Identifying Subgroups of Cannabis Users Based on Help-Seeking Preferences: A Latent Class Analysis

Marleen I.A. Olthof\textsuperscript{a, b} Matthijs Blankers\textsuperscript{a, c} Margriet W. van Laar\textsuperscript{a} Anna E. Goudriaan\textsuperscript{b, c, d}

\textsuperscript{a}Trimbos Institute, Netherlands Institute of Mental Health and Addiction, Utrecht, The Netherlands; \textsuperscript{b}Amsterdam UMC Location University of Amsterdam, Department of Psychiatry, Amsterdam, The Netherlands; \textsuperscript{c}Arkin Mental Health Care, Amsterdam, The Netherlands; \textsuperscript{d}Amsterdam Public Health Research Institute, Amsterdam, The Netherlands

Keywords
Cannabis use · Cannabis use disorder · Help-seeking · Treatment · Latent class analysis

Abstract

Background: The majority of people with cannabis use disorder do not seek treatment. If we were able to gain more insight into different subgroups of cannabis users based on help-seeking preferences, we could use this information to inform the development and promotion of interventions targeted at specific subgroups of cannabis users, to ultimately narrow the treatment gap. Methods: An online survey was conducted among 1,015 Dutch frequent cannabis users (18–72 years) to assess their cannabis use, help-seeking preferences, psychopathology, and psychological distress. Latent class analysis was used to identify classes of cannabis users based on their help-seeking preferences. Differences between the identified classes in terms of sociodemographics, cannabis use, and psychopathology were examined. Results: We identified four classes with distinct preferences for support. Class 1 ("no support/only social," \( n = 548 \)) had a low probability of finding any form of support appealing other than social support. Class 2 ("online help," \( n = 170 \)) had relatively high probabilities of finding online help appealing. Class 3 ("GP/outpatient," \( n = 208 \)) had a relatively high probability of finding support from the general practitioner and outpatient substance use disorder treatment appealing. Class 4 ("all sources," \( n = 89 \)) had moderate to high probabilities for all sources of support. In terms of sociodemographics, differences between the classes were found with regard to gender and level of education. The classes were fairly similar with regard to cannabis use, only the "online help" class scored significantly lower on both cannabis use frequency and quantity compared to most of the other classes. In terms of psychopathology, the "GP/outpatient" class and the "all sources" class experienced more cannabis use-related problems and were more likely to report multiple past quit attempts than the "online help" class and the "no support/only social" class. Conclusions: Our study shows that there is a lot of inter-individual variation in how appealing various forms of help are to cannabis users. Our findings emphasize the importance of promoting a variety of treatment modalities for cannabis users, including real-life and digital options, and indicate what might appeal to whom.

© 2022 The Author(s). Published by S. Karger AG, Basel

This article is licensed under the Creative Commons Attribution 4.0 International License (CC BY) (http://www.karger.com/Services/OpenAccessLicense). Usage, derivative works and distribution are permitted provided that proper credit is given to the author and the original publisher.
Introduction

The majority of people with substance use disorder (SUD) do not receive treatment [1]. In 2018, 21.2 million people aged 12 years or older qualified for SUD treatment in the USA, while only 2.4 million (11%) received SUD treatment [1]. In Europe, a similar treatment gap seems to exist for substance use problems, including cannabis use problems. In 2018, 3.3 million people aged 15–64 years in Europe (1%) used cannabis daily or almost daily [2]. It is estimated that between 25% and 50% of daily cannabis users will meet the criteria for dependence [3, 4]. In 2018, 135,000 people entered SUD treatment in Europe for cannabis use problems [2]. Thus, it seems that roughly one-fifth of the adults with cannabis use problems seek treatment.

Numerous studies have been conducted to identify barriers to treatment-seeking for cannabis use problems and other substance use problems [1, 5, 6]. Common barriers to substance use treatment include factors associated with the healthcare system, e.g., not being able to afford the cost of treatment, long waiting lists, and not being able to attend treatment during office hours [1, 5]. Commonly reported barriers also include patient factors, e.g., the feeling that treatment is not necessary, not being ready to stop, and the preference for support from friends and family [5, 6].

Removing the identified barriers to treatment is often proposed as a possible solution to narrow the treatment gap. However, in none of these studies, a distinction is made between different types of treatment available for substance use problems and experienced barriers to treatment. As there is a wide diversity of treatments available, ranging from online self-help to inpatient therapy, barriers to treatment may differ based on treatment type. In addition, the available studies tend to use a variable-centered approach. The aim of the variable-centered approach is to explain relationships between variables in a population [7]. This means that the entire sample of substance users is described as a whole, resulting in a relatively low amount of specificity, i.e., how precise the results are in describing the individual subjects [7]. Person-centered approaches, such as latent class analysis (LCA), identify subgroups in a population based on a chosen set of variables and can be more specific [7]. If we were able to gain more insight into different subgroups of cannabis users based on help-seeking preferences, we could use this information to inform the development and promotion of interventions targeted at specific subgroups of cannabis users.

