Drug and Alcohol Dependence 273 (2025) 112728

Contents lists available at ScienceDirect

Drug and Alcohol Dependence

journal homepage: www.elsevier.com/locate/drugalcdep

Cannabis consumption patterns, adverse events, and cannabis risk beliefs: A latent profile analysis in WA State

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ARTICLE INFO

Keywords:
Cannabis
Patterns of use
Frequency of use
Latent profile analysis
Adverse events
Cannabis products

ABSTRACT

Cannabis legalization has increased the diversity of products available to people wishing to purchase cannabis. Understanding profiles of people who use cannabis, including use of different product types and how these relate to adverse events and risk beliefs may aid public health professionals, clinicians, and people who use cannabis who are seeking to reduce the risk of cannabis use. This cross-sectional study used data from Washington State residents between 16 and 65 years old collected between 2019 and 2022 as part of the International Cannabis Policy Study to characterize of patterns of use through Latent Profile Analysis. The study describes six cluster groups made up of those who reported past year cannabis use (N = 3298) that differed by frequency of use of cannabis product types, ranging from the lowest use group that averaged weekly use of primarily flower to a group characterized by daily use of concentrates. Contrasting with clinical studies that indicate that adverse events increase with THC levels and frequency of use, this group reported significantly fewer adverse events than the group with the next most frequent use who reported a greater variety of product types. These findings may be influenced by transitions between groups, which are not captured in this cross-sectional study. The four groups with most frequent use and greatest variety of product types, were all significantly more likely to self-identify as "addicted" than the lowest use, primarily flower, group. There were few differences in risk beliefs between groups. Efforts to reduce cannabis risk should focus on reducing frequency of use and possibly limiting poly-modal cannabis use.

1. Introduction

Cannabis legalization has changed the landscape of products available to people who want to purchase cannabis (Spindle et al., 2019), complicating measures of THC concentration and methods of cannabis use. Prior to 2014, when cannabis stores opened in Washington State (WA), one of the first two states to legalize cannabis for adult use in the U.S., individuals reported primarily smoking flower. With legalization came the diversification of product type to include manufactured edibles, cannabis drinks, vape pen cartridges, and concentrates (Carlini et al., 2017; Caulkins et al., 2018; Firth et al., 2020), and an increase in poly-cannabis use (Krauss et al., 2017), with those in WA who used cannabis in the past 12 months using an average of 5.1 cannabis product types in a 12-month period (Hammond et al., 2023). In 2020, concentrates represented 35 % of the WA cannabis market up from 9 % in 2014 (*WA State House and Gaming Commission work session*, 2020), a concern because concentrates contain more than triple the THC of cannabis flower (about 68.7 % compared to 20.6 % in flower; Smart et al., 2017). The evolution of the product market in Washington State mirrors market trends in other states that have legalized cannabis and national trends more broadly (Hammond et al., 2022). In this environment, the question becomes one of how people use each of these products and what outcomes are associated with variations in the frequency of use of different product types.

Early research in this area held the generally correct assumption that the product being consumed was cannabis flower (Chung et al., 2006; Fischer et al., 2010). A few studies used Latent Class Analysis to describe patterns of cannabis use with consideration of product type. Craft et al. (2020) grouped people who use cannabis by products consumed in the past 12 months (sinsemilla, herbal/flower, hashish, concentrates, kief, edibles). Seven classes were identified, and class membership was used to predict mental health outcomes, including cannabis dependence.

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https://doi.org/10.1016/j.drugalcdep.2025.112728
Received 30 October 2024; Received in revised form 28 April 2025; Accepted 18 May 2025
Available online 21 May 2025

Relative to the herbal/flower class, use of more concentrated forms of cannabis increased cannabis dependence severity; while classes characterized by use of concentrates reported higher rates of having ever received a mental health diagnosis. Because this analysis grouped on any past-year use of each mode, differences in patterns of use by product was not described.

Another study (Gunn et al., 2020) grouped cannabis-using college students by frequency of use of any cannabis product, use modes, and hours high per day to examine use patterns on negative outcomes. Among five classes, people who reported high-frequency use of all-products had higher rates of cannabis use disorder (CUD) compared to all four other groups, including those reporting high-frequency flower use. Use of additional product types, beyond flower, was associated with increased reports of negative consequences generally. Frequency of use by unique product type was not considered, so for those who indicated using a variety of products, it was unclear which was more regularly consumed.

