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Patterns of Substance Use Among Individuals Seeking Treatment for Substance Use Disorders in Uganda: A Latent Class Analysis

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Abstract

Background:

Substance use disorders (SUDs) are an increasing public health concern in low- and middle-income countries, where treatment services often encounter individuals with heterogeneous and complex substance use that challenge treatment approaches organized around single substances. Empirical evidence describing such patterns among treatment-seeking populations in sub-Saharan Africa remains limited. This study identified distinct substance use patterns among individuals seeking SUD treatment in Uganda and examined their correlates.

Methods:

We conducted a cross-sectional analysis of baseline data from a longitudinal cohort of 445 individuals seeking SUD treatment at three treatment facilities in Uganda. Latent Class Analysis (LCA) identified distinct substance use patterns based on self-reported psychoactive substance use. Model fit was assessed using information criteria, entropy, and posterior classification probabilities. Multinomial regression was used to examine associations between participant characteristics and latent class membership, with the alcohol-dominant class as the reference group. Ridge-penalized regression was conducted as a sensitivity analysis.

Results:

A four-class model best characterized substance use patterns in the sample. The alcohol-dominant class (51.3%) was characterized by older age, rural residence, and formal employment. The cannabis–alcohol class (29.4%) comprised predominantly younger adults with housing instability, unemployment, urban residence, and elevated acute psychosis risk. The prescription drug class (10.8%) was marked by legal opioid, sedative-hypnotic, and anticholinergic misuse with strong association with injection drug use and acute psychosis risk. The high-risk illicit class (8.5%) showed near-universal illegal opioid (88.8%) and cocaine/crack cocaine (89.1%) use with the strongest association with injection drug use.

Conclusion:

Individuals seeking treatment for SUD in Uganda present with four clinically distinct patterns of substance use that differ substantially in severity, clinical complexity, psychosocial adversity, and broader structural vulnerabilities. These findings challenge the single-substance framing of existing treatment services and provide an empirical basis for differentiated, person-centred care including integrated mental health support, harm reduction and context-specific treatment approaches for high risk groups in Uganda and resource-limited settings.

Background

Substance use disorders (SUDs) represent a significant global public health challenge (1, 2), contributing substantially to morbidity, mortality, and social vulnerability (3). An increasing share of this burden is now borne by low- and middle-income countries (LMICs), particularly in the African region (4–6). Although sub-Saharan Africa (SSA) has historically reported lower levels of substance use compared to other regions, recent evidence indicates a rapidly expanding burden of SUDs, driven by profound shifts in substance availability, patterns of use, and associated harms (2, 6, 7). These changes have been linked to socio-economic transitions, rapid urbanization, and youth unemployment (8, 9), widening inequalities and weak regulatory and enforcement systems (10, 11), and expanding drug trafficking networks (6, 12). Consequently, SSA has emerged as one of the fastest-growing regions for drug trafficking, production, and consumption, particularly for cannabis, opioids, amphetamines, and emerging psychoactive substances (12).

Within the evolving landscape of substance use in SSA, alcohol remains the most widely used psychoactive substance, even as the use of illicit drugs continues to rise. Increasing use of tramadol, methamphetamine, and locally produced mixtures containing pharmaceuticals, solvents, and plant materials are widely reported and associated with severe or fatal outcomes (13). The 12-month prevalence of Alcohol Use Disorders (AUDs) is estimated at 9.5% (14) with substantial variation across SSA countries, ranging from 0.1% to 33.2% (15, 16). Importantly, alcohol use increasingly occurs within a broader context of multi-substance exposure. Despite this growing complexity, substance use treatment services across SSA operate under constrained resources and face substantial structural and non-structural barriers to access (10, 17).

In Uganda, the burden of SUDs mirrors trends observed across the region. Uganda has one of the highest per-capita alcohol consumption rates globally, estimated at 12.2 litres per person per year, while cannabis, khat, and pharmaceutical sedatives are commonly reported among people who use drugs. In recent years, heroin and other opioids have become more visible in urban centres, alongside rising concerns about injection drug use and associated harms (18, 19). The prevalence of AUD among adults is approximately 10% (20), while some studies suggest that over 25% of individuals below 18 years have a SUD (21, 22). However, widespread underreporting likely results in substantial underestimation of the true burden of SUDs (15). The impact of SUDs is further compounded by an already under-resourced mental health and addiction care system, characterized by significant barriers to care, including internalized stigma, limited awareness of available services, and minimal implementation of coordinated prevention, treatment, and substance control strategies (10, 23).

