191 (2026) 210067

Contents lists available at ScienceDirect

Journal of Substance Use and Addiction Treatment

journal homepage: www.journals.elsevier.com/journal-of-substance-use-and-addiction-treatment

Baseline recovery capital and substance use history as determinants of recovery residence length of stay examined through cox regression and survival mixture clustering

Matthew J. Belanger [a,*], Kurt D. Lebeck [b,c], Adela Bunaciu [d], Arun Sondhi [e,f], David W. Best [f,g]

[a] Department of Sociology, Social Policy and Criminology, Faculty of Social Sciences, University of Stirling, Stirling, UK
[b] Howl Collaborative LLC dba RCADE Tools, Albuquerque, NM, USA
[c] Behavioral Health Institute, Heller School for Social Policy and Management, Brandeis University, Waltham, MA, USA
[d] Division of Psychology, University of Dundee, Dundee, UK
[e] Therapeutic Solutions (Addictions) Ltd., London, UK
[f] Centre for Addiction Recovery Research, Leeds Trinity University, Leeds, United Kingdom
[g] STAR Recovery Ltd., Portsmouth, UK

A R T I C L E I N F O

Keywords:
Recovery capital
Recovery housing
Substance use disorder
Survival analysis
Cluster analysis
Retention
Social determinants of health
Cox

A B S T R A C T

Introduction: Individuals starting a recovery journey enter recovery housing with diverse sociodemographic backgrounds, substance use histories, and levels of recovery capital, which influence the length of stay in recovery housing. This study examined which admission characteristics correspond to length of stay in recovery residences and used survival mixture clustering to characterise heterogeneity in retention trajectories.
Methods: This study included data from 2534 residents across 61 U.S. recovery residences between 2019 and 2023. Cox proportional-hazards regression identified baseline correlates of length of stay, with cluster-robust standard errors at the residence level. A complementary survival mixture clustering algorithm jointly modelled latent retention trajectories and survival functions using sociodemographic characteristics, recovery capital, barriers, unmet service needs, and substance use indicators.
Results: Older age, higher quality of life, greater recovery group participation, an unmet alcohol treatment need, and criminal legal system involvement associated with longer stays. By contrast, a history of cannabis use, drug use within 90 days before admission, and an unmet drug treatment need associated with shorter stays. Survival mixture clustering supported a nine-cluster solution, with median lengths of stay ranging from 29 to 91 days. Clusters with shorter stays exhibited lower recovery capital, higher unmet needs, and greater recent substance use, whereas longer-stay clusters demonstrated higher quality of life, stronger engagement with support structures, and higher proportions of criminal legal system involvement. Model discrimination was modest overall, indicating that baseline characteristics explain only part of the variation in retention trajectories.
Conclusion: Residents reporting recent drug use before admission to recovery housing or an unmet drug treatment need may benefit from proactive support at admission, while peer engagement and structured support pathways may promote longer lengths of stay. Because effect sizes were modest and discharge outcomes were heterogeneous, these findings should inform adaptive and equity-conscious service responses rather than individual risk classification. Future research should disaggregate accrual and loss of recovery capital during initial residence and distinguish between disengagement and recovery-readiness exits.

1. Introduction

Recovery from a substance use disorder (SUD) requires a holistic, personalised, and socially embedded approach to sustained wellness. Scholarship defines recovery as a "process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential" (SAMHSA, 2012, p.3). Conceptually, the process of recovery involves the accumulation of recovery capital and the elimination of barriers to health and well-being (White & Mojer-Torres, 2010). Recovery occurs in three stages: early (the first

* Corresponding author at: University of Stirling, Stirling, FK9 4LA, United Kingdom.
E-mail address: matthew.belanger@stir.ac.uk (M.J. Belanger).

https://doi.org/10.1016/j.josat.2026.210067
Received 12 November 2025; Received in revised form 23 June 2026; Accepted 7 July 2026
Available online 11 July 2026

year), sustained (1–5 years), and stable (beyond year five), with the five-year mark widely regarded as the transition to primarily self-sustaining recovery (Dennis et al., 2007; The Betty Ford Institute Consensus Panel, 2007). Throughout these stages, individuals draw on internal (e.g., self-efficacy, coping skills) and external resources (e.g., meaningful employment, supportive relationships) while overcoming barriers such as housing instability or ongoing legal involvement.