Negative consequences associated with frequent use is well documented (Namkee et al., 2023; National Academies of Sciences, Engineering, and Medicine 2017) but less is known about how patterns of use by product type may contribute to the experience of negative medical or mental health reactions. In one Canadian survey, approximately 30 % of people reporting past year consumption experienced at least one cannabis adverse event (AE), defined as "any adverse or negative health effect", in the prior 12 months and 6–7 % reported a serious AE, meaning it "required in-patient hospitalisation or prolongation of existing hospitalisation, caused congenital malformation, resulted in persistent or significant disability or incapacity, was life-threatening or resulted in death" (Marquette et al., 2024). It is well documented that smoking dried cannabis flower can harm respiratory function and is associated with an increased risk of cough, wheezing, and sputum production (Ghasemiesfe et al., 2018). Edibles and cannabis drinks have been notably associated with an increase in ED visits related to overconsumption (Monte et al., 2019). Vape products that may contain unknown solvents or contaminants have been connected with lung injury (Marrocco et al., 2022), and use of high-THC concentrates has been shown to increase the risk of acute negative reactions, such as panic or paranoia, psychosis, nausea and vomiting, breathing difficulty, and cardiovascular irregulatities, as well as chronic conditions such as CUD (Bidwell et al., 2018; Fischer et al., 2022; Freeman and Winstock, 2015; Jeffers et al., 2024; National Academies of Sciences, Engineering, and Medicine 2017).

While AEs are more likely with frequent use, people who use cannabis frequently have lower perceptions of harm than people who use infrequently or not at all (Goodman and Hammond, 2022; Pacek et al., 2015; Salloum et al., 2018). Little is known about risk beliefs among those with different cannabis use patterns. To help people avoid negative consequences associated with cannabis use, interventions need to be designed for those most at risk and tailored to their unique characteristics. Understanding the patterns of use that are most likely to be associated with experiencing adverse outcomes and risk beliefs of different types of consumption should inform interventions to reduce harm.

This study uses Latent Profile Analysis (LPA) to characterize cannabis use patterns by frequency of use of a variety of cannabis product types and identifies groups (clusters) who present distinct patterns when compared to other clusters. We focus on WA State, which has a relatively developed and stable market, hoping that findings may be informative for newer markets. We hypothesized that frequency of cannabis use and use of high-THC products (concentrates) would be positively associated with a greater number of AEs, and that beliefs about risks of cannabis use would vary by use patterns.

2. Methods

2.1. Data

The International Cannabis Policy Study (ICPS) is an ongoing annual survey of cannabis use, attitudes, risks and harms, and myriad related factors (Corsetti et al., 2022). Data for WA over four waves, 2019—2022, were provided to University of Washington researchers through a partnership with the Washington State Liquor and Cannabis Board. Each wave is a cross-section of residents of WA ages 16–65, conducted in the fall of each year via web-based surveys. A small proportion of sample members in a given wave, from 1 % to 4 %, responded to one or more previous waves. This level of repeated measures (and correlated modeling error) is ignored in the current exploration.

A non-probability sample of respondents was recruited through the Nielsen Consumer Insights Global Panel and their partners' panels. The Nielsen panels are recruited using a variety of probability and non-probability sampling methods. For the ICPS surveys, Nielsen draws stratified random samples from the online panels, with quotas based on age and state/province of residence. Upon completion, respondents receive remuneration in accordance with their panel's usual incentive structure. Monetary incentives have been shown to increase response rates and decrease response bias in subgroups under-represented in surveys, including disadvantaged subgroups. The cooperation rate, which was calculated based on American Association for Public Opinion Research Cooperation Rate #2 (American Association for Public Opinion Research, 2016) as the percentage of respondents who completed the survey of eligible respondents those who accessed the survey link, was 62.9 % in 2019, 62.0 % in 2020, 60.8 % in 2021, and 60.7 % in 2022. The study was reviewed by and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#31330). A full description of the study methods can be found in the Technical Reports (e.g., Corsetti et al., 2022) and methodology paper (Hammond et al., 2018).

2.2. Analysis

Respondents were clustered based on their reported days of use in the past year of 10 different product types queried in the ICPS. For each product type, days of use ranged from 0 to 365. Once assigned to clusters, participants were compared on a select group of characteristics, including demographics, experience of adverse effects, recognition of addiction and treatment seeking, and beliefs about cannabis. We restricted analysis to those reporting any cannabis use in the past year.

2.2.1. Clustering

In the first stage, we grouped participants based on their reported days use (0−365) of 10 cannabis product types:

- Herb: dried flower
- Drops: oils or liquid
- Capsules
- Oil or liquid vaping
- Edibles
- Drinks
- Concentrates (e.g. wax, shatter, budder etc.)
- Hash
- Tinctures
- Topicals

Frequency of use was assessed in a series of retrospective questions querying and confirming average days use per week among those reporting weekly use, per month among those reporting monthly use, or per year among those reporting less than monthly use, which were extrapolated to average days use per year. Those reporting daily use were coded as having 365 days of use. Where helpful, additional descriptions were included. For example, when asking about dried herb products, respondents were instructed "Please include any flavoured joints, blunts or blunt wraps. Don't include flavoured vaped or edibles—we'll ask about these later." In addition, images were shown to help people differentiate between product forms, which are consistent with how products are presented and purchased in retail settings. Complete ICPS survey questions are publicly available at https://cannabisproject.ca/methods/.