Emerging evidence suggests that many individuals seeking treatment for SUDs do not use substances in isolation but rather engage in complex patterns of concurrent or sequential substance use (24–26). Such patterns are shaped by local substance availability, cultural practices, regulatory environments, and broader social determinants, and may differ substantially from those observed in high-income countries. Understanding how substances cluster among individuals seeking treatment is important because different combinations are associated with distinct clinical trajectories, psychosocial needs, relapse risks

and treatment challenges, and classifying individuals solely by a “primary substance” can obscure clinically meaningful heterogeneity (24, 27). Several studies have therefore attempted to describe these patterns of use using person-centred approaches, such as latent class analysis (LCA) (28, 29), though mainly in high-income countries.

Research in SSA has largely focused on prevalence estimates, dominant substances of use, or binary distinctions such as single versus polysubstance use (9, 14, 30). While informative, such approaches provide limited insight into how substances co-occur within individuals or how distinct patterns of use emerge among treatment-seeking populations. Identifying distinct subgroups within treatment-seeking populations can support the development of differentiated care models, guide allocation of limited resources, and help identify high-risk groups requiring enhanced monitoring, integrated care for co-occurring conditions, or specialized interventions (29). However, there remains a notable gap in the application of person-centred methods to characterize substance use patterns among treatment-seeking populations in SSA (17). A search of the published literature identified only one LCA study in the region among community-based polysubstance users in South Africa(31) with no published LCA studies identified in treatment-seeking SUD populations across SSA, including Uganda. This represents a significant evidence gap in a region with a growing and diversifying substance use burden.

The present study uses LCA to identify and characterize distinct patterns of substance use among individuals seeking treatment for SUDs at a specialized treatment facility in Uganda. Specifically, we sought to identify the number and nature of latent classes of substance use patterns and examine associations between class membership and treatment-related variables. By providing the first comprehensive characterization of substance use patterns among treatment seekers in Uganda using a person-centred analytical approach, this study aims to generate evidence to inform the development of tailored treatment protocols and guide policy decisions for substance use disorder services in Uganda and similar sub-Saharan African settings.

Methods

Study Design and Setting

We conducted a cross-sectional analysis using baseline data from a longitudinal cohort assessing the patient-reported outcomes among service users seeking SUD treatment in Uganda. Participants were recruited from three treatment facilities representing different levels of care within the national mental health and addiction service system. These included Butabika National Referral Mental Health Hospital (BNRMH) in Kampala, which is the highest-level psychiatric referral centre in Uganda, the Mental Health Unit at Gulu Regional Referral Hospital (GRRH), which serves a regional-level facility providing specialized mental health and SUD services, and Hope and Beyond Recovery Centre, a private treatment facility in Kampala. These facilities collectively capture a broad spectrum of patients from across Uganda with diverse socio-demographic backgrounds, clinical presentations, and patterns of substance use.

Study population

This study was conducted among service users aged 18 years and above, seeking treatment for SUDs at the selected facilities. The study population consisted of individuals diagnosed with SUDs, as defined by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria, who had initiated a new treatment episode within the past 14 days and were able to provide informed consent. Both “new” cases and previously known cases were eligible, provided they began a new treatment episode during the recruitment period. Each participant underwent a comprehensive assessment using the Structured Clinical Interview for DSM-5, conducted by trained clinicians. We excluded service users with severe cognitive impairment or acute psychiatric conditions that hindered their ability to provide informed consent and would preclude reliable participation.

Sample size and recruitment procedure

Four hundred and forty-five participants (n = 445) were included in the analysis, drawn from a cohort study powered at 80%, with a two-sided α of 0.05 to detect differences between service user profiles. The overall sample was allocated proportionately across the three treatment facilities based on their average daily number of new service user admissions. At each facility, consecutive sampling was conducted in both the inpatient and outpatient departments until the targeted number of participants was enrolled. Participants’ enrollment took place between June 2023 and May 2024.

Data Collection Procedures

Eligible participants were informed about the study aims, procedures, and confidentiality safeguards by trained research assistants, and written informed consent was obtained prior to participation. Baseline data were collected upon participants’ enrollment into the longitudinal cohort. Trained research assistants with experience in mental health and substance use assessment conducted face-to-face structured interviews in private rooms using a pre-programmed questionnaire on tablets equipped with a customized version of the Open Data Kit software. The questionnaires were available in English and translated into relevant local languages (Luganda and Acholi). All data were uploaded directly to a secure, password-protected cloud server following each interview, enabling real-time data aggregation and monitoring. All participants were assigned a unique study identification number to maintain confidentiality.

Measurements and tools

Data was collected using a structured questionnaire that captured sociodemographic and clinical information, including age, gender, marital status, education level, employment status, income, living situation, medical comorbidities, treatment history, and current treatment approach. Participants also reported the primary substance that led them to seek treatment, as well as secondary substances used. Symptoms of depression, anxiety and stress were

assessed using the Depression Anxiety Stress Scales – 21 (DASS-21), a validated 21-item self-report instrument scored on a four-point Likert scale and coded as screen-positive based on validated cut-offs: depression ≥ 10, anxiety ≥ 8, and stress ≥ 15 (32, 33).