To the best of our knowledge, no studies have been conducted that aim to identify subgroups of cannabis users based on help-seeking preferences. However, previous research suggests that such subgroups may exist. Vunder Pol et al. [6] compared non-treatment seeking cannabis dependent users with cannabis dependent patients receiving specialized addiction treatment. The cannabis dependent users in treatment reported more cannabis use, more symptoms of dependence, and more mental problems compared to the non-treatment seekers. These results suggest that non-treatment seeking cannabis users and cannabis users in specialized addiction treatment have different characteristics, and perhaps could be seen as different subgroups of cannabis users.

As a further example, Vederhus et al. [8] investigated whether there were differences between cannabis users who made use of a Norwegian unguided cannabis cessation app and cannabis users in face-to-face outpatient treatment. Vederhus et al. [8] hypothesized that the cannabis users in treatment would have more severe problems than the cannabis users using the app. This hypothesis was not confirmed. Cannabis use frequency and severity of dependence did not differ between groups, but the group using the app experienced more depressive symptoms and had a lower level of perceived well-being compared to the treatment group. There were no differences in sociodemographics between groups, except that there were significantly more women in the app group than in the treatment group (46% vs. 26%). Hence, it seems that the app did appeal to a specific subgroup of cannabis users.

In this study we therefore addressed the following research questions. (1) Can we identify latent classes of cannabis users based on their preferences for certain types of help for cannabis use problems? (2) Are there differences between the classes in terms of sociodemographics, cannabis use, psychopathology, and psychological distress?

Materials and Methods

Participants

This study was part of a broader survey on cannabis use, quit intentions, and attitudes toward seeking treatment [9]. A total of 1,510 Dutch cannabis users were recruited through targeted Facebook and Facebook audience network campaigns. Cannabis users were eligible to participate in this study if they: (1) were 18 years of age or older, (2) had used cannabis in the past 6 months, and (3) had ever used cannabis regularly (at least once a week for at least 6 months). As an external motivator to take part in the study, the participants who completed the survey were entered into a raffle to win a 300 euro gift card.
Materials and Procedure
This study has been approved by the Trimbos Ethics Review Board. Self-reported data were obtained via an online survey for which we recruited from April 2018 to June 2018. Participants were first presented with an introduction page containing information about the purpose of the study. After giving their informed consent, the online survey started. The survey comprised the following thematic sections and instruments

Demographics
Age, gender, living situation, level of education, and employment status were recorded.

Cannabis Use
The number of cannabis use days in the past 30 days, the number of joints smoked per typical cannabis use day and the number of joints typically rolled from 1 g of cannabis product was assessed. Based on these values the amount of cannabis (grams) used in the past 30 days was calculated. Van der Pol et al. [10] validated different measures of self-reported cannabis dose against objective measures. The reported number of joints made from 1 g was one of the least problematic options.

Cannabis Use Motives
Cannabis use motives were assessed using the Marijuana Motives Measure (MMM) [11, 12]. The MMM is a 27-item questionnaire and consists of six validated subscales: coping (“to forget about my problems”), enhancement (“because I like the feeling”), social (“to be sociable”), conformity (“to fit in with the group I like”), expansion (“to expand my awareness”), and routine (“out of habit”).

Psychopathology and Psychological Distress
Severity of dependence was measured by counting the self-reported number of DSM-5 criteria met for cannabis use disorder [13]. Psychological distress was assessed using the Brief Symptom Inventory (BSI) [14, 15]. This 53-item questionnaire covers nine symptom dimensions. The Global Severity Index – which is the mean of all 53 items – is an indicator of the overall level of psychological distress.

The Ultrashort Questionnaire for ADHD (UKVA), a brief screening instrument for ADHD, was also included [16]. Besides the 4-items of the UKVA, the participants were asked if they ever received formal treatment for ADHD or ADD to assess lifetime diagnosis of ADHD/ADD.

Help-Seeking Preferences
Participants were first presented with a short description of a specific type of support or treatment for cannabis use problems. Subsequently, they were asked whether or not this type of help was appealing to them using a 5-point Likert scale ranging from “definitely not appealing” to “definitely appealing.” In this way, the attractiveness of the following ten different types of support or treatment for cannabis use problems was assessed: information on the Internet, Internet forums, self-help books, social support, general practitioner, unguided online self-help, guided online self-help, outpatient substance use treatment, inpatient substance use treatment, and self-help groups.