LPA, similar to latent class analysis but with non-discrete dimensions, is a form of finite mixture modeling (Fraley and Raftery, 2002). Such models assume the observed dimensions—each respondent's reported days of use of each cannabis product type—reflect an underlying set of distributions. LPA is particularly useful in a situation like this, where people do not use only one product type, because it captures overlapping use of multiple products. The mclust package (Scrucca et al., 2023) for R (R Core Team, 2024) was used to generate and automate cluster model solution selection. The algorithm iterates through possible solutions and selects the best model based on the Bayesian Information Criterion. This best fitting model creates groups of people more similar to each other on days reported for each of the 10 product types than they are to people in other clusters. Clusters are based on average days use across all 10 types, and use of a given product type will not be a requirement for cluster membership in favor of the overall pattern of reported days use. An observation is assigned to a cluster if the estimated probability of cluster membership is above .5.

The clustering is agnostic to the underlying meaning of the dimensions. The 10 dimensions are treated as independent, although conceptually there might be overlap between drops and tinctures or vaping and concentrates. Where respondents saw these as different, and endorsed one and not the other, will be reflected in the clusters. Clustering is also agnostic to year of participation, such that a market shift that resulted in a change in consumption of a particular product would result in a unique cluster. The years included in the analysis, 2019–2022, occur after the rapid initial market fluctuations, and when cannabis product types and prevalence of use began to stabilize somewhat in a more mature market (Hammond et al., 2024).

2.2.2. Cluster differences

Our next step was to broadly examine characteristics that might differ across clusters. To simplify this, all characteristics were dichotomized so that the results are expressed as relative (regression-adjusted) shares of each cluster in the resulting descriptive group (e.g., percent female), all analyzed via logistic regression (in R). Other than demographic indicators, the models included ICPS-requested control variables: sex at birth, age (continuous, in whole years), education (less than high school, completed high school, some college, bachelor's or higher), income adequacy (ease of making ends meet, on 5-point Likert scale from very difficult to very easy), race and ethnicity (seven categories), device used (phone, tablet, or computer/laptop), and survey wave. The results modeled with these controls were:

- Experienced **any** adverse effect of cannabis use in the past year, defined as yes to any of the following: nausea/vomiting, heart/blood pressure problems, feeling faint/dizzy or passing out, panic reactions, hallucinations/psychosis, flashbacks, depression, dissociation/depersonalization, lung/breathing problems, and "other" (not asked in 2019)
- Sought medical attention for an adverse effect in the past year (not asked in 2019)
- Sought help for cannabis use in the past year
- Identified as addicted
- Ever used cannabis for medicinal purposes
- From a series of questions about beliefs about cannabis use, participants endorsing that:
  - o Cannabis smoke can be harmful
  - o Cannabis use during pregnancy and breastfeeding can be harmful
  - o Driving or operating machinery after cannabis use is dangerous
  - o Cannabis can be addictive
  - o Cannabis increases risk of psychosis and schizophrenia
  - o Teenagers are at greater risk of harm from cannabis use than adults

For demographic variables—age (25 and younger), education (HS or less), race and ethnicity (simplified to any minority ethnic group membership), income inadequacy (reporting it is difficult or very difficult to make ends meet for the household), and female sex at birth, the corresponding control variable was dropped from the model. For example, modeling percent achieving HS or less education, all listed control variables except the four-category education variable were included in the model.

After modeling, we turned the resulting logistic regressions into expected probabilities or regression-adjusted shares of each cluster, with control variables set to their modal value, with 95 % confidence intervals. To account for all model uncertainty, this was accomplished in the simcf package (Adolph, 2023) using 10,000 draws from the multivariate normal space defined by the resulting model variance-covariance matrix. We filter pairwise differences based on effect size, judging whether one cluster is more or less likely to have the characteristic than another is by whether these 95 % confidence intervals overlapped.

2.2.3. Weighting

The ICPS provides post-stratification sample weights estimated by raking on age-by-sex, education, race, and age-by-tobacco-smoking status group sizes from US Census Bureau estimates. State-specific weights were rescaled to the state sample size. To pool waves, within-wave weights were rescaled by the proportion of the sample in that wave used in the given analysis (i.e. proportion of complete cases) before combining. The LPA was not weighted, such that the resulting cluster percentages are unweighted shares of the pooled sample in that cluster. The goal was not to estimate the proportion of people who used cannabis in the past year in a given cluster, which has limited external generalizability, but to explore differences between clusters. As such, the second stage modeling was weighted, using the survey package (Lumley, 2023) in R. The expected values and confidence intervals incorporated the weights via their inclusion in the logistic regression models.

3. Results

Across the four waves, there were 3681 respondents who reported past year cannabis use, of whom 3298 had complete information for days of use of all 10 product types. Overall (survey-weighted) means of the reported days are in the top part of Table 1. Shares of the available sample reporting the dichotomized comparison characteristics are in the bottom of the table. The available sample for the adverse effects indicators is lower because the questions were not asked in 2019 and varies for the beliefs questions due to respondents skipping individual questions.