Post-traumatic stress disorder (PTSD) was screened using the Primary Care PTSD Screen for DSM-5 (PC-PTSD-5) and dichotomised as screen-positive with score ≥ 3 indicating probable PTSD versus screen-negative (34). ADHD was assessed using the Adult ADHD Self-Report Scale (ASRS-v1.1) Part A and dichotomised as screen-positive (Likert score ≥ 14) versus screen-negative, in line with validated scoring conventions for this instrument (35).

Functional impairment was evaluated using the 12-item version of the World Health Organization Disability Assessment Schedule (WHODAS) 2.0. Item responses were scored from 0 (none) to 4 (extreme or cannot do) and summed to produce a total raw score ranging from 0 to 48, with higher scores indicating greater disability. The raw score was converted to a 0–100 scale and cut-off thresholds were applied, consistent with established severity gradations for WHODAS 2.0 (36). Disability severity was categorised as no disability (0–4), mild (5–24), moderate (25–49), and severe (50–100) (37). For regression analyses, disability was dichotomised into no disability (0–4) and any disability (> 4), representing the presence of at least mild functional limitation.

Overall quality of life was assessed using the WHOQOL-BREF (38)which measures four domains physical health, psychological wellbeing, social relationships, and environment, alongside a single global item ("How would you rate your quality of life?"). Domain scores were transformed to a 0–100 scale per the WHO scoring algorithm, with higher scores indicating better quality of life. Domain scores are reported descriptively. For regression analyses, the global item was rated on a five-point scale from very poor to very good and dichotomised as good (good or very good; n = 195, 43.8%) versus not good (neither poor nor good, poor, or very poor) (38).

Substance use was assessed based on self-reported use of psychoactive substances in the three months preceding the interview. Substances assessed included alcohol, cannabis, cocaine, crack cocaine, legal opioids (e.g., Pethidine, Tramadol), illegal opioids (e.g., Heroin), sedative-hypnotics (barbiturates, benzodiazepines), anticholinergics (e.g. Benzhexol, Promethazine), hallucinogens, organic solvents/glue, and khat. Each substance was coded as a binary indicator reflecting any reported use during the reference period.

The sociodemographic and clinical variables collected through the structured questionnaire and screening tools were examined as correlates of the identified substance use patterns. These variables were not treated as predictors or outcomes but were used to describe differences across latent classes. Age was categorized into four groups: young adults (18–24 years), early adulthood (25–34 years), midlife adulthood (35–44 years), and late adulthood (≥ 45 years, reference). Gender was coded as a binary variable (male/female; female as reference). Marital status was categorised as single/never married, married or cohabiting, divorced or separated, and widowed. Employment status was categorised as officially employed (reference), self-employed, casual labourer, student or pupil, and unemployed. Education level was categorised as no formal schooling (reference), primary, secondary, and tertiary. Area of residence was categorised as rural (reference), semi-urban, and urban. Housing stability was coded as a binary variable (stable housing vs. unstable housing, i.e., lacking a fixed, regular, and adequate night-time residence). Injection drug use was dichotomised as ever injected versus never injected (reference). Previous SUD treatment was binary (yes/no; no as reference). Mental status at baseline was a binary clinical variable recorded by the assessing clinician at treatment entry, indicating whether the participant met DSM-5 criteria for acute psychosis at the time of assessment (psychotic vs. not psychotic; not psychotic as reference).

Data analysis

Data was analyzed in RStudio *Version 2024.12.1 + 563*, an integrated development environment for R software version 4.4.1 (2024-06-14) (39). Descriptive statistics were used to summarize socio-demographic, clinical, psychosocial, and substance use-related characteristics. For continuous variables, we computed means with standard deviations, while frequencies and proportions were reported for categorical variables with 95% confidence intervals (CI). CI for proportions were calculated using the exact binomial method.

The LCA was performed using the poLCA software package (40, 41) to identify distinct patterns of substance use based on the binary substance use indicators. LCA was conducted binary indicators of substances use including alcohol, cannabis, sedative-hypnotics/anticholinergics, illegal opioids, legal opioids, cocaine/crack cocaine, hallucinogens, and khat.

To assess the robustness of the LCA solution and reduce the risk of converging on local rather than global maxima, each model was estimated using 50 random sets of starting values. For each class solution (one to six classes), the run yielding the highest log-likelihood was retained for model comparison. The expectation-maximisation algorithm was used for parameter estimation, with a convergence tolerance of 1×10^{-10} and a maximum of 3,000 iterations.

Model selection was guided by model fit statistics, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with lower values indicating better fit (42, 43), alongside entropy (above 0.8 as desired, although no definitive cutoff exists) and the theoretical interpretability of classes (44). In selecting the optimal class solution, statistical fit indices were considered alongside substantive interpretability, parsimony, and minimum class size (44, 45). The four-class solution was selected based on the lowest BIC and was replicated across multiple random starts, confirming a stable solution.

