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Alcohol, cannabis, and nicotine use have distinct associations with COVID-19 pandemic-related experiences: An exploratory Bayesian network analysis across two timepoints

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ABSTRACT

Background: Substance use trends during the COVID-19 pandemic have been extensively documented. However, relatively less is known about the associations between pandemic-related experiences and substance use. *Method:* In July 2020 and January 2021, a broad U.S. community sample (N = 1123) completed online assessments of past month alcohol, cannabis, and nicotine use and the 92-item Epidemic-Pandemic Impacts Inventory, a multidimensional measure of pandemic-related experiences. We examined links between substance use frequency, and pandemic impact on emotional, physical, economic, and other key domains, using Bayesian Gaussian graphical networks in which edges represent significant associations between variables (referred to as nodes). Bayesian network comparison approaches were used to assess the evidence of stability (or change) in associations between the two timepoints.

Results: After controlling for all other nodes in the network, multiple significant edges connecting substance use nodes and pandemic-experience nodes were observed across both time points, including positive- (r range 0.07–0.23) and negative-associations (r range -0.25 to -0.11). Alcohol was positively associated with social and emotional pandemic impacts and negatively associated with economic impacts. Nicotine was positively associated with economic impact. Cannabis was positively associated with emotional impact. Network comparison suggested these associations were stable across the two timepoints.

Conclusion: Alcohol, nicotine, and cannabis use had unique associations to a few specific domains among a broad range of pandemic-related experiences. Given the cross-sectional nature of these analyses with observational data, further investigation is needed to identify potential causal links.

1. Introduction

The COVID-19 pandemic had sudden, stark, and long-term impact across multiple life domains at the individual, family, and community levels, including social isolation and loneliness induced by stay-at-home orders, economic instability, physical illness, and pandemic-related anxiety, stress, and worry. Our aim was to examine cross-sectionally whether (and how) these known pandemic impacts were associated with three of the most widely used and co-used substances: alcohol, nicotine, and cannabis. A large body of evidence documenting changes in substance use in the early stages of the pandemic has been summarized in multiple meta-analytic and systematic reviews. Findings from these reviews suggest changes in alcohol use varied by country (Acuff et al., 2022; Bakaloudi et al., 2021; Kilian et al., 2022; Sohi et al., 2022) and the most common correlates of increased alcohol were mental health factors including stress, depression, anxiety, and pre-pandemic level of use (Acuff et al., 2022; Kilian et al., 2022; Kumar et al., 2022; Roberts et al., 2021; Schmidt et al., 2021). Many of these mental health

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factors were also associated with increases in cannabis use (Chong et al., 2021). Sociodemographic characteristics such as age, sex, and race, as well as changes in work and childcare during COVID-19 were predictive of increased drinking (Acuff et al., 2022). Global trends in tobacco use suggested similar proportions of individuals either increased or reduced their use, and approximately half showed no changes (Sarich et al., 2022). Among youth samples, alcohol, cannabis, and nicotine had an overall trend of decline during the pandemic (Layman et al., 2022). Together, these existing reviews indicate that there is considerable heterogeneity in pandemic substance use trends, which warrants further investigation.

Network analysis provides an avenue for understanding factors that may contribute to variation in substance use and/or that are impacted by substance use. In this approach, variables are represented as nodes in a network connected by edges that typically measure conditional associations (i.e., the associations between two nodes after controlling for all other nodes in the network) (Borsboom et al., 2021). This framework has been used to investigate relations among substance use disorder (SUD) symptoms (Rhemtulla et al., 2016; Rutten et al., 2021); to improve the understanding of links between symptoms of SUD and other mental health syndromes or personality traits (Afzali et al., 2020; Blondino and Prom-Wormley, 2022; López-Toro et al., 2022; Moriarity et al., 2021; van Buitenen et al., 2020; Wasil et al., 2020); to identify SUD symptoms associated with overdose (Ingram et al., 2022); to examine the potential impact of stress on SUD symptom connectivity (Lin et al., 2020); and to compare substance use patterns between clinical and population samples (Huth et al., 2022). Understanding the links between use of specific substance types and pandemic related stressors may generate testable hypotheses about potential points of intervention, which can facilitate development of targeted prevention and early intervention strategies for future pandemics.