3.1. Clustering

The algorithm found a clear preference for a solution comprised of six clusters (Table 2). The resulting average days of use reported for each product type is in Table 3, with color-coded higher and lower values to aid interpretation. At the bottom of Table 3 are the cluster results. Cluster proportions are the (unweighted) share of the sample falling in each cluster. Mixing probabilities are the average of the membership probabilities for that cluster for all observations. Uncertainties represent how often observations had relatively high membership probabilities for multiple clusters. Here, the uncertainties were fairly low and the mixing probabilities similar to the actual cluster proportions, implying that most observations fit into one and only one cluster.

To aid interpretation, we have ordered the clusters in terms of share

Table 1
Days of use (used in clustering) and cluster comparison characteristics among those with past-year consumption (N = 3298, varies by question).

Characteristic	Mean/ %	SE of mean	N
Days use in past 12-months: herb/flower	117.9	3.1	3298
drops	17.6	1.3	
capsules	7.9	0.9	
oil or liquid vaping	53.8	2.3	
edibles	35.6	1.8	
drinks	10.7	1.1	
concentrates	38.3	2.2	
hash	11.8	1.1	
tinctures	11.5	1.1	
topicals	32.1	1.7	
Race/Ethnicity: Non-Hispanic white*	75.1		3298
Hispanic white	8.2		
Black or African American	4.6		
Asian	2.7		
American Indian or Alaska Native	1.7		
Native Hawaiian or Pacific Islander	0.4		
Other or 2 + races	5.5		
Missing	1.7		
Age 25 and under	17.2		3298
Female at sex-at-birth	48.1		3298
Perceived income inadequacy	35.5		3298
High school or less education	27.7		3298
Any adverse effect	32.9		2451
Sought medical care for any adverse or negative health effect	7.3		2451
Sought help for use	6.6		3298
Identify as addicted	27.1		3298
Ever used cannabis for mental or physical health	80.2		3298
Beliefs: smoke can be harmful	43.2		2941
use during pregnancy/breastfeeding harmful	54.7		2840
driving after use is dangerous	72.4		3155
can be addictive	45.3		3064
increases risk of psychosis	20.0		2308
teenagers at greater risk of harm	48.6		2848

Note: * Race/ethnicity dichotomized to any minoritized status, i.e. the inverse of Non-Hispanic white.

reporting daily or near daily cannabis use (and, by happenstance, reverse order of cluster size). Cluster A, represents the least frequent use, with members averaging 58 days or slightly more than weekly use of dried flower and two days of edibles. These are averages; 55 % of this cluster reported less than monthly use of all cannabis products, whereas 18 % reported near daily use. This cluster represents those with occasional use of either herb or edibles and little, if any, use of any other product type, as further illustrated in Table 4. The second lowest use group was cluster B, who on average partook more of flower and edibles than cluster A and were also more likely to vape (although rarely reported concentrate use) and used topicals. Over half of cluster B reported less than weekly use, and 32 % reported daily or near daily use. Cluster C, in contrast to cluster B, used edibles and topicals slightly less often but everything else slightly more often, including nearly double the days use of flower. Cluster D, in turn, essentially used more of everything. While clusters A, B, C, and D all used herb and/or edibles predominantly, how often they used herb versus edibles and the extent to which they dabbled or mixed in weekly (or bi-weekly) use of other product types differentiates them.

Cluster E represents something of a catch-all group, with relatively high use of all product types. This group was most likely to report any use of drops, capsules, tinctures, and topicals, which are often associated with medicinal use. They also reported relatively high use of concentrates, hash, drinks, and edibles, so those who avoided smoking flower may be more likely to fall in this group.

We have left what might be the most unique result of this clustering for last. Cluster F has an uncertainty of 0 because *every single member reported daily use of concentrates*. This distinct characteristic makes it the smallest cluster. They are the group mostly likely to have reported using oil and liquid for vaping, a product type also likely to be of high potency. Members of cluster F did not solely use concentrates, however, as 9 in 10 reported any use of flower in the past year and they have the second highest average days of herb use at 170 days (more than 3 days per week).

3.2. Cluster differences

As cluster A was the largest and represents the lowest use group, we used it as the reference category for contrasting the clusters. Figs. 1–3 show expected probabilities and confidence intervals, with the reference cluster at the top of each graph. For example, in Fig. 1, just over 60 % of cluster B was female, whereas 54 % of cluster A and less than half of each of the other clusters were female. Cluster E was least likely to be non-white and to be 25 and under. None of these demographic contrasts were notably large: All the confidence intervals overlapped.

To further illuminate the cluster differences, we focused on the cluster of people who use concentrates daily (cluster F). The size of the confidence intervals in Figs. 1 to 3 are a function of group size as well as the model uncertainty, and so cluster F tends to have the largest confidence intervals. For example, they appear to be the youngest group, mostly likely to be male, and most likely to report income difficulties, but none of these differences were significant. In Fig. 2, we see that cluster F was less likely than cluster E to have reported any adverse effect from cannabis use, and less likely than all other clusters to have reported seeking medical attention for such an effect. (This is difficult to see, given the low rates of medical attention overall, but the top of the confidence interval for cluster F rounds to 0.000 while the bottom of that for all other clusters is 0.001 or greater.) Cluster F (characterized by daily concentrate use) was essentially right at the average rate of identifying as addicted, no different than clusters C, D, and E and significantly more likely than the cluster with least frequent use (cluster A).