After we identified the best class model, participants were assigned to their most likely latent class based on their posterior class membership probabilities. Item-response probabilities were used to characterize and label each identified substance use pattern. To examine factors associated with latent class membership, bivariate likelihood ratio (LR) tests were performed for each candidate variable by comparing multinomial logistic regression models with and without the variable. Variables with a p-value < 0.25 were retained for consideration in the multivariable analysis. Variables meeting this criterion, together with those considered clinically relevant, were entered simultaneously into a multivariable multinomial logistic regression model to examine associations with latent class membership. The alcohol-dominant class (Class 1) was specified as the reference category. Adjusted relative risk ratios (aRRRs) and 95%

confidence intervals (CIs) were estimated for each class relative to the reference. These analyses were intended to describe differences across latent classes and should be interpreted as associative rather than causal.

Given evidence of sparse data and extreme estimates in some categories, a ridge-penalised (L2) multinomial logistic regression was fitted as a sensitivity analysis using the glmnet package (version 4.1–10) in R, with the same set of predictors as the primary model. The penalty parameter (lambda) was selected via 10-fold cross-validation using the lambda.1se criterion, which applies a conservative degree of shrinkage to improve estimate stability. The random seed was set to 123 to ensure reproducibility. Ridge-penalised estimates are reported as adjusted relative risk ratios (aRRR = exp(β)) alongside primary model estimates for comparison, and were not used for primary inference.

Results

Characteristics of Service Users

As seen in Table 1, participants had a mean age of 33.2 years (SD = 9.91), were predominantly male (82.2%) and single (56.8%). Unemployment or casual labour accounted for over half the sample. Half of the participants lived in urban areas (50.3%) and most reported stable housing (85.2%). Alcohol was the most frequently used primary substance (58.4%), followed by cannabis (19.3%), with a minority reporting injection drug use (13.9%). Approximately half had previously received SUD treatment (49.4%).

At treatment entry, nearly one third (31.0%) presented with acute psychosis. Symptom screening using validated instruments identified higher rates of probable psychopathology; 70.6% screened positive for depression and over half for anxiety 51.9% on the DASS-21. Overall, quality of life was rated as not good by most participants (56.2%).

Table 1 near here

Latent class analysis of substance use

Latent class models with one to six classes were estimated and compared using information criteria, classification diagnostics, and class size distributions (Table 2). Log-likelihood and AIC values decreased progressively with increasing class numbers, while the BIC reached its lowest value at the four-class solution (BIC = 3879.8) before increasing for the five and six class solutions, indicating overextraction.

In selecting the optimal model, BIC was prioritised as the primary selection criterion, consistent with recommendations for LCA. Model selection was further guided by considerations of parsimony, minimum class size, and substantive interpretability of the identified classes. The four-class solution yielded adequately sized classes (38 participants, 8.5%), and the additional classes in the five- and six-class solutions were smaller and less interpretable.

Entropy and average latent class posterior probabilities (ALCPP) were examined to assess classification quality rather than to determine the number of classes. The four-class model demonstrated high entropy (0.92) and strong classification certainty (ALCPP = 0.914), indicating good separation between classes.

Although the models with five and six classes yielded marginally lower AIC values, they were associated with higher BIC values, lower entropy, smaller minimum class sizes (≤5.3% and ≤3.8%, respectively), and poorer classification quality (ALCPP <0.75). Taken together, the four-class model was considered to provide the best balance of statistical fit, classification quality, parsimony, and substantive interpretability.

Substance use profiles of the selected four class model

LCA identified four distinct substance-use patterns among treatment service users, with clear variation in class sizes. Figure 1 shows the conditional probabilities of participants' substance use in the selected four latent class solution. The alcohol-dominant profile (ALC-dom, 51.3%), was the largest and was exclusively characterized by universal alcohol use (100%). The cannabis–alcohol profile (CAN–ALC, 29.4%), showed omnipresent cannabis use (100%) and substantial alcohol use (76.7%), with moderate khat use (27.2%) and low probability of other substance use. The PRES profile (10.8%) was characterised by elevated probabilities of legal opioid use (49.7%), sedative-hypnotics/anticholinergics (28.1%), and cannabis use (31.7%), with moderate alcohol use (24.7%) and near-zero probabilities of illegal opioid and cocaine/crack cocaine use. The high-risk illicit drug profile (HR-ILL, 8.5%) was the smallest and exhibited very high probabilities of illicit opioid use (88.8%) and cocaine/crack cocaine use (89.1%), with substantial cannabis use (71.0%) and moderate alcohol use (31.8%), representing a clinically high-risk subgroup.