Results
In total, 495 responses were excluded from the initial survey dataset. 448 participants did not meet the inclusion criteria for this study; 49 participants were aged under 18 years, 208 participants responded that they had never used cannabis regularly, and 191 participants responded that they did not use cannabis in the past 6 months. Nine participants were excluded due to too many missing values (≥15%), 12 participants were removed due to multivariate outliers (mean Mahalanobis distance ≥ 3.5 SD) and 26 participants were excluded due to missing values on the LCA indicator variables. Hence, we had a final study sample of 1,015 participants (67% male, M age = 24.8, SD = 7.4, range = 18–72). On average, the participants used cannabis on 20.9 (SD = 10.4) days in the past 30 days.

Latent Class Analysis

Statistical Analysis
Missing data were not imputed. Cases with too many missing values (≥15%) and cases with missing values on one or more of the LCA indicator variables were excluded from the dataset. Pairwise deletion was used to handle missing data in the remaining analyses.

Latent GOLD (version 6.0) was used to conduct the LCA. The attractiveness scores of the ten types of help for cannabis use problems were included as indicators in the LCA. In line with Garthus-Niegel et al. [17] and MacLeod et al. [18], the indicator items were dichotomized, e.g., scores 1–3 were coded as “not appealing,” scores 4 and 5 were coded as “appealing.”

Since there was no theoretically expected number of classes, models ranging from two to ten classes were estimated. Penalized goodness-of-fit indices were used to compare the models and to identify the most parsimonious model that fitted the observed data well. The models were compared using the Akaike information criterion (AIC) [19], Bayesian information criterion (BIC) [20], the sample size adjusted BIC (aBIC) [21], Entropy [22], and the bootstrap likelihood ratio test (BLRT) [23]. In general, lower AIC, BIC, and aBIC values indicate better fit; a significant BLRT value indicates that there is a significant improvement in fit compared to a model with one class less. Entropy values range from 0 to 1, with higher values indicating a clearer separation of classes.

After selecting the most appropriate model, the bias-adjusted three-step approach (BCH method) was used to explore differences between classes [24]. In this approach, respondents are assigned to latent classes and the classification scores are saved [25]. Next, these latent classification scores are related to variables of interest. In order to avoid bias, a correction is made for the classification error [25].
indicated optimal fit of the 10-class model and the Entropy indicated optimal fit of the 2-class model. After inspection of the interpretability of the classes, the 4-class model was selected as the optimal solution.

Figure 1 shows the profile plot for the 4-class solution, and online supplement 1 (for all online suppl. material see www.karger.com/doi/10.1159/000524938) shows the item response probabilities within each of the 4 classes.

Table 1. Fit indices for the 2- to 10-class models

| Classes, n | LL      | AIC      | BIC      | aBIC     | Entropy | BLRT |
|------------|---------|----------|----------|----------|---------|------|
| 2          | -4,443.84 | 8,929.68 | 9,033.05 | 8,966.35 | 0.74    | 0.00 |
| 3          | -4,380.98 | 8,825.95 | 8,983.48 | 8,881.84 | 0.69    | 0.00 |
| 4          | **-4,337.07** | **8,760.14** | **8,971.82** | **8,835.25** | **0.66** | **0.00** |
| 5          | -4,324.22 | 8,756.44 | 9,022.26 | 8,850.76 | 0.67    | 0.11 |
| 6          | -4,313.26 | 8,756.52 | 9,076.49 | 8,870.05 | 0.68    | 0.19 |
| 7          | -4,299.15 | 8,750.29 | 9,124.41 | 8,883.03 | 0.69    | 0.05 |
| 8          | -4,291.19 | 8,756.39 | 9,184.66 | 8,908.34 | 0.68    | 0.44 |
| 9          | -4,277.55 | 8,751.10 | 9,233.52 | 8,922.26 | 0.66    | 0.06 |
| 10         | -4,265.89 | 8,749.78 | 9,286.34 | 8,940.15 | 0.69    | 0.14 |

LL, log-likelihood; AIC, Akaike information criterion; BIC, Bayesian information criterion; aBIC, sample size-adjusted BIC; BLRT, bootstrap likelihood ratio test.

All the classes had moderate to high probabilities of finding social support appealing. Class 1 (“no support/only social,” n = 548) had the lowest probability (0.32) of finding social support appealing and had even lower probabilities (all ≤0.06) of finding the other types of support/treatment appealing. Class 2 (“online help,” n = 170) had moderate probabilities (0.41–0.49) for online sources of support/treatment. Class 3 (“GP/outpatient,” n = 208)
had high probabilities (≥0.60) of finding help from the general practitioner and outpatient SUD treatment appealing and had the lowest probability (0.00) of finding online unguided self-help appealing. Of all the classes, class 4 (“all sources,” n = 89) had the highest probability (≥0.74) of finding online unguided and guided self-help appealing and had moderate to high probabilities (0.37–0.80) for all other sources of support/treatment, including the general practitioner and outpatient SUD treatment.