Cluster E, the group including people most likely to have reported use of multiple product types, including drops, tinctures, and topicals, were more likely to have reported ever using cannabis to help with a physical or mental health issue than cluster A, but so were clusters C and D. Note that cluster D had the second highest average days use of drops, tinctures, and topicals, although it was a distant second to cluster E. Cluster E was also more likely to report potentially being addicted to cannabis than clusters A and B.

As noted above, missing data was more likely with the questions querying beliefs about the risks of cannabis use. As such, the confidence intervals in Fig. 3 are a bit wider. Cluster E, our “use everything” cluster, was less likely to believe that cannabis use is harmful during pregnancy and breastfeeding than cluster A and less likely to recognize the risk of driving after cannabis use than cluster B.

Table 2
Clusters.

A. Least frequent use, mostly dried flower and edibles
B. A little more flower and edibles than cluster A, some vape and topicals.
C. Less edible and topicals than B, but everything else slightly more often.
D. Use more of everything than the 3 clusters described above.
E. “Catch-all” cluster, with relatively high use of all methods from drops, capsules, tinctures, and topicals to concentrates, hash, drinks, and edibles.
F. Smallest group where every single member report daily use of concentrates and the second highest average days of flower (more than 3 days a week) plus other methods.

Table 3
Average days of use in past 365 days by cluster and clustering characteristics (N = 3298).

cluster:	A	B	C	D	E	F
Days use: herb/flower	58.1	90.5	158.7	175.3	148.6	169.9
drops	0.0	0.2	5.3	55.8	107.4	0.5
capsules	0.0	0.0	0.3	2.2	91.7	0.0
oil or liquid vaping	0.3	57.8	67.0	87.9	104.9	134.1
edibles	2.1	50.1	43.0	44.3	101.5	20.1
drinks	0.0	0.1	1.1	14.4	82.8	0.5
concentrates	0.0	0.2	7.3	95.6	68.9	365.0
hash	0.0	0.2	4.5	40.4	43.7	1.5
tinctures	0.0	0.0	1.3	10.7	128.2	0.2
topicals	0.1	41.9	38.7	62.0	108.2	42.9
N	1026	857	536	526	252	101
Cluster proportions	0.311	0.260	0.163	0.159	0.076	0.031
Mixing probabilities	0.311	0.260	0.161	0.161	0.077	0.031
Uncertainty	0.0003	0.0027	0.0128	0.0043	0.0035	0

*Green indicates lower (closer to 0) and red higher (closer to 365) average number days of use in past 365 days.

Table 4
Percentage within cluster reporting any days of use in past 12 months (N = 3298).

cluster:	A	B	C	D	E	F
Any use: herb/flower	63.1%	65.3%	74.8%	75.1%	63.1%	90.1%
drops	0.0%	8.8%	33.2%	42.2%	48.4%	11.9%
capsules	0.0%	0.0%	9.9%	17.1%	55.2%	4.0%
oil or liquid vaping	12.7%	49.0%	51.3%	60.1%	50.8%	76.2%
edibles	44.2%	69.2%	70.5%	68.3%	72.6%	64.4%
drinks	0.0%	6.2%	31.2%	42.2%	56.3%	25.7%
concentrates	0.0%	12.4%	40.7%	54.9%	37.7%	100.0%
hash	0.0%	12.6%	39.4%	49.0%	34.5%	47.5%
tinctures	0.0%	3.9%	31.7%	38.4%	62.3%	12.9%
topicals	6.7%	39.6%	39.0%	45.6%	62.7%	30.7%

*Green indicates lower (closer to 0 %) and red higher (closer to 100 %) percentage of cluster reporting any days use in past 365 days.

4. Discussion

This study described six distinct cannabis use patterns based on frequency of use of different product types among people who use cannabis in WA and how those use patterns relate to adverse outcomes and beliefs. Most notable given the increased availability of concentrates in WA was cluster F, characterized by daily use of cannabis concentrates by 100 % of its members. Prevalence of cannabis concentrate use was largely undocumented prior to legalization, but since then comparisons between legal and nonlegal jurisdictions have reported higher rates of concentrate use in legal jurisdictions (Hammond et al., 2022; Hasin et al., 2021). In general, trends in WA are similar to those in other legal U.S. states with flower being most commonly consumed, but with concentrates taking up an increasing share of the market (Hammond et al., 2022). This ready availability makes concentrated products easy to consume regularly, and in this analysis, was frequently complemented by flower and vaping. Consistent with previous studies, we identified a great deal of poly-cannabis use, especially among people with more frequent use (Gunn et al., 2020; Krauss et al., 2017); however, to our knowledge, this was the first to identify a group characterized by daily use of concentrates.