Bivariate multinomial regression screening of covariates

Bivariate likelihood ratio (LR) tests were conducted to assess the global association between each candidate predictor and latent class membership. Results are presented in Table 3. Of the 18 predictors examined, 14 met the pre-specified inclusion threshold of $p < 0.25$ and were retained for consideration in the multivariable model: age group, injection drug use, employment status, religion, area of residence, gender, education, housing stability, acute psychosis at treatment entry, PTSD, disability, depression, previous treatment for SUD, and marital status. However, anxiety, stress, quality of life, and ADHD did not meet the inclusion threshold and were therefore excluded from the multivariable analysis.

Multivariable multinomial regression: independent correlates of latent class membership

In the multivariable multinomial logistic regression analysis using ALC-dom as the reference class, 14 covariates were examined, of which 10 showed at least one statistically significant independent association with latent class membership across the CAN-ALC, PRES, and HR-ILL profiles (see Additional file

1). Ridge-penalised estimates are reported alongside primary model estimates in Additional file 1; for associations with extreme aRRRs, the ridge-penalised β is noted in the text as an indicator of direction and relative magnitude under coefficient shrinkage.

Compared with individuals aged ≥45 years, young adults (18–24 years) had higher odds of CAN-ALC membership (aRRR 354.96, 95% CI 38.98–3232.31; ridge β=1.52, consistent with a large positive association) and PRES membership (aRRR 37.46, 95% CI 5.94–236.16; ridge β=0.98, consistent with a positive association). Early adulthood (25–34 years) was also strongly associated with CAN-ALC membership (aRRR 38.88, 95% CI 4.99–302.58; ridge β=0.47), and midlife adulthood (35–44 years) with moderately increased odds of CAN-ALC (aRRR 10.89, 95% CI 1.31–90.31) and PRES membership (aRRR 4.55, 95% CI 1.00–20.76). Male sex was associated with increased odds of CAN-ALC membership (aRRR 4.20, 95% CI 1.73–14.82) but was not significantly associated with PRES or HR-ILL membership.

Compared with rural residence, urban residence was associated with higher odds of CAN-ALC (aRRR 2.22, 95% CI 1.01–4.89), PRES (aRRR 7.73, 95% CI 1.53–39.03), and HR-ILL membership (aRRR 89.83, 95% CI 4.89–1648.55; ridge β=0.48, consistent with a positive association). Semi-urban residence was similarly associated with PRES (aRRR 10.80, 95% CI 2.08–55.99) and HR-ILL membership (aRRR 62.11, 95% CI 3.02–1278.84; ridge β=0.07, suggesting a modest positive association under shrinkage and should be interpreted with caution). Compared with official employment, unemployment was associated with higher odds of CAN-ALC (aRRR 5.05, 95% CI 1.70–15.03) and HR-ILL membership (aRRR 50.93, 95% CI 3.37–770.21; ridge β=0.70, consistent with a positive association). Religion was independently associated with class membership; Muslim and Pentecostal participants had significantly higher odds of PRES membership (aRRR 4.10, 95% CI 1.16–14.56 and aRRR 4.17, 95% CI 1.08–16.10 respectively), while Catholic participants had substantially lower odds of HR-ILL membership (aRRR 0.10, 95% CI 0.02–0.47), all relative to Anglican/Protestant participants. Among education categories, primary education was associated with lower odds of PRES membership compared with no formal schooling (aRRR 0.13, 95% CI 0.02–0.93).

Injection drug use showed the strongest and most consistent associations across all non-alcohol classes. Participants who had ever injected drugs had substantially higher odds of CAN-ALC (aRRR 7.84, 95% CI 2.05–29.90), PRES (aRRR 51.21, 95% CI 12.55–208.93; ridge β=1.49, consistent with a large positive association), and HR-ILL membership (aRRR 401.61, 95% CI 62.09–2597.57; ridge β=1.90, consistent with a large positive association). Acute psychosis at treatment entry was associated with increased odds of CAN-ALC (aRRR 2.76, 95% CI 1.43–5.30) and PRES membership (aRRR 3.84, 95% CI 1.57–9.42). Housing instability was associated with higher odds of CAN-ALC membership (aRRR 2.71, 95% CI 1.11–6.61). Previous treatment for SUDs was associated with increased odds of PRES (aRRR 2.67, 95% CI 1.29–5.52) and HR-ILL membership (aRRR 3.10, 95% CI 1.00–10.60).

Disability and depressive symptoms were inversely associated with HR-ILL membership. Individuals with any disability had lower odds of CAN-ALC (aRRR 0.37, 95% CI 0.16–0.83) and HR-ILL membership (aRRR 0.16, 95% CI 0.04–0.67), while depression was associated with reduced odds of HR-ILL membership (aRRR 0.20, 95% CI 0.06–0.74). PTSD, marital status, and most education categories showed no statistically significant independent associations with class membership in the multivariable model.