Associations between Class Membership and Demographic, Cannabis Use, and Psychopathological Variables

Table 2 shows the associations between class membership and demographic, cannabis use, and psychopathological variables. There was no significant difference in age between classes. There was a significant difference in gender across classes (Wald = 24.77, p < 0.001). Paired comparisons showed that the proportion of males was significantly higher in the “no support/only social” class (75.1%) compared to the other classes (53.0–62.7%) (all p ≤ 0.012). There was also a significant difference in level of education (Wald = 41.25, p < 0.001) and in employment status (Wald = 16.56, p = 0.01) across classes. The proportion of participants with a part-time job was significantly higher in the “online help” class compared to all the other classes (all p ≤ 0.03).

Cannabis use frequency – the number of cannabis use days in the past 30 days – was also significantly different across classes (Wald = 10.35, p = 0.02). Paired comparisons indicated that the mean number of cannabis use days was significantly lower in the “online help” class (M = 18.13, SE = 0.99) compared to the “no support/only social” class (M = 21.70, SE = 0.48, p = 0.002) and the “GP/outpatient” class (M = 21.40, SE = 0.95, p = 0.03). In addition, there was a statistically significant difference in

| Class 1 no support/only social (n = 548) | Class 2 online help (n = 170) | Class 3 GP/outpatient (n = 208) | Class 4 all sources (n = 89) | Total (n = 1,015) | Class difference, p value |
|----------------------------------------|-----------------------------|-------------------------------|-----------------------------|----------------|---------------------------|
| Age, mean (SE)                         | 24.89 (0.36)                | 23.83 (0.64)                 | 24.35 (0.58)                | 27.17 (1.22) | 24.79 (0.23)              | 0.15 NS                  |
| Female, %                              | 24.9                        | 37.3                         | 47.0                        | 39.8          | 32.9                      | <0.001 1 ≠ 2, 3, 4       |
| Living situation, %                    |                            |                              |                             |               |                           |                          |
| Alone                                  | 20.4                        | 16.2                         | 26.9                        | 27.7          | 21.5                      |                          |
| With parents                           | 42.4                        | 38.8                         | 28.8                        | 28.8          | 37.8                      |                          |
| With partner                           | 13.1                        | 18.7                         | 16.5                        | 22.7          | 15.8                      | 0.05                     |
| With partner and children              | 8.9                         | 3.4                          | 8.6                         | 7.0           | 7.6                       |                          |
| Other                                  | 15.2                        | 23.0                         | 19.2                        | 13.8          | 17.3                      |                          |
| Level of education, %                  |                            |                              |                             |               |                           |                          |
| Low                                    | 28.4                        | 9.0                          | 20.6                        | 17.1          | 22.0                      | 1 ≠ 2, 4                 |
| Medium                                 | 55.3                        | 48.5                         | 59.5                        | 54.1          | 54.6                      | <0.001 3 ≠ 2             |
| High                                   | 16.3                        | 42.6                         | 19.9                        | 28.8          | 23.4                      |                          |
| Employment status, %                   |                            |                              |                             |               |                           |                          |
| Full time (>35 h/wk)                   | 33.1                        | 25.1                         | 30.5                        | 26.9          | 30.4                      | 2 ≠ 1, 3, 4              |
| Part time (<35 h/wk)                   | 36.5                        | 57.4                         | 36.9                        | 37.8          | 40.8                      | 0.01                     |
| Unemployed                             | 30.4                        | 17.5                         | 32.6                        | 35.4          | 28.7                      |                          |
| Cannabis use frequency (days/30 days), mean (SE) | 21.70 (0.48) | 18.13 (0.99) | 21.40 (0.95) | 20.73 (1.36) | 20.85 (0.32) | 0.02 2 < 1, 3 |
| Cannabis use quantity (grams/30 days), mean (SE) | 26.93 (1.35) | 12.02 (1.61) | 26.00 (2.91) | 21.88 (3.25) | 23.34 (0.85) | <0.001 1 ≠ 2, 3, 4 |
| Marijuana Motives Measure subscale scores, mean (SE) |                          |                              |                             |               |                           |                          |
| Coping                                 | 2.05 (0.05)                 | 2.00 (0.09)                  | 2.45 (0.10)                 | 2.45 (0.15)   | 2.15 (0.03)               | <0.001 1, 2 < 3, 4       |
| Enhancement                            | 2.95 (0.04)                 | 3.08 (0.07)                  | 3.16 (0.07)                 | 2.99 (0.10)   | 3.02 (0.02)               | 0.04 1 < 3               |
| Social                                 | 2.17 (0.04)                 | 2.35 (0.07)                  | 2.25 (0.08)                 | 2.12 (0.10)   | 2.22 (0.02)               | 0.17 NS                  |
| Conformity                             | 1.05 (0.01)                 | 1.08 (0.02)                  | 1.06 (0.02)                 | 1.13 (0.06)   | 1.06 (0.01)               | 0.18 NS                  |
| Expansion                              | 1.98 (0.05)                 | 1.93 (0.08)                  | 2.08 (0.09)                 | 2.05 (0.13)   | 2.00 (0.03)               | 0.65 NS                  |
| Routine                                | 2.45 (0.05)                 | 2.57 (0.10)                  | 2.85 (0.10)                 | 2.85 (0.15)   | 2.59 (0.03)               | 0.001 1 < 3, 4           |
| Cannabis use-related problems, mean number |                        |                              |                             |               |                           |                          |
| DSM-5 symptoms (SE)                    | 3.35 (0.13)                 | 3.77 (0.27)                  | 4.89 (0.28)                 | 5.20 (0.43)   | 3.90 (0.09)               | <0.001 1, 2 < 3, 4       |
| Multiple (≥2) past cannabis quit attempts, % BSI | 21.2                       | 24.0                         | 38.1                        | 47.0          | 27.4                      | <0.001 1 < 2, 3, 4       |
| GSI score, mean (SE)                   | 0.49 (0.03)                 | 0.60 (0.05)                  | 0.83 (0.06)                 | 0.92 (0.10)   | 0.62 (0.02)               | <0.001 1, 2 < 3, 4       |
| ADHD/ADD, %                            | 51.1                        | 52.0                         | 60.9                        | 60.4          | 54.0                      | 0.19 NS                  |
| Positive screening UKVA                | 34.7                        | 38.4                         | 29.3                        | 31.6          | 30.2                      | 0.02 2 < 1               |