Researchers conceptualised recovery capital as the internal and external biopsychosocial resources necessary to initiate and sustain recovery (Cloud & Granfield, 2008; Granfield & Cloud, 1999). Recovery capital theory expanded in 2008 to differentiate between negative and positive aspects of recovery capital (Cloud & Granfield, 2008). However, in recent years, its application began to include social, structural, and tangible assets and barriers that either facilitate or hinder engagement in recovery services, particularly for vulnerable populations (Alegría et al., 2023; Altekruse et al., 2020; Feld et al., 2023; Lewis et al., 2024; Mejia et al., 2024). Positive recovery capital includes strong social support, stable housing, and employment. By contrast, negative recovery capital can refer to barriers such as recent substance use, criminal legal system (CLS) involvement, housing instability, and limited access to healthcare or vocational programmes (Cloud & Granfield, 2008; Patton et al., 2022).

Recovery residences offer individuals recovering from a SUD a safe, clean, and stable environment during early recovery stages or after discharge from an inpatient facility or carceral custody (Johnson et al., 2022; Mericle et al., 2017; Reif et al., 2014; Vilsaint et al., 2025; Wittman et al., 2017). When moving into recovery housing, individuals with a SUD experience a transitional phase between a controlled, abstinence-focused environment and their previous settings where substance use was common and accessible (Jason et al., 2007). For those transitioning from inpatient facilities, recovery housing offers stability and support as they prepare to live independently (Reif et al., 2014). The National Alliance for Recovery Residences (NARR) delineates four levels of recovery residences, ranging from Level I democratically run homes to Level IV residences with on-site clinical services. Research acknowledges that stable housing is a significant protective factor in recovery, and recovery residences augment the growth of recovery capital and help mitigate the risk of recurrence of substance use.

Residents typically must maintain employment to pay rent and expenses and there are generally expectations to perform household chores (Jason, 2021; Wittman et al., 2017). Further, residents should stay abstinent from substances during their stay (Polcin, 2015). While attending outpatient or formal treatment programmes is encouraged, many recovery homes do not mandate such attendance (Reif et al., 2014; SAMHSA, 2019). A vital aspect of recovery housing is the social support that fellow residents provide (Johnson et al., 2022; Mericle et al., 2022). Peer-based support is a critical component of the social recovery model, which places experiential peer support and community at the centre of enacting change (Borkman et al., 1998). Recovery housing thus creates structures of social networks where residents support and motivate each other through their recovery journeys (Jason, 2021). Because of their peer-driven nature, residents who do not abstain from substance use are likely to be removed from the house due to the risks this imposes on other household members (Reif et al., 2014).

Entering recovery housing after inpatient treatment improves positive outcomes and sustained abstinence (Jason et al., 2007; Polcin et al., 2010; Tuten et al., 2012, 2017). Studies indicate that individuals who move into recovery housing are less likely to be incarcerated post-treatment (Jason et al., 2007) and report higher rates of abstinence and employment (Tuten et al., 2017). For those recovering from opioid use, living in a recovery home significantly lowers the risk of increased substance use in the following six months compared to those who do not enter recovery housing after detoxification (Reif et al., 2014; Tuten et al., 2017).

Importantly, the diversity of residents' experiences and needs presents challenges in personalising treatment approaches and effectively allocating resources. For example, Dewey et al. (2024) contend that recovery housing directors view the coordination of housing and services as complex due to legal restrictions, limited bed availability, and the diverse individual needs of residents. Previous research categorised individuals based on post-treatment functioning. For example, Wilson et al. (2016) used Latent Profile Analysis (LPA) in large multi-site clinical trials to explore differences in post-treatment psychosocial functioning among treatment "failures" and "successes." Similarly, Witkiewitz et al. (2019) identified four distinct recovery profiles post-treatment for alcohol use disorder. They concluded that some individuals who engage in heavy drinking post-treatment may function as well as those who are mostly abstinent in terms of psychosocial functioning, employment, life satisfaction, and mental health. These studies provide valuable insights into longer-term trajectories of recovery. However, because their emphasis is on post-treatment outcomes, they offer limited guidance for addressing the immediate challenges that arise during the early stages of recovery, when retention and stabilisation are especially critical. This study seeks to address this gap by exploring factors associated with retention in recovery housing and categorising residents using baseline information collected at admission (including sociodemographic factors, substance use history prior to admission, quality of life, levels of personal, social, and community recovery capital, commitment to sobriety, barriers to recovery, and unmet service needs). We contextualise the findings with the discharge outcomes recorded after the residents left the residence.