In the context of the COVID-19 pandemic, pandemic-related thoughts (e.g., belief that threat is exaggerated), emotions (e.g., worry), and behaviors (e.g., compulsive checking), have been examined in network analyses which revealed links between alcohol use (including at-risk drinking behavior) and traumatic stress symptoms related to the pandemic as well as disregard for social distancing (Taylor et al., 2021). We aimed to expand on this work in several key ways. First, we examined cannabis and nicotine in addition to alcohol, given that the use of these substances often overlaps (Schlienz and Lee, 2018), and that changes in the use of one have been shown to impact changes in the use of the others (Allsop et al., 2014; Metrik et al., 2011). Second, our analysis included a wide range of pandemic impacts in addition to stress reactions. Lastly, we compared networks across two timepoints which allowed us to test whether relations among substance use and pandemic-related experiences were temporally stable. We expected there would be co-use of the three substances, and the network models were designed to test whether there were unique associations between specific substances and pandemic-related experiences. Given the exploratory nature of this analysis, we did not make specific hypotheses about the cross-sectional associations between substances and pandemic-related experience, or hypotheses about the temporal stability of relationships.

2. Material and methods

2.1. Study design and cohort

We used data from the COVID-Dynamic project (http://www.covidd ynamic.caltech.edu; Rusch et al., 2023; study preregistration http://osf. io/sb6qx), a longitudinal U.S. dataset of self-report measures and behavioral data collected in 16 waves from April 2020 to January 2021. Participant (N=1797) recruitment began on April 4, 2020 via the online platform Prolific (prolific.co) according to the following criteria: aged 18–100, fluent in English, current resident of one of the 50 U.S. states, previous participation in a minimum of 5 Prolific studies, and Prolific approval rating \geq 98%. To ensure geographic diversity, recruitment was spread equally across the U.S. East Coast, Middle U.S., and U.S. West Coast (see Rusch et al., 2023 for details). To ensure diversity in participant age, a portion of the recruitment targeted individuals between the ages of 40 and 100. Each wave, participants were given 140 minutes to complete an hour-long survey (survey measure composition varied from wave to wave; see Rusch et al., 2023 for details). Participants were compensated at a rate of \$10 per estimated hour of survey time as well as with regular pseudo-randomly distributed bonuses. Participants were excluded from the longitudinal study based on performance and commitment metrics (see Rusch et al., 2023 for a detailed characterization of excluded participants).

Our analyses focused on measures collected in July 2020 and January 2021 (waves 9 and 16 of the COVID-Dynamic project, henceforth referred to as T1 and T2, respectively). These were the only two timepoints that included the key assessments of interest to our research question. Inclusion criteria for this study were: 1) participated in at least one of the two timepoints and 2) had no more than one incorrect attention check. From the original sample of 1797 individuals that were recruited for the COVID-Dynamic project, 993 participated in the T1 assessment and 861 participated in the T2 assessment (N = 1123 unique participants after removing 14 that did not meet the attention check criterion). The percentage of missing data for the variables included in our network analyses ranged from 11.6% to 11.8% at T1 and from 23.3% to 25.5% at T2 (Table 1), which primarily reflects the proportion of individuals that did not participate in one of the two time-points. This human-subjects study was deemed exempt by the Institutional Review Boards of California Institute of Technology and Rutgers University.

2.2. Measures

The Monthly Substance Use Questionnaire was created for COVID-Dynamic to assess past 30 day substance-use frequency, where 0 = nouse, 1=1-2 days, 2=3-5 days, 3=6-9 days, 4=10-19 days, and 5=20-29 days (Rusch et al., 2023). In this study, the nicotine category reflects the highest response for cigarettes, e-cigarettes, tobacco from a water pipe, cigars/little cigars/cloves, or smokeless tobacco.

The Epidemic-Pandemic Impacts Inventory (EPII; http://www.phe nxtoolkit.org/toolkit_content/PDF/Grasso_EPII.pdf), is a 92-item inventory of pandemic-related experiences that was developed by an interdisciplinary team of experts (Grasso et al., 2021). Items were grouped across several domains: work impact (e.g., "reduced work hours or furloughed", "hard time making the transition to working from home"), home impact (e.g., "had to spend a lot more time taking care of a family member", "increase in verbal arguments or conflict with other adults in home"), social impact (e.g., "separated from family or close friends", "planned travel or vacations canceled"), economic impact (e.g., "unable to pay important bills like rent or utilities", "unable to get enough food or healthy food"), emotional health impact (e.g., "increase in mental health problems or symptoms", "increase in sleep problems or poor sleep quality"), physical health impact (e.g., "got less medical care than usual", "increase in health problems not related to this disease"), infection and isolation (e.g., "isolated or quarantined due to symptoms of this disease", "tested and currently have this disease"), and positive impact (e.g., "paid more attention to personal health", "increase in exercise or physical activity"). Summary results were generated by creating a sum score for each domain of impact composed of the items answered "yes" (self or person in household) (Table 1). Since our goal was to examine how these pandemic experiences were related to substance use reported in the Monthly Substance Use Questionnaire, we removed two items from the EPII that asked participants about substance use. Specifically, we removed "Increase in use of alcohol or substances" from the group of items related to emotional health, and we removed "Less use of alcohol or substances" from the group of items related to positive change.