BSI, Brief symptom inventory; GSI, Global severity index; UKVA, Ultrashort questionnaire for ADHD.
cannabis use quantity across classes (Wald = 47.48, p < 0.001). Paired comparisons showed that the mean number of grams used in the past 30 days was significantly lower in the “online help” class (M = 12.02, SE = 1.61) compared to all the other classes (M = 21.88–26.93, all p ≤ 0.003).

There was also a statistically significant difference in coping motives scores across classes (Wald = 17.68, p < 0.001). Paired comparisons showed that the mean score on coping motives was significantly higher in the “GP/outpatient” class (M = 2.45, SE = 0.10) and the “all sources” class (M = 2.45, SE = 0.15) compared to the “no support/only social” class (M = 2.05, SE = 0.05) and the “online help” class (M = 2.00, SE = 0.09, all p ≤ 0.02). In addition, the routine motives score was also different across classes (Wald = 15.90, p = 0.001). The mean score on routine motives was significantly higher in the “GP/outpatient” class (M = 2.85, SE = 0.10) and the “all sources” class (M = 2.85, SE = 0.15) class compared to the “no support/only social” class (M = 2.45, SE = 0.05, all p ≤ 0.01), based on paired comparisons.

**Associations between Class Membership and Psychopathological Variables**

There was also a statistically significant difference in the mean number of self-reported DSM-5 symptoms across classes (Wald = 38.61, p < 0.001). Paired comparisons indicated that both the “GP/outpatient” class (M = 4.89, SE = 0.28) reported a significantly higher mean number of DSM-5 symptoms than the “online help” class (M = 3.77, SE = 0.27, p = 0.008) and the “no support/only social” class (M = 3.35, SE = 0.13, p < 0.001), and the “all sources” class (M = 5.20, SE = 0.43) reported a significantly higher mean number of DSM-5 symptoms than the “online help” class (p = 0.009) and the “no support/only social” class (p < 0.001). Besides, the “GP/outpatient” class and the “all sources” class also had a significantly higher proportion of participants who reported two or more past quit attempts (38.1% and 47.0%) compared to the “no support/only social” class (21.2%) and the “online help” class (24.0% all p ≤ 0.04).

The Global Severity Index, an indicator of the overall level of psychological distress, was significantly different across classes as well, Wald = 40.76, p < 0.001. The GSI score was significantly lower in the “no support/only social” class (M = 0.49, SE = 0.03) and the “online help” class (M = 0.60, SE = 0.05) compared to the “GP/outpatient” class (M = 0.83, SE = 0.06) and the “all sources” class (M = 0.92, SE = 0.10, all p ≤ 0.01). The proportion of participants with an estimated lifetime ADHD/ADD diagnosis was significantly lower in the “online help” class (18.4%) compared to the “no support/only social” class (34.7%) (p = 0.003).

**Discussion**

In this study, we investigated latent classes of cannabis users based on their preferences for certain types of support or treatment for cannabis use, and we examined differences between these classes in terms of sociodemographics, cannabis use, and psychopathology. We found four classes with distinct preferences for support.