While increased recovery capital associates with higher rates of abstinence (Subbaraman et al., 2023), treatment completion (Sánchez et al., 2020), and improvements in key social determinants of health (Altekruse et al., 2020; Feld et al., 2023; Mejia et al., 2024), relatively few studies examined the role of recovery capital at the point of entry into recovery housing. Recent research indicates that retention in recovery housing is higher among older residents with strong social support and employment, while younger residents, women, and those with housing needs are more likely to drop out (Härd et al., 2022); similarly, another study showed that residents not using substances, not identifying as Black or African American, and with fewer housing barriers show higher retention (Best et al., 2023). Understanding how variations in recovery capital influence the length of stay in a recovery residence is essential for informing care provision strategies.

Cluster methods are particularly suitable for this question because recovery processes are inherently heterogeneous, with individuals differing across sociodemographic, psychosocial, and structural dimensions. Segmentation, therefore, enables the identification of how complex, non-linear relationships between levels of recovery capital, substance use history, and barriers/unmet needs come together to affect length of stay. In the context of recovery housing (i.e., where residents vary widely in needs at intake), cluster methods provide a statistically rigorous means of capturing this diversity and linking it to sustained retention or dropout patterns. Despite advances in survival modelling, a crucial gap exists in the lack of integrated approaches that can simultaneously identify clinically relevant segments of the population and predict individual time-to-event outcomes. Conventional models separate clustering from survival prediction, thereby limiting their ability to account for the complex, multifaceted nature of recovery. This separation is particularly problematic in heterogeneous populations, where diverse barriers and needs contribute to individual recovery trajectories in different ways.

The present study examines which baseline characteristics associate with length of stay in recovery housing, using Cox proportional-hazards regression on time to discharge as the primary inferential analysis. Recent developments in machine learning offer further approaches that jointly learn latent clusters and survival functions; thus, we employ a time-to-event clustering algorithm as a secondary, descriptive analysis to characterise the heterogeneity of residency trajectories. We considered the following research questions:

RQ1: Which baseline characteristics (recovery capital measures, sociodemographics, and pre-admission substance use characteristics) associate with a longer or shorter length of stay in recovery residences?

RQ2: What is the distribution of length of stay trajectories across the sample, and how do baseline characteristics differ across the emergent clusters?

2. Methods

2.1. Sample characteristics

This study used an administrative dataset of 2534 admission episodes from 2534 unique individuals, recorded across 61 recovery residences in the United States between August 2019 and November 2023. The mean age was 39.25 years (SD = 10.84; range 17 to 77; we retained five cases with unrecorded ages for survival analysis but excluded them from this descriptive summary). Men comprised 65.48% of the sample (N = 1658). Approximately 62.60% reported drug or alcohol use within 90 days prior to admission (N = 1585). The majority of the sample identified as Caucasian (N = 1690, 66.75%); the remainder identified as Black or African American (N = 647, 25.55%), Hispanic (N = 112, 4.42%), or, due to small individual counts, Other Ethnicity (N = 83, 3.28%; comprising 69 originally coded as Other, 11 Asian, 2 Native American, and 1 Native Alaskan). Length of stay ranged from 0 to 796 days (mean = 102.16, SD = 122.48, median = 56 days). The most common discharge reasons were Abandonment (N = 494, 19.51%), Other Voluntary Discharge (N = 484, 19.12%), Completed Programme (N = 465, 18.36%), Other Involuntary Discharge (N = 410, 16.19%), Recurrence of Use (N = 329, 12.99%), Other (N = 164, 6.48%), and CLS Discharge (N = 68, 2.69%). We restricted the sample to individuals with a single admission episode to ensure that the baseline REC-CAP assessment unambiguously corresponded to a unique residential stay and to avoid complications introduced by multiple admission episodes. We plan to examine those with multiple admission episodes in a future study.

2.2. Data collection

Recovery housing staff assessed baseline levels of recovery capital measures upon admission to a recovery residence using the REC-CAP (Cano et al., 2017). The REC-CAP is a comprehensive assessment that measures the recovery capital strengths and barriers of an individual, incorporating a range of validated measures, including the Assessment of Recovery Capital (ARC, Groshkova et al., 2013a), Recovery Group Participation Scale (RGPS, Groshkova et al., 2013b), Commitment to Sobriety Scale (CSS, Kelly & Greene, 2014), and components of the Treatment Outcome Profile (TOP, Delgadillo et al., 2013). The instrument evaluates personal, social, and community strengths, as well as recovery barriers and unmet service needs. Staff in clinical and support settings use the REC-CAP globally to measure net change in recovery capital over time. This instrument also facilitates individualised recovery goal planning. All participants underwent informed consent procedures. The Leeds Trinity University School of Social Sciences Ethics Committee granted ethical approval for this study. All procedures further adhered to institutional and national ethical standards, as well as the principles outlined in the 1964 Helsinki Declaration and its subsequent amendments.

