile may have potentially engaged in higher levels of several addictive behaviours as a method of coping with increased anxiety related to the COVID-19 pandemic and the related quarantine and social isolation measures adopted.

Limitations, Future Research, and Implications

The value of the current research should be considered on the basis of its several significant strengths. Firstly, it has been one the few studies to investigate whether different types of cross-addiction profiles occur, while taking into consideration an extensive range of proposed addictive behaviours. Secondly, it employed a large sample, recruited during the development of the COVID-19 pandemic. Thirdly, it implemented a sequence of 20 LCA models, varying regarding both their parameterization and the possible number of profiles examined. In spite of these strengths, the current study also embraces significant limitations, such as the lack of use of qualitative assessments (e.g. clinical interviews and/or clinical observations), the use of a community online sample, and the use of self-report measures which are susceptible to subjectivity and/or situational biases. The above inevitably invite cautiousness when generalizing the study conclusions and should be addressed by future research in the field.

Nevertheless, it could be suggested that albeit these limitations, the findings pose several important contributions and implications. Firstly, from a taxonomic and/or diagnostic perspective, the study provides evidence for the broadening of the addictions' umbrella to include behavioural addictions. Secondly, from an assessment perspective, it could be concluded that higher emphasis be given to substance addiction symptoms to identify the severity profile one may be classified within. Thirdly, from a prevention perspective, appropriate practices and/or policy can be developed to consider a significantly high proportion of the population (i.e. > 1/3) potentially at risk for concurrent addictions during the COVID-19 pandemic or for future pandemics. Fourthly, for prevention intervention for addictive behaviours may be incorporated to address addiction transitions, through efforts such as psychoeducational (i.e. raising awareness) or cognitive behavioural therapy techniques (i.e. aiming to restructure rationalized arguments allowing permissiveness towards "less severe" addictions).

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Declarations

Ethical Standards–Animal Rights All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Conflict of Interest The authors declare no competing interests.

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