Our hypothesis, that frequency of cannabis use and THC concentration levels would be positively associated with a greater number of AEs, was not confirmed. Somewhat surprisingly, cluster F was less likely to report any AE from cannabis use than cluster E, the cluster with the next highest rate of use. Cluster E includes people who reported a greater variety of products than any other group, including products with potentially higher levels of THC. They reported a fair amount of concentrate use in the past year (37.7 % used concentrates) but were far less likely than cluster F to use concentrates regularly. Other researchers

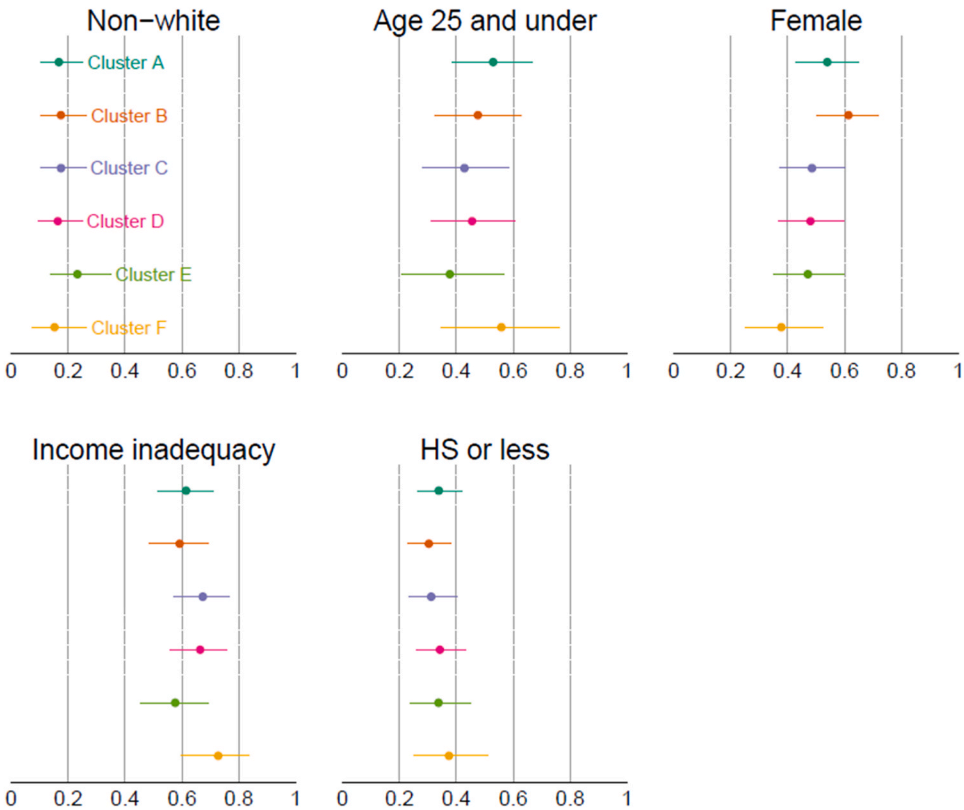

Fig. 1. Shares by cluster: demographic differences.