Admission and discharge dates originated from administrative records maintained by the recovery residences with which our research group partners. We computed length of stay as an individual's discharge date minus admission date in the number of days. We assessed pre-admission substance use based on REC-CAP items reporting any use of alcohol, cannabis, opioids (heroin or street fentanyl), or stimulants (cocaine, crack, methamphetamine, or amphetamines) within 90 days prior to admission.

2.3. Analysis

To identify which baseline characteristics associate with length of stay, we estimated a Cox proportional-hazards model on time to discharge. We mean-centred continuous predictors (age, quality of life, personal recovery capital, social recovery capital, recovery group participation, commitment to sobriety) so that the baseline hazard refers to a resident at sample-mean values. Caucasian was used as the ethnicity reference category; we collapsed categories with fewer than 30 cases (Asian, Native American, Native Alaskan) into the Other category to avoid sparsity. Variance inflation factors (VIFs) provided a screening of multicollinearity; the majority of VIFs were below 2, except personal and social recovery capital (each approximately 3.1, reflecting a modest but expected correlation between the two REC-CAP scales), and no predictor exceeded the conventional threshold for concerning collinearity. We report the full VIF results in the Supplementary Materials Section A. The sandwich estimator produced cluster-robust standard errors at the recovery-residence level, using the residence identifier from the source admission records to account for within-residence correlation. We tested the proportional-hazards assumption via Schoenfeld residuals (Schoenfeld, 1982), retained predictors showing evidence of non-proportional hazards in the primary specification, and report a sensitivity analysis stratifying on the two predictors with the strongest evidence of violation (personal recovery capital and Black or African American ethnicity) alongside the primary results. The Cox fit treated same-day discharges (N = 5) as time = 0.5 days rather than time = 0. To complement the primary inferential analysis, we then used a time-to-event clustering algorithm to characterise the heterogeneity of length of stay trajectories. The clustering uses the same baseline predictor set as the Cox model and serves to identify subgroups of residents with distinct length of stay distributions. The remainder of this section describes the clustering algorithm and its specification.

To classify individuals into distinct risk groups, we employed SurvMixClust, an algorithm that jointly clusters survival data and predicts survival functions for each group (Buginga & de Souza e Silva, 2024). This algorithm is available at https://github.com/LAND-UFRJ/SurvMixClust and is run using Python. Survival analysis, also known as time-to-event analysis, predicts the likelihood of events occurring over time. This study treats time until discharge as the event of interest. This approach models the distribution of events and assesses the impact of various features on the timing of events. SurvMixClust suited this analysis because it jointly optimises clustering and survival prediction, unlike traditional survival models that focus solely on event timing (Cox, 1972; Ishwaran et al., 2008). The algorithm also treats censored cases as informative observations and integrates them into survival curve estimation, which reduces the bias that would arise if censored individuals were discarded. Finally, the algorithm's iterative expectation-maximisation procedure updates both cluster memberships and survival functions simultaneously, which helps avoid artefactual groupings produced by initial random assignments or large subgroup imbalances. These features limit confounding and produce clusters that more accurately reflect differences in survival trajectories.

The clustering covariate set included only baseline information available at admission. The covariate set comprised sociodemographic characteristics (age, gender, ethnicity), positive recovery capital (quality of life, personal recovery capital (PRC), social recovery capital (SRC), recovery group participation (RGPS), commitment to sobriety (CSS)), recovery barriers (housing, risk-taking behaviour, CLS involvement, lack of meaningful activities, recent substance use), unmet service needs (alcohol treatment, drug treatment, and mental health treatment; housing support; family relationships counselling; employment support; primary medical care; other), and pre-admission substance use (within 90 days prior to admission), in addition to variables indexing whether the individual had a history of alcohol, cannabis, stimulant, and/or opioid use. To contextualise the findings, discharge reason appears only descriptively within the cluster characterisation and never entered the model. The model assigned each participant to the cluster with the highest estimated posterior probability. We report full per-cluster posterior summaries in the Supplementary Materials Section B. We ran five random restarts per cluster specification to reduce the influence of unfavourable expectation-maximisation initialisations on the reported fit metrics.