The largest class, the “no support/only social” class, had a low probability of finding any form of support appealing other than social support. The second largest class, the “GP/outpatient” class, had a relatively high probability of finding support from the general practitioner and outpatient SUD treatment appealing. The second smallest class, the “online help” class, had a preference for online sources of help. The smallest class, the all sources class, had moderate to high probabilities of finding all sources of help appealing.

In terms of sociodemographics, differences were found between the classes with regard to gender and level of education. The classes were fairly similar with respect to cannabis use; only the “online help” class scored significantly lower on both cannabis use frequency and quantity compared to the other classes. In terms of psychopathology, however, some profound differences between the classes were found. The “GP/outpatient” class and the “all sources” class experienced more cannabis use-related problems and were more likely to report multiple past quit attempts than the “online help” class and the “no support/only social” class. Besides, the “GP/outpatient” class and the “all sources” class scored higher on coping motives than the “online help” class and the “no support/only social” class. Research shows that coping motives are a predictor of cannabis dependence [4]. Thus, it could be hypothesized that the classes that had a preference for face-to-face treatment or that found all the sources of help appealing were also more in need of treatment than the other classes.

On the contrary, the class that found none of the types of support/treatment very appealing and the class that was particularly attracted to online help also experienced less cannabis use-related problems and reported a relatively low level of psychological distress. Thus, it could be hypothesized that these classes were not as much in need of treatment as the other classes. However, it seems that
these classes could benefit greatly from a preventive intervention to curb the development of cannabis use-related problems.

The results found in our study confirm and extend the findings from previous research by Tomczyk et al. [26], in which a LCA was conducted to examine subgroups of German adults with mental health problems based on help-seeking behaviors. Just as in our study, four classes were identified in that study and all classes had high probabilities of seeking social support. This raises the question of how effective social support is in reducing cannabis use compared to other forms of help.

Treatment programs based on cognitive behavioral therapy, contingency management, and motivational interviewing are proven to be effective for the treatment of cannabis use disorders and are thus recommended [27]. Research also suggests that online help for cannabis users can be effective. Boumparis et al. [28] recently published a meta-analysis on digital interventions to reduce cannabis use. The meta-analysis revealed a small yet significant effect in favor of digital interventions over control conditions [28]. Research findings regarding the effectiveness of social support for reducing cannabis use, however, are less uniform.

Social support as an addition to SUD treatment or following SUD treatment, can improve treatment adherence and may prevent relapse [29–31]. In addition, a number of studies have demonstrated that peer recovery support can reduce relapse rates and improve treatment retention [32]. Peer recovery support may also be effective in an online setting [33]. However, Dobkin et al. [30] found that higher levels of social support at the time of intake did not predict reductions in drug use at follow-up among patients in SUD treatment. All in all, the effectiveness of social support to reduce substance use is still a matter of debate. Since the majority of our sample of cannabis users had a preference for social support, future research should consider exploring the effectiveness of social support (online or live; through peers or friends and family) as a stand-alone intervention for cannabis use cessation.

The classes that were found in our study could also have implications for public health campaigns. For instance, instead of focusing on increasing awareness of a specific form of support or treatment, several intervention types (online, face-to-face) could be targeted in public health campaigns to diminish the treatment gap for problematic cannabis use, as a campaign focusing on one type of support, may not appeal to other subgroups of problematic cannabis users.

Limitations

Our study has some limitations which have to be acknowledged. First, not all the fit indices were optimal for the selected 4-class solution. Especially, the entropy value was relatively low compared to the entropy values for some of the other solutions. This suggests that there might not be a perfect separation of classes. Second, all data used in this study are based on self-report measures. Research has shown that the convergent validity of self-reported cannabis use and objective measures of cannabis use, such as urine samples, is quite satisfactory [34, 35]. However, it could be debated whether participants who reported fewer DSM-5 symptoms actually had less cannabis use-related problems or just had less awareness of these problems. The questionnaire that was used to assess the number of DSM-5 symptoms is highly similar to the substance use module of the MATE-Q. Research has demonstrated that a self-reported version of the MATE-Q has acceptable concurrent validity with the interviewer version of the MATE [36]. Third, participants were recruited through targeted Facebook network campaigns for our cross-sectional study. Hence, our study sample may not be truly representative of the whole population of Dutch frequent cannabis users and the results may not be generalizable to all cannabis users. Our study, however, shows that targeted Facebook campaigns can be used to recruit a substantial amount of participants, in this case, 1,015 non-treatment seeking Dutch frequent cannabis users, in a relatively short period of time, with limited costs.