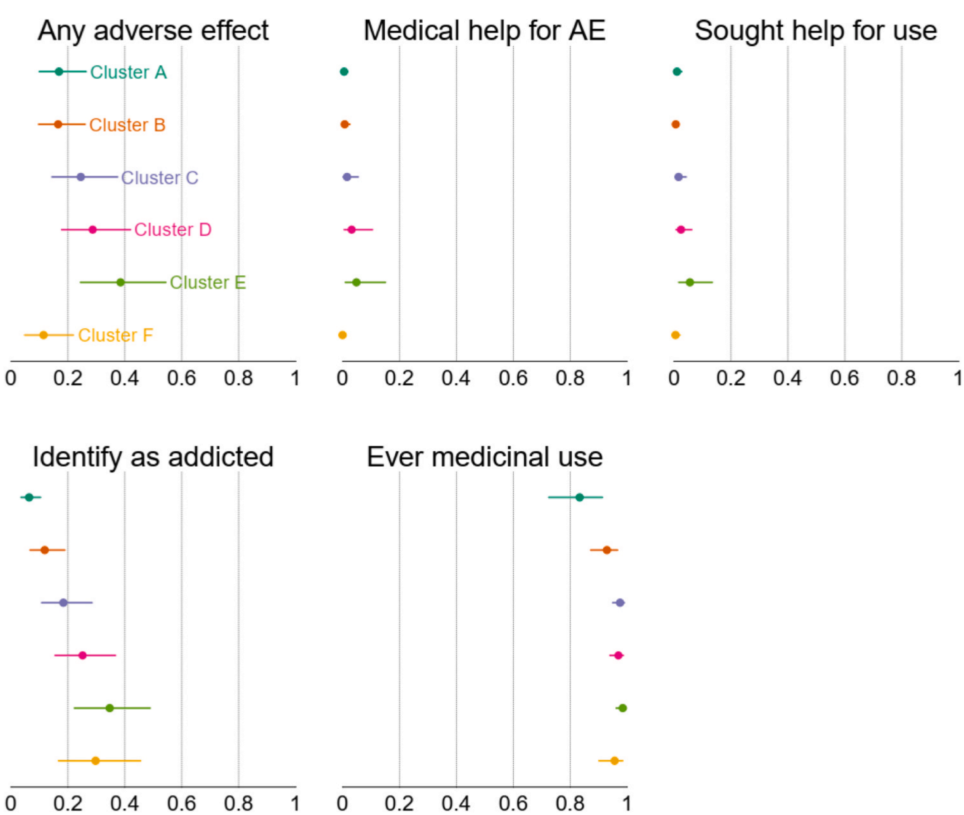

Fig. 2. Shares by cluster: adverse effects, help seeking, identifying as addicted, and lifetime medicinal use.

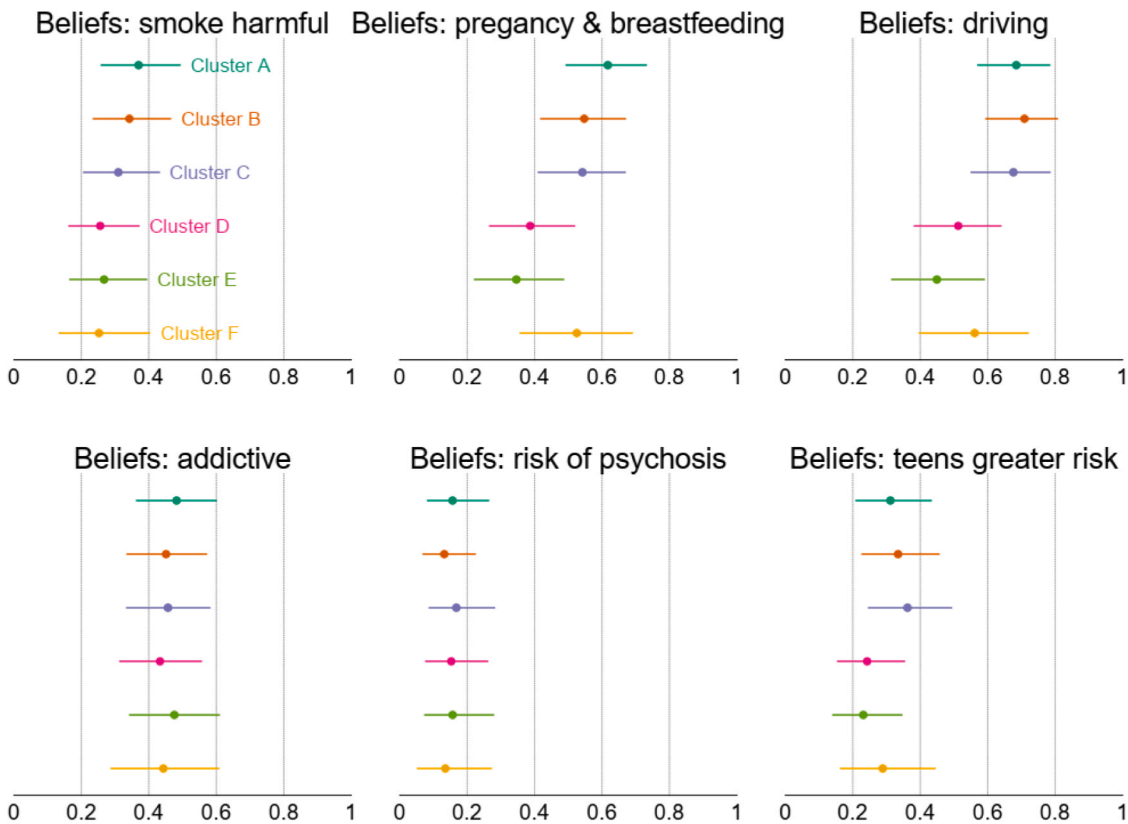

Fig. 3. Shares by cluster: cannabis risk endorsement.

have similarly found that people with more frequent use are less likely to experience and to seek help for an AE and have suggested that AEs may be related to inaccurate dosing (Marquette et al., 2024), which may be more likely among those who switch products more often and need to adjust their dose to new modes of use. If this is the case, cluster F, who used primarily two or three product types (concentrates, flower/herb, and vaping), may represent people with more experience using cannbis and who are well practiced in achieving the desired effect, which may mitigate the risk of overconsumption. This group was also least likely to seek medical help for an AE, potentially because experience has taught them that if they ride it out, the AE will abate. Another possibility, though, is that people who experience an AE change their cannabis use in response to that negative experience, and in this cross-sectional analysis appear in a different cluster. In other words, clusters A-E might be in part comprised of individuals who engaged in daily concentrate use *until having an AE*, after which they cut back use and/or turned to other modes that they perceived as having lower risk. Lastly, long term mental health adverse effects, such as schizophrenia, were not included in this analysis. It's unclear how frequency of use of different products might affect the risk of chronic mental health diagnoses, an area for further investigation.