Table 1

Descriptive statistics of variables included in the networks.

-		
Network node	T1 (July 2020)	T2 (January 2021)
Alcohol use (last month)		
none	504 (44.9%)	447 (39.8%)
1–2 days	124 (11.0%)	118 (10.5%)
3–5 days	115 (10.2%)	91 (8.1%)
6–9 days	80 (7.1%)	55 (4.9%)
10–19 days	71 (6.3%)	68 (6.1%)
20–29 days	59 (5.3%)	40 (3.6%)
daily	39 (3.5%)	39 (3.5%)
missing	131 (11.7%)	265 (23.6%)
Cannabis use (last month)		
none	826 (73.6%)	732 (65.2%)
1–2 days	33 (2.9%)	22 (2.0%)
3–5 days	25 (2.2%)	22 (2.0%)
6–9 days	16 (1.4%)	12 (1.1%)
10–19 days	14 (1.2%)	14 (1.2%)
20–29 days	23 (2.0%)	14 (1.2%)
daily	53 (4.7%)	45 (4.0%)
missing	133 (11.8%)	262 (23.3%)
Nicotine use (last month)	100 (111070)	202 (201070)
none	784 (69.8%)	693 (61.7%)
1–2 days	14 (1.2%)	13 (1.2%)
3–5 days	15 (1.3%)	6 (0.5%)
6–9 days	9 (0.8%)	8 (0.7%)
10–19 days	9 (0.8%)	8 (0.7%)
20–29 days	11 (1.0%)	8 (0.7%)
daily	127 (11.3%)	101 (9.0%)
missing	154 (13.7%)	286 (25.5%)
Work impact, range 0–8	101 (101/70)	200 (2010/0)
mean (SD)	1.19 (1.34)	1.19 (1.38)
median [Q1, Q3]	1.00 [0.00, 2.00]	1.00 [0.00, 2.00]
Home impact, range 0–12	100 [0100, 2100]	100 [0000, 2000]
mean (SD)	0.79 (1.39)	0.79 (1.39)
median [Q1, Q3]	0.00 [0.00, 1.00]	0.00 [0.00, 1.00]
Social impact, range 0–10	0100 [0100, 1100]	0100 [0100, 1100]
mean (SD)	3 (2.04)	3.27 (2.23)
median [Q1, Q3]	3.00 [1.00, 5.00]	3.00 [1.00, 5.00]
Economic impact, range 0–5	0.00 [1.00, 0.00]	0100 [1100, 0100]
mean (SD)	0.25 (0.66)	0.22 (0.6)
median [Q1, Q3]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]
Emotional impact, range 0–7	0100 [0100, 0100]	0100 [0100, 0100]
mean (SD)	1.69 (1.35)	1.69 (1.4)
median [Q1, Q3]	1.00 [1.00, 3.00]	1.00 [1.00, 3.00]
Physical impact, range 0–8	100 [100, 000]	100 [100, 000]
mean (SD)	2.04 (1.55)	2.17 (1.6)
median [Q1, Q3]	2.00 [1.00, 3.00]	2.00 [1.00, 3.00]
Infection and isolation, range 0–9	2100 [1100, 0100]	2100 [1100, 0100]
mean (SD)	0.9 (1.34)	1.23 (1.62)
median [Q1, Q3]	0.00 [0.00, 1.00]	1.00 [0.00, 2.00]
Positive impact, range 0–18		[0.00, 2.00]
mean (SD)	5.58 (3.88)	5.5 (3.69)
median [Q1, Q3]	5.00 [2.00, 8.00]	5.00 [3.00, 8.00]
<i>Note.</i> Networks included 1123 participants with data in at least one of the two		

Note. Networks included 1123 participants with data in at least one of the two time points. The percentage of missing data ranged from 11.6% to 13.7% at T1 and from 23.3% to 25.5% at T2.