The sensitivity analyses using ridge-penalised multinomial logistic regression indicated the direction and relative magnitude of associations were largely consistent with the primary model, with penalisation attenuating extreme estimates while preserving the overall pattern of findings.

Additional file 1: Table 4

Discussion

This study identified four distinct patterns of substance use among 445 individuals seeking SUD treatment in Uganda, with marked variation in class size and clinical profile. The alcohol-dominant profile was the largest, comprising just over half of participants exclusively using alcohol, reflecting the well-documented predominance of AUDs in Uganda and across SSA (2, 9). The cannabis-alcohol profile accounted for nearly one-third of participants, while smaller but clinically important profiles included a prescription drug class characterised by legal opioid, sedative-hypnotic use and moderate alcohol use, and a high-risk illicit class distinguished by co-use of illicit opioids, cocaine/crack cocaine, and cannabis. Latent class membership was differentially associated with younger age, injection drug use, urban residence, religion, unemployment, and acute psychosis, with these factors clustering in the smaller higher-risk profiles and thus have direct implications for the targeting and tailoring of treatment services in Uganda.

Collectively, these findings challenge the prevailing single-substance framing of addiction treatment in Uganda and across much of SSA. Research suggests that encountering more than one addiction, whether simultaneously or sequentially is more common than encountering a single one across the life course (24, 26). Yet, treatment systems in the region continue to be organised primarily around a dominant or "primary" substance. The four empirically derived classes identified here, three of which involve multi-substance profiles with distinct clinical and social characteristics, highlight the need to move towards integrated, person-centred care that reflects the complexity of substance use as presents in treatment settings.

The ALC-dom class was the largest, a finding that aligns with Uganda's high levels of alcohol consumption reported globally, supported by the wide availability of both commercial and traditional beverages, permissive regulatory environments, and strong cultural acceptance of drinking(20). This predominance aligns with prior evidence showing alcohol as the most commonly reported primary substance among treatment-seeking populations in the region (9, 14). Treatment seeking individuals in this class were more likely to be older (≥ 35 years), reside in rural areas, and be formally employed, features that may signal relatively greater social stability compared with individuals in multi-drug profiles. This pattern is consistent with life-course transitions in substance use trajectories, whereby older adults may be more likely to present with established single-substance use disorders (46). The relative absence of multi-drug involvement, together with rural predominance, may reflect reduced exposure to urban-concentrated illicit drug markets (47, 48), alongside longstanding cultural traditions of alcohol production and consumption in rural communities (49).

This ALC-dom class may benefit from evidence-based alcohol-specific interventions, including brief interventions, pharmacotherapy and psychosocial approaches such as motivational interviewing and cognitive-behavioral interventions (50, 51). Additionally, given the rural distribution of this class, targeted prevention and treatment programming outside major urban centers and policy efforts to strengthen regulation of informal or unregulated alcohol outlets may be particularly important for reducing alcohol-related harm (52, 53).

The CAN-ALC class highlights the growing prevalence of cannabis use in Uganda and SSA more broadly (7, 54). Concurrent use of cannabis and alcohol has been associated with increased addiction severity, greater psychosocial impairment, cognitive and functional deficits, increased social and behavioural harms, and elevated risk of mental health comorbidities, particularly psychosis and mood disorders (55, 56). Consistent with previous research, the CAN-ALC class largely consisted of younger adults (below 35 years), males, and people experiencing housing instability (54, 57). Membership in this class was also associated with acute psychosis at presentation, supporting the documented link between cannabis use and psychosis (56, 58). Interventions for this class should therefore integrate social services that address housing and mental health needs (59, 60). Given the prominence of acute psychosis in this profile, early screening for psychotic symptoms and prompt linkage to psychiatric care are critical components of treatment.

The prescription drug class represents a clinically distinct and concerning pattern characterized by misuse/non-medical use of controlled medications in the Ugandan treatment population, particularly legal opioids (e.g., tramadol, pethidine) and sedative-hypnotics. This pattern has been previously documented in Uganda and is plausibly facilitated by the increasing availability of prescription medications through formal and informal pathways, diversion, and self-medication for pain, sleep problems, and psychological distress, including unregulated pharmacies, drug shops, and illicit markets (11). Suboptimal compliance with controlled prescription drug regulations among Uganda's pharmacies has been documented (11), with poor adherence to stock control requirements undermining accountability and creating opportunities for diversion from licensed pharmacies to illicit markets. National laws restrict prescribing authority for controlled medications to authorized medical, dental, and veterinary practitioners, and dispensing to licensed pharmacies under pharmacist supervision, requiring valid prescriptions for all controlled substance dispensing (61). However, inadequate enforcement encourages inappropriate dispensing practices, further increasing population exposure to these medications.