When asked about perceived addiction, people in cluster F were no more likely to self-identify as "addicted" than the other groups, except for the reference group (cluster A). Cluster E was more likely to identify as addicted than both of the lowest use groups. It makes sense that more frequent use would put people at an increased risk of addiction. Notably, clusters C, D, and E endorsed the largest variety of products, consistent with Gunn et al. (2020)'s finding that the high-frequency all-product group was more likely to score higher on CUD symptoms than any other group, including high-frequency flower only. It may be that frequent use combined with a tendency toward poly-modal cannabis consumption increases addiction risk, or conversely that those with cannabis use disorder are more likely to try multiple methods of consumption.

The three groups with the most frequent use (D, E, & F) were also more likely than the reference group (cluster A) to report using cannabis for medical reasons, and indeed were the three groups with the greatest use of tinctures, drops, and capsules. All three were also more likely to identify as addicted. This argues against oversimplifying discussions of potential harms into "medical = safe" and "recreational = harmful". In fact, as we have learned from experience with opioids, people can feel beneficial effects of use while still having the potential for developing a substance use disorder, and there is some indication that this may be the case here. Despite over one-quarter of the overall sample self-identifying as addicted, only 6.6 % had sought help for their use, and no group differences emerged.

We identified few between group differences in beliefs about cannabis risk. Cluster E perceived less risk in using cannabis during pregnancy and while driving that the lower use groups. Cluster E was comprised of people reporting the second-most frequent use and the resulting tolerance may make them feel more capable while driving after use. They also report more medicinal use and so may be judging the risks in the context of low THC, high CBD consumption.

This study provides clues to where harm reduction efforts may be focused, for example in discouraging poly-modal cannabis use. More work needs to be done, though, to understand whether similar profiles emerge in other markets and how people shift their use over time.

4.1. Limitations and strengths

With cross-sectional data, causality cannot be inferred. Although it is reasonable to expect that cannabis use would lead to cannabis-related outcomes, it may be that an AE might lead to decreased use, creating an inverse relationship; this analysis does not answer questions about how individuals might transition from one group to another. Non-probability-based sampling was used, so results are not necessarily generalizable to all of WA, although the intent was not to provide prevalence estimates, but to characterize patterns of cannabis use. Two years of data collection, 2020 and 2021, occurred during the COVID pandemic which is likely to have altered consumption patterns. The selection of non-overlapping 95 % confidence intervals was chosen as a conservative indicator of significant cluster differences that are suggestive of notable differences between clusters that may warrant further, more vigorous study. Finally, as with all survey data, it relies on accurate self-reports and may be subject to social desirability and recall bias. Self-reports of AEs and addiction, however, may capture experiences that would otherwise go unreported due to low rates of help-seeking for these events.

4.2. Conclusion

This is the first study that associates clusters based on frequency of use of a variety of product types with adverse outcomes and risk beliefs. This study suggests that people who differ in frequency of use of different products can be grouped into distinct categories, and that those can predict adverse outcomes, and to a lesser extent, beliefs about cannabis risks. Specifically, it identified a small, but important group of people who use cannabis concentrates daily but report fewer adverse effects compared to people who use a variety of products frequently. Future research should seek to understand why people who use concentrates daily were less likely to report adverse reactions than those with high frequency multi-modal use. Like previous research, we found that greater use of a larger variety of products was associated with potential CUD. This risk does not appear to be diminished among those who are most likely to use cannabis medically. Understanding these patterns of use can help inform those seeking to identify ways of reducing harm from cannabis use.

This analysis was limited to data collected in WA State, whose market has been operating for more than a decade now, with an immense variety of products and a solid presence in society. Because of this, WA is unique in having an entire generation of young adults who grew up exposed to cannabis retail stores and cannabis marketing which likely influenced certain behavior patterns. We believe this analysis offers a model that could be applied to other jurisdictions to compare differences in patterns of use between distinct markets.

CRediT authorship contribution statement

Garrett Sharon: Writing – review & editing, Writing – original draft, Project administration, Methodology, Conceptualization. **Jason Williams:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Beatriz H. Carlini:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **David Hammond:** Writing – review & editing, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sharon Garrett reports financial support was provided by Washington State Legislature. Jason Williams reports financial support was provided by Washington State Legislature. Beatriz Carlini reports financial support was provided by Washington State Legislature. David Hammond reports financial support was provided by Canadian Institutes of Health Research. David Hammond reports financial support was provided by Public Health Agency of Canada. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Funding for the ICPS was provided by a Canadian Institutes of Health Research (CIHR) Project Bridge Grant (PJT-153342) and a CIHR Project Grant. Additional support was provided by the Public Health Agency of Canada-CIHR Chair in Applied Public Health. Manuscript preparation and analysis was funded by the Washington State Legislature through ESSB 5187 (2023) and by the University of Washington's Cannabis Dedicated Account.

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