2.3. Network analyses

Analyses were conducted in the open-source statistical software *R* version 4.2.1 (R Core Team, 2013); the full analytic code and output are provided in Appendix 1 of the Supplementary Material. Bayesian Gaussian graphical models (BGGM) were estimated with the *BGGM* package (Williams, 2021). We selected the BGGM package because it handles non-normal and zero-inflated data using a semi-parametric copula approach, uses multiple imputation to estimate the strength of each edge within a network, and estimates differences in edge strength across networks using unimputed data (Williams et al., 2020). This allowed us to 1) examine the links between substance use and pandemic-related experiences, and 2) test whether these associations were stable or different across time. Edges in the networks with 95% credible intervals (CI) that did not cross zero were considered significant. Networks were compared by subtracting posterior distributions of

edge strengths across the two time points; edges were considered significantly different when the 95% CI of the estimated difference did not cross zero. Although all potential edges in the network were estimated, our focus was on the links connecting substance use to pandemic experiences. Given the number of potential edges, it is important to consider whether this approach is prone to identifying false edges (i.e., spurious associations). In extensive simulation studies that compared multiple network analytic methods (Isvoranu and Epskamp, 2021), BGGM with 95% CIs had a precision of 0.94 (i.e., 94% of edges included in the estimated network also appeared in the true network) and a specificity of 0.95 (i.e., 95% of the edges that were not part of the true network were also excluded from the estimated network).

2.4. Post hoc analyses

In the review process, reviewers suggested controlling for demographic variables and testing associations in negative binomial regression models that treat variables as a count. To address these suggestions we re-analyzed each substance use outcome (alcohol, cannabis, and nicotine) across each of the two time-points in negative binomial regression models that included the other substances and the pandemicrelated experiences, and controlled for demographic variables that were self-reported in the baseline assessment of the parent study: age (in years), sex (female or male), Hispanic or Latino ethnicity (yes or no), race (binary 1/0 indicators for Asian, Black, multiracial, and White), education level (eight levels ranging from some high school to a doctorate degree), and a binary variable indicating whether the participant was in a committed relationship (including marriage) or not. Individuals coded 0 on all racial categories identified as American Indian or Alaskan Native, Native Hawaiian or Other Pacific Islander, or other; creating separate indicators for these categories was not possible because the sample sizes were too low. These analyses included all participants with complete data (965 at T1 and 834 at T2). The full analytic code and output of these analyses are provided in Appendix 2 of the Supplementary Material.

3. Results

Approximately half of participants were female (50.4%), with a mean age of 39.5 (SD = 13.9, range 18–77), and 52.2% reported being in a committed relationship (including marriage). The self-identified race of most participants was White (75.7%), followed by Asian (9.9%), Black (7.1%), multiracial (4.5%), other (2.2%), American Indian or Alaskan Native (0.4%), and Native Hawaiian or Other Pacific Islander (0.1%); 10.2% reported Hispanic or Latino ethnicity. Most participants reported that their highest level of education included a college degree: Associate's (10.6%), Bachelor's (34.5%), some graduate school (3.2%), Master's (13.3%), or doctorate (3.4%); the remainder reported some college (23.1%), a high school degree (11.1%), or some high school (0.9%). At T1, 50.0% reported no children living in the household, 23.5% reported living with children, and 26.4% had missing responses. Table 1 provides descriptive statistics of all the variables included in the network analyses. Across the two time points, there were no meaningful differences in the frequency of alcohol, cannabis, or nicotine use, or in the number of pandemic experiences reported across the different EPII domains.

Fig. 1 shows the network plots across the two waves; here we report partial r and 95% CIs for the edges containing substance use nodes. While these values are generally small, they reflect the strength of the association across each node pair after controlling for all other nodes in the network. In the T1 network there were five significant edges connecting substance use nodes with pandemic experiences. Alcohol use was positively associated with social impact, r = 0.17 [0.07, 0.23], and work impact, r = 0.07 [0.01, 0.18], and negatively associated with economic impact, r = -0.15 [-0.27, -0.05]. Nicotine use was positively associated with home impact, r = 0.13 [0.03, 0.25] and negatively

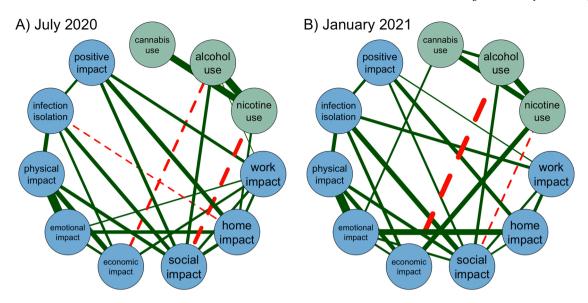


Fig. 1. Plots of the Bayesian Gaussian graphical network models. *Note.* Green nodes represent substance use variables, and blue nodes represent pandemic-related impacts. Solid green edges indicate positive associations, and dashed red edges indicate negative associations. Edge thickness conveys the strength of the pairwise association, after controlling for all other nodes in the network.

associated with social impact, r = -0.21 [-0.28, -0.07]. Nicotine use also had significant associations with alcohol use, r = 0.36 [0.22, 0.43], and with cannabis use, r = 0.32 [0.22, 0.45].