Conclusion

Our study shows that there is a lot of inter-individual variation in how appealing various forms of help are to cannabis users. As sociodemographic characteristics seem only a little indicative of class membership, it will be difficult to determine which cannabis users prefer which type of treatment based only on their sociodemographic profile. However, there are some characteristics that are associated with class membership; these include the number of self-reported DSM-5 symptoms, multiple previous quit attempts, and the Global Severity Index score. Perhaps, these characteristics can be used for the promotion of interventions targeted at specific subgroups. All in all, our findings emphasize the importance of promoting a wide variety of treatment modalities for cannabis users, including real-life and digital options.
Statement of Ethics

This study protocol was reviewed and approved by the Trimbos Ethics Review Board (approval no. 2499150). All participants provided informed consent digitally prior to participation.

Conflict of Interest Statement

Anna E. Goudriaan is editor of European Addiction Research. Matthijs Blankers is an editorial board member of European Addiction Research. The authors declare that they have no competing interests.

Author Contributions

All authors are responsible for the design of the study. M.I.A. Olthof analyzed the data. M.I.A. Olthof and M. Blankers interpreted the analyses and wrote the first draft of the manuscript. M.W. van Laar and A.E. Goudriaan revised the manuscript critically. All authors contributed to and approved the final manuscript.

Data Availability Statement

The anonymized datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Funding Sources

The study is funded by the Dutch Ministry of Health, Welfare and Sport. The funder had no role in the design, data collection, analysis, and writing of this manuscript.

References

1 Substance Abuse and Mental Health Services Administration. Key substance use and mental health indicators in the United States: results from the 2018 national survey on drug use and health. Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. 2019. Available from: https://www.samhsa.gov/data/sites/default/files/cbhsq-reports/NSDUHNationalFindingsReport2018/NSDUHNationalFindingsReport2018.pdf.

2 EMCDDA. European drug report 2020: trends and developments. 2020. Available from: https://www.emcdda.europa.eu/publications/pods/frequent-cannabis-users.

3 EMCDDA. Perspective on drugs: characteristics of frequent and high-risk cannabis users. 2013. Available from: https://www.emcdda.europa.eu/publications/pods/frequent-cannabis-users.

4 van der Pol P, Liebregts N, De Graaf R, Korf DJ, Van den Brink W, van Laar M. Predicting the transition from frequent cannabis use to cannabis dependence: a three-year prospective study. Drug Alcohol Depend. 2013 Dec;133(2):352-9.

5 Gates P, Copeland J, Swift W, Martin G, Martin G. Barriers and facilitators to cannabis treatment. Drug Alcohol Rev. 2012 May;31(3):311-9.

6 van der Pol P, Liebregts N, De Graaf R, Korf DJ, Van den Brink W, van Laar M. Predictors and barriers in treatment seeking for cannabis dependence. Drug Alcohol Depend. 2013 Dec;133(2):776-80.

7 Howard MC, Hoffman ME. Variable-centered, person-centered, and person-specific approaches: where theory meets the method. Organ Res Methods. 2018 Oct;21(4):46-76.

8 Vederhus JK, Rerendal M, Bjelland C, Skar AKS, Kristensen Ø. Can a smartphone app for cannabis cessation gain a broader user group than traditional treatment services? Subst Abuse. 2020 Feb;14(1):9.

9 Blankers M, Olthof M, van Laar M. Intentie om te minderen of te stoppen met blowen en opvatten over hulp zoeken. Utrecht, The Netherlands: Trimbos-instituut; 2020. p. 56. Dutch. Available from: https://www.trimbos.nl/aanbod/webwinkel/product/a1759-intentie-om-te-minderen-of-te-stappen-met-blowen-en-opvatten-over-hulpzoeken.

10 van der Pol P, Liebregts N, De Graaf R, Korf DJ, Van den Brink W, van Laar M. Validation of self-reported cannabis dose and potency: an ecological study. Addiction. 2013 Oct;108(10):1801-8.

11 Benschop A, Liebregts N, Van der Pol P, Schaap R, Buismann R, van Laar M, et al. Reliability and validity of the marijuana motives measure among young adult frequent cannabis users and associations with cannabis dependence. Addict Behav. 2015 Jan;40:91-5.

12 Simons J, Correia CJ, Carey KB, Borsari BE. Validating a five-factor marijuana motives measure: relations with use, problems, and alcohol motives. J Couns Psychol. 1998;45(3):265-73.

13 American Psychiatric Association. Diagnostic and statistical manual of mental disorders. 5th ed. London, UK: American Psychiatric Association; 2013.

14 de Beurs E, Zitman FG. De Brief Symptom Inventory (BSI): De betrouwbaarheid en validiteit van een handzaam alternatief voor de SCL-90. [The brief symptom inventory: the reliability and validity of a brief alternative of the SCL-90]. Maandbl G sectiegzond. 2006;61:120–41, Dutch.