This PRES profile was strongly associated with younger age, muslim and pentocostal religion, urban and semi-urban residence, injection drug use, and previous treatment for SUDs. The high proportion with prior treatment history suggests that this group cycles through treatment services, consistent with the chronic relapsing nature of prescription drug dependence. Educational attainment appeared protective, with lower odds among those with primary and secondary education compared with those having no formal schooling. The association between Muslim and Pentecostal religion and PRES membership reflects the prohibition on alcohol and illicit substances within these religions, which may channel substance use toward prescription and pharmaceutical products perceived as medically or socially acceptable. The association between urbanization and the PRES class reflects differential access to pharmacies and healthcare facilities, as urban centers have higher densities of drug outlets, including unregulated sources(11). Additionally, there was a strong association between the PRES class and injection drug use. Injection use has been associated with elevated risks of infectious complications, including HIV, hepatitis C, and bacterial infections (62, 63). The co-use of sedative-hypnotics further compounds overdose risk and complicates withdrawal management (64). There is thus a need for harm reduction services, including needle and syringe programs, opioid agonist therapy and overdose prevention education in this group (65, 66).

There was an association between the PRES class and acute psychosis and while opioids are not typically associated with primary psychotic symptoms, multiple substance use involving stimulants, cannabis, or other agents may contribute to psychotic presentations, as may withdrawal states or substance-induced delirium(67). Alternatively, individuals with pre-existing psychotic disorders may engage in self-medication with sedatives or opioids to manage distressing symptoms, a phenomenon documented in dual diagnosis populations (68, 69).

The HR-ILL class, although the smallest, showed the most severe patterns of substance use characterized by near-universal illegal opioids and cocaine/crack cocaine use alongside substantial cannabis use. The pattern of substance use in this profile is associated with high risks of overdose, intoxication or withdrawal complications, and infectious-disease transmission through injection use(70). Uganda's position along major East African drug trafficking routes, with growing evidence of local consumption alongside transit activity, provides the structural context for this profile (71, 72).

The HR-ILL class was strongly associated with injection drug use, unemployment, urban and semi-urban residence, male gender, and younger age, consistent with global patterns in which experimentation and high-risk drug use peak during late adolescence and early adulthood (7, 8, 73), and reflecting a profile of severe social marginalization and structural vulnerability to high-risk substance use. Unemployment may both precede and perpetuate substance use, as economic hardship drives substance use as a coping mechanism, while chronic substance use further impairs employment prospects (74). High youth unemployment, limited formal sector opportunities, and precarious labour in Uganda compound this vulnerability (75), while rapid urbanization concentrates drug market activity including trafficking, distribution, and consumption (48, 76) in urban environments that offer greater anonymity and more established drug use networks (77). Given this profile, expanding access to opioid agonist therapy which reduces injection drug use, HIV transmission, overdose mortality, and criminal activity (78), alongside needle and syringe programs, naloxone distribution, and drug checking services, should be a policy priority for Uganda and the broader SSA region (66).

Counterintuitively, HR-ILL class membership was associated with lower odds of screening positive for depression and disability compared to the alcohol-dominant reference class. This may reflect underreporting of psychological distress due to acute intoxication or cognitive impairment at assessment (79), or survival bias whereby individuals with the most severe comorbidities may not survive to present for treatment (80).

Sensitivity analyses using penalized multinomial regression yielded similar associations to the primary models, suggesting that the findings were robust despite potential sparse data and quasi-separation and so strengthen confidence in the identified class-specific correlates.

Study Limitations

The study's cross-sectional design precludes any causal inference; the observed associations between class membership and covariates may reflect reverse causation. Longitudinal research is needed to elucidate the temporal dynamics of substance use trajectories and their determinants.

The sample was drawn from individuals seeking treatment at specialized addiction facilities, which may not be representative of the broader population of people with SUDs in Uganda. Treatment-seeking populations may differ systematically from non-treatment-seekers in terms of severity, comorbidity, social support, and other characteristics. The generalizability of findings to community-dwelling individuals with SUDs is uncertain.

The study was conducted across three facilities (national referral hospital, regional hospital, private centre) representing different levels of care, which may attract systematically different patient profiles. While this diversity enhances coverage, facility-level differences may introduce heterogeneity that the study was not powered to examine. Additionally, substance use data were based on self-report, which is subject to recall bias and social desirability bias.

Psychiatric comorbidities were assessed using validated screening instruments rather than structured clinical interviews, which may overestimate the true prevalence of these conditions. Screen-positive results should be interpreted as indicative of probable rather than confirmed diagnoses

Some associations in the multivariable model were estimated with low precision, as reflected by large effect sizes and wide confidence intervals in certain comparisons. This likely reflects sparse data and small cell sizes in some categories, particularly within the smaller latent classes. While ridge-penalized regression was used to improve model stability, the magnitude of some estimates should be interpreted with caution. Accordingly, interpretation focuses on the direction and relative pattern of associations rather than the exact size of the estimated effects. Replication in larger samples is warranted.