In the T2 network, there were five significant edges connecting substance use nodes with pandemic experiences, all of which were also significant in the T1 network. Cannabis use was positively associated with emotional impact, r = 0.12 [0.002, 0.23]. Alcohol use was positively associated with social impact, r = 0.15 [0.05, 0.23], and negatively associated with economic impact, r = -0.25 [-0.35, -0.10]. Nicotine use was positively associated with social impact, r = -0.23 [0.06, 0.37], and negatively associated with social impact, r = -0.11 [-0.26, -0.03]. Nicotine use also had significant associations with alcohol use, r = 0.28 [0.14, 0.37], and with cannabis use, r = 0.24 [0.14, 0.41]. Cannabis and alcohol use were also associated, r = 0.16 [0.05, 0.29].

Across both timepoints, there were a total of seven edges linking substance use and pandemic experiences; of these, three were significant across both networks. The Bayesian model comparison of model edges linking substance use to pandemic experiences all had 95% CI that included zero. This suggests that the links between substance use and pandemic experiences were not significantly different across time. In fact, when considering all edges in the networks, only the association between work and economic impact of the pandemic was significantly different (weaker) at T2 compared to T1, $\Delta r = -0.18$ [-0.34, -0.01].

Supplementary Tables 1-6 contain results from the negative binomial regressions for each substance use outcome at each timepoint that contained the other substance use variables, the EPII variables, and adjusted for an additional nine demographic variables. Consistent with the network analyses at T1, social and work impacts were significantly associated with alcohol use, and home and social impacts were significantly associated with nicotine use (Supplementary Tables 1–3). Consistent with the network analyses at T2, emotional impacts were associated with cannabis use, economic impacts were associated with alcohol use, and social impacts were associated with nicotine use (Supplementary Tables 4–6). The remaining significant associations that were observed in the network analyses did not reach significance in the regression analyses; however, all estimates were in the same direction (i. e., positive or negative coefficients) across the two analytic approaches. Note that because these are negative binomial models, the coefficients reflect the predicted difference in log odds of the expected count in the response variable per unit change in the predictor variable (after

controlling for all other variables in the model).

4. Discussion

Results from our Bayesian network analysis suggest associations among the use of alcohol, cannabis, and nicotine; additionally, each of these substance use variables showed distinct associations to negative impacts of the pandemic on emotional, social, economic, home, and work domains. Alcohol was the most frequently used substance in this sample, and endorsement of more types of social impacts was associated with greater alcohol use across both timepoints (this association was also significant at T1 in the negative binomial regression that controlled for an additional nine variables). This is consistent with a large systematic review that found social isolation was consistently linked with increases in alcohol use during the pandemic (Roberts et al., 2021). Although these cross-sectional network analyses cannot determine whether alcohol use exacerbated or was exacerbated by these pandemic experiences, they highlight the specificity of links between alcohol use and social consequences of the pandemic, which were present after controlling for all other pandemic experiences in the network. Alcohol use also showed a significant but negative association with economic impact across both timepoints (this association was also significant at T2 in the negative binomial regression that controlled for an additional nine variables). Items in this domain included inability to afford food, rent, utilities, and medications, which suggests that economic factors may have limited access to alcohol. Together, these findings are consistent with a systematic review that suggested two opposite patterns of consumption were likely operating during the pandemic: potential increase related to distress and decrease due to economic impact (Rehm et al., 2020).

Nicotine use was the second most frequently used substance in this sample and showed strong associations to both alcohol and cannabis use. However, in contrast to alcohol use, nicotine showed a negative association with social impact across both timepoints (these associations were also significant in the negative binomial regression that controlled for an additional nine variables). It is plausible that individuals that primarily smoked in social situations reduced their smoking if the pandemic impacted their social life and reduced contextual exposure to smoking-related cues (Jackson et al., 2021). At T2 there were higher rates of nicotine use among participants that reported more economic impact, which is consistent with research preceding the pandemic that showed that financial stress was associated with lower likelihood of quitting smoking, and higher likelihood of smoking relapse (Siahpush and Carlin, 2006).