15 Derogatis LR, Melisaratos N. The brief symptom inventory: an introductory report. Psychol Med. 1983 Aug;13(3):595–605.

16 Kooij JJS. ADHD bij volwassenen. Diagnostiek en behandeling. 4e druk. Amsterdam, The Netherlands: Pearson Assessment and Information; 2017, Dutch.

17 Garthus-Niegel S, Staudt A, Kinser P, Haga SM, Drozd F, Baumann S. Predictors and changes in paternal perinatal depression profiles - insights from the DREAM study. Front Psychiatry. 2020 Oct;11:563761.

18 MacLeod MA, Tremblay PF, Graham K, Bernards S, Rehm J, Wells S. Psychometric properties and a latent class analysis of the 12-item World Health Organization Disability Assessment Schedule 2.0 (WHODAS 2.0) in a pooled dataset of community samples. Int J Methods Psychiatr Res. 2016 Dec;25(4):243–54.

19 Akaike H. Factor analysis and AIC. Psychometrika. 1987 Sept;52(3):317–32.

20 Schwarz G. Estimating the dimension of a model. Ann Stat. 1978 Mar;6(2):461–4.

21 Sloce SL. Application of model-selection criteria to some problems in multivariate analysis. Psychometrika. 1987 Sept;52(3):333–43.
Identifying Subgroups of Cannabis Users Based on Help-Seeking Preferences

22 Celeux G, Soromenho G. An entropy criterion for assessing the number of clusters in a mixture model. J Classif. 1996;13(2):195–212.
23 McLachlan GJ. On bootstrapping the likelihood ratio test statistic for the number of components in a normal mixture. Appl Stat. 1987;36(3):318–24.
24 Bakk Z, Tekle FB, Vermunt JK. Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches. Socio Methodol. 2013 Aug;43(1):272–311.
25 Bakk Z, Vermunt JK. Step-3 tutorial #1: step-3 models with covariates, distal outcomes, and multiple latent variables. Available from: https://www.statisticalinnovations.com/wp-content/uploads/LGtutorial.Step3_.1.pdf.
26 Tomczyk S, Schomerus G, Stolzenburg S, Muehlan H, Schmidt S. Who is seeking whom? A person-centred approach to help-seeking in adults with currently untreated mental health problems via latent class analysis. Soc Psychiatry Psychiatr Epidemiol. 2018 Jun;53:773–83.
27 Davis ML, Powers MB, Handelsman P, Medina JL, Zvolensky M, Smits JAJ. Behavioral therapies for treatment-seeking cannabis users: a meta-analysis of randomized controlled trials. Eval Health Prof. 2015 Mar;38(1):94–114.
28 Boumparis N, Loheide-Niesmann L, Blankers M, Ebert DD, Korf D, Schaub MP, et al. Short- and long-term effects of digital prevention and treatment interventions for cannabis use reduction: a systematic review and meta-analysis. Drug Alcohol Depend. 2019 Jul;200(1):82–94.
29 Broome KM, Simpson DD, Joe GW. The role of social support following short-term inpatient treatment. Am J Addict. 2002;11(1):57–65.
30 Dobkin PL, De Civita M, Paraherakis A, Gill K. The role of functional social support in treatment retention and outcomes among outpatient adult substance abusers. Addiction. 2002 Mar;97(3):347–56.
31 Havassy BE, Hall SM, Wasserman DA. Social support and relapse: commonalities among alcoholics, opiate users, and cigarette smokers. Addict Behav. 1991;16(5):235–46.
32 Reif S, Braude L, Lyman DR, Dougherty RH, Daniels AS, Ghose SS, et al. Peer recovery support for individuals with substance use disorders: assessing the evidence. Psychiatr Serv. 2014 Jul;65(7):853–61.
33 Liu Y, Kornfield R, Shaw BR, Shah DV, McTavish F, Gustafson DH. Giving and receiving social support in online substance use disorder forums: how self-efficacy moderates effects on relapse. Patient Educ Couns. 2020 Jun;103(6):1125–33.
34 Basurto FZ, Montes JMG, Cubos PF, Santed FS, Rios FL, Moreno AM. Validity of the self-report on drug use by university students: correspondence between self-reported use and use detected in urine. Psicothema. 2009 May;21(2):213–9.
35 Hjorthøj CR, Hjorthøj AR, Nordentoft M. Validity of timeline follow-back for self-reported use of cannabis and other illicit substances: systematic review and meta-analysis. Addict Behav. 2012 Mar;37(3):225–33.
36 Oudejans S, de Weert-van Oene G, Spits M, de Wildt W, Merkx M, Dekker J, et al. A self-reported version of the Measurements in the Addictions for Triage and Evaluation-Q: concurrent validity with the MATE 2.1. Eur Addict Res. 2020 Oct;26(1):20–7.