Conclusions

This study identified four distinct latent classes of substance use among treatment-seeking individuals in Uganda. These classes differed in their sociodemographic and clinical profiles with important implications for treatment planning, harm reduction, and health policy in Uganda and the broader SSA region. The alcohol-dominant class represented the reference group with comparatively lower clinical and social risk, whereas the cannabis–alcohol, prescription drug, and high-risk illicit classes were characterized by progressively greater levels of psychosocial adversity, mental health comorbidity, and risky substance use behaviours. Injection drug use, younger age, urban residence, unstable housing, and acute psychotic symptoms emerged as key features of the higher-risk classes, underscoring the intersection between substance use severity, mental health burden, and structural vulnerability.

These findings emphasize the need for differentiated and integrated treatment approaches. Individuals in high-risk and prescription drug classes may benefit from enhanced harm-reduction services, psychiatric care, and social support interventions. Incorporating routine mental health screening, housing support, and targeted psychosocial interventions into substance use treatment services is therefore critical. From a policy perspective, the results support the development of stratified care pathways within Uganda's addiction treatment system, aligned with the specific needs of distinct client subgroups. Future research should examine longitudinal transitions between classes and evaluate whether tailored interventions based on class membership improve treatment engagement and long-term outcomes. Overall, this study provides evidence on the wide heterogeneity of substance use patterns in treatment-seeking populations in Uganda and offers a foundation for more responsive, person-centred, and integrated SUD services in similar LMIC settings.

Abbreviations

ADHD: Attention Deficit Hyperactivity Disorder

AIC: Akaike Information Criterion

ALC-dom: Alcohol-dominant class

ALCPP: Average Latent Class Posterior Probability

aRRR: Adjusted Relative Risk Ratio

ASRS-v1.1: Adult ADHD Self-Report Scale version 1.1

BIC: Bayesian Information Criterion

BNRMH: Butabika National Referral Mental Health Hospital

CAN-ALC: Cannabis-Alcohol class

CI: Confidence Interval

DASS-21: Depression Anxiety Stress Scales — 21 item version

DSM-5: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition

GRRH: Gulu Regional Referral Hospital

HIV: Human Immunodeficiency Virus

HR-ILL : High-Risk Illicit

LCA: Latent Class Analysis

LMIC: Low- and Middle-Income Country

LR: Likelihood Ratio

PC-PTSD-5: Primary Care PTSD Screen for DSM-5

PRES: Prescription Drugs dominant class

PTSD: Post-Traumatic Stress Disorder

SD: Standard Deviation

SSA: Sub-Saharan Africa

SUD: Substance Use Disorder

UNODC: United Nations Office on Drugs and Crime

WHO: World Health Organization

WHODAS 2.0: World Health Organization Disability Assessment Schedule 2.0

WHOQOL-BREF:World Health Organization Quality of Life — Brief Version

Declarations

Ethics approval and consent to participate

Ethical approval for this study was obtained prior to data collection from the Makerere University School of Public Health Research Ethics Committee (MakSPH-REC) as part of the AQUALEFF study (Advancing Quality and Effectiveness of Treatment of Substance Use Disorders in Uganda) under reference number *SPH-2023-381*. The study was subsequently registered with the Uganda National Council for Science and Technology in accordance with national research guidelines under Registration Number HS6699ES. Additionally, administrative clearance to conduct research at the treatment facilities was obtained. All participants provided written informed consent before data collection. Participation was voluntary, and confidentiality was assured throughout the study and beyond. Data was securely stored in encrypted digital folders, accessible only to the core research team. Ethical guidelines were strictly adhered to during all stages of the research.

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and analysed during the current study are not publicly available due to the sensitive and confidential nature of the clinical data, which includes personal health information from individuals seeking treatment for substance use disorders, and the terms of ethical approval granted for this study. However, the datasets are available from the corresponding author on reasonable request, subject to the conditions of the original ethical approval and institutional data sharing agreements.

Competing interests

The authors declare that they have no competing interests

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Authors' contributions

CB conceived and designed the study, led the data collection with the support of research assistants, conducted the statistical analysis, and wrote the first draft of the manuscript. WV, DLS, and NMT contributed to the conception and design of the study. WV and NMT provided critical oversight of the research and senior guidance on the study design and implementation. DLS and BBM provided critical input into the research process. DMK contributed to the statistical analysis and review of the manuscript. DLS, DK, KK, VS, JNM, WV, and NMT reviewed the manuscript and provided critical feedback. All authors read and approved the final manuscript.

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Tables

Tables 1 to 3 are available in the Supplementary Files section.

Figures



Figure 1

Conditional probabilities of participants' substance use in the selected four latent class solution

Supplementary Files

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- Tables.docx
- Additionalfile1Table4.xlsx