At T2, cannabis use showed a positive association with negative emotional experiences resulting from the pandemic (this association was also significant in the negative binomial regression that controlled for an additional nine variables). Although this association should not be interpreted causally, other studies have documented that reduction of psychological distress is frequently cited as the primary reason for cannabis use (Glodosky and Cuttler, 2020). Moreover, having a mental health condition was associated with nearly double the odds of increased use of medicinal cannabis during the pandemic (Vidot et al., 2021).

In contrast to the regression analyses, network analyses also provided estimates of associations between pandemic experiences. Although our goal was to examine links between pandemic experiences and substance use, several things stand out in the associations among pandemic impact domains. First, it is clear from Fig. 1 that there are many positive associations among pandemic variables, which indicates that the impact of the pandemic was highly distributed across the diverse domains measured. Interestingly, reporting more types of negative experiences across work, home, and social domains was associated with reporting more positive types of pandemic experiences, such as increasing physical activity and exercise, spending more time outdoors or engaging in hobbies, having time to cook to improve diet and nutrition, and spending more time with family and friends (even if virtually). This suggests that many individuals may have adapted to the negative pandemic impacts by adjusting behavioral lifestyle habits and engaging with social supporters.

The only edge in the network to show a significant change across the two timepoints was between economic and work impact, which showed a positive relationship at T1 that significantly reduced by T2. It should be noted that within the work domain, the measured impacts varied from layoff to difficulty adjusting to remote work; it is possible that as time progressed through the pandemic, the types of work-related impact that were reported were less likely to be associated with economic challenges.

4.1. Limitations

We note several limitations. An online survey platform was used to facilitate collection of data, given pandemic-related restrictions and safety protocols, which has the potential for biased responses (e.g., social desirability considerations around reporting of substance use; community sample, rather than population-based sample). Although the sample included participants with a wide age range and nearly equal representation between males and females, several racial and ethnic groups including Hispanic or Latino and Black were underrepresented. Additionally, the sample included participants from all 50 states in the US but given the international differences in pandemic-related policies, findings may not generalize to other countries. Although we report frequency of substance use over the past month assessment period, we did not document quantity of use; this is a study limitation. The inclusion of two timepoints allowed us to test the stability of the estimated networks, but given the subsequent Delta and Omicron waves, it is possible that these relationships continued to evolve throughout the remainder of the pandemic. Moreover, the associations in these crosssectional network analyses should not be interpreted as causal. Most (but not all) of the associations observed in the network model remained significant when we examined associations between pandemic variables and substance use using negative binomial regressions that controlled for an additional nine demographic variables. This suggests that some of the results were sensitive to distributional assumptions and/or to confounding related to the demographic covariates. It is also possible that the strength of associations between EPII variables and substance use is moderated by demographic variables. We did not explore this given the number of potential comparisons; however, future work can test targeted hypotheses about potential sex, age, race, and/or ethnic differences in the associations of the variables we examined. Finally, some findings (or lack of) may have been confounded by the fact that there are several items in the EPII home and work domains that are only applicable to individuals who have (and live with) children.

5. Conclusions

These network analyses suggest specific and nuanced relationships between pandemic-related emotional, economic, and social impacts and the use of alcohol, cannabis, and nicotine in a sample with a broad range of use patterns. Notably, more endorsement of emotional impacts was positively associated with cannabis use at the latter timepoint, whereas links with social impacts were positive or negative depending on the substance. Although findings are consistent with other studies showing some associations between the use of substances for coping with emotional impact and social isolation, further research is needed to investigate potential causal links.

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CRediT authorship contribution statement

Santiago Papini: Conceptualization, Methodology, Software, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. Teresa López-Castro: Conceptualization, Funding acquisition, Project administration, Writing – review & editing. Peggy Swarbrick: Conceptualization, Writing – original draft, Writing – review & editing. Lynn K. Paul: Data curation, Investigation, Writing – original draft, Writing – review & editing. Damian Stanley: Conceptualization, Data curation, Investigation, Methodology, Project administration, Validation, Writing – review & editing. Alexandria Bauer: Conceptualization, Writing – original draft, Writing – review & editing. Denise A. Hien: Conceptualization, Funding acquisition, Project administration, Resources, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

No conflict declared.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.drugalcdep.2023.109929.

S. Papini et al.

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