2.4. Sample allocation and missingness

The raw data comprised 29,719 REC-CAP records and 22,548 paired admission records. The first filter limited admission records from the recovery residences to those belonging to individuals with a released REC-CAP record (N = 9438; dropped 13,110), and a further restriction kept only clients with a single admission episode to ensure that each baseline REC-CAP assessment corresponded unambiguously to a unique residential stay (N = 4032; dropped 1953). Removing one case with negative residency days left N = 4031 (dropped 1). Dropping duplicate REC-CAP records left N = 3929 (dropped 102). Joining REC-CAP records to admission episodes and then removing episodes with missing or invalid gender recordings or missing discharge reason left N = 3881 (dropped 48). Excluding episodes without a discharge reason left N = 2756 (dropped 1125). Removing episodes where the REC-CAP assessment date preceded the admission date left N = 2748 (dropped 8), and excluding episodes where the first assessment was not a genuine baseline (i.e., >45 days after admission) left N = 2543 (dropped 205). Excluding one record with a refused ethnicity response left N = 2542 (dropped 1), and a final deduplication step removed eight duplicate records, producing a final sample of 2534 unique individuals across 61 recovery residences. All 2534 cases in the final sample held complete data on every variable entered into the models; the sequential inclusion filters applied during data preparation therefore fully addressed missingness.

3. Results

The results appear in three stages. First, we report the Cox proportional-hazards model identifying baseline predictors of length of stay, together with a sensitivity analysis stratified on predictors with evidence of non-proportional hazards. Second, we compare alternative cluster specifications and identify the selected solution. Third, we describe the composition of the identified clusters in terms of sociodemographic, recovery capital, and substance use characteristics.

3.1. Cox proportional hazards

A Cox proportional-hazards model on time to discharge identified several baseline associations with length of stay in recovery residences (Table 1; N = 2534; 61 residences; concordance index = 0.590; likelihood-ratio test $\chi^2(27) = 173.65$, $p < 0.001$). Hazard ratios (HRs) below 1 indicate slower discharge (i.e., a longer stay); HRs above 1 indicate faster discharge (i.e., a shorter stay). Standard errors are cluster-robust at the recovery residence level, using the sandwich estimator to account for the non-independence of residents within the same residence. Continuous predictors are mean-centred, so HRs reflect the change in the hazard of discharge per one-unit increase from the sample mean. Five baseline characteristics corresponded to longer length of stay. Older age at admission corresponded to longer length of stay (HR = 0.993 per year above the sample mean, $p < 0.005$). Higher quality of life at admission corresponded to longer length of stay (HR = 0.993, $p < 0.001$), as did higher recovery group participation (HR = 0.982, p =

Table 1
Cox proportional hazards model examining baseline correlates of length of stay in recovery residences. Coefficients, hazard ratios, confidence intervals, and significance are presented from the multivariable Cox proportional hazards regression model, alongside stratified sensitivity analysis results for the two predictors with the strongest evidence of non-proportional hazards. Hazard ratios >1 are associated with faster discharge; hazard ratios below 1 are associated with slower discharge. Standard errors were estimated using the cluster-robust sandwich estimator, with observations clustered by recovery residence. Bolded rows indicate conventional significance at α=0.05. Coef = Coefficient, HR = Hazard Ratio, SE = Standard Error, CI = Confidence Interval, LB = Lower Bound, UB = Upper Bound.

Variable	HR	95% CI LB	95% CI UB	p	HR (stratified)	p (stratified)	Coef	SE	z
Demographics									
Age	**0.993**	**0.990**	**0.996**	**0.000**	**0.993**	**0.000**	**−0.007**	**0.002**	**−4.184**
Gender (Man)	1.018	0.905	1.145	0.763	1.031	0.623	0.018	0.060	0.302
Black or African American Ethnicity	1.092	0.983	1.213	0.101	–	–	0.088	0.054	1.641
Hispanic or Latino Ethnicity	1.148	0.982	1.341	0.082	**1.174**	**0.046**	0.138	0.079	1.737
Other Ethnicity	0.960	0.735	1.253	0.762	0.941	0.655	−0.041	0.136	−0.303
Measures of Recovery Capital (REC-CAP)									
Quality of Life	**0.993**	**0.990**	**0.996**	**0.000**	**0.993**	**0.000**	**−0.007**	**0.001**	**−5.118**
Personal Recovery Capital	**1.018**	**1.006**	**1.030**	**0.004**	**–**	**–**	**0.017**	**0.006**	**2.885**
Social Recovery Capital	0.995	0.980	1.011	0.570	1.002	0.843	−0.005	0.008	−0.568
Recovery Group Participation Score	**0.981**	**0.967**	**0.996**	**0.014**	**0.981**	**0.010**	**−0.019**	**0.008**	**−2.463**
Commitment to Sobriety	1.010	0.988	1.032	0.383	1.010	0.364	0.010	0.011	0.872
Alcohol Treatment Need	**0.810**	**0.722**	**0.909**	**0.000**	**0.805**	**0.000**	**−0.211**	**0.059**	**−3.573**
Drug Treatment Need	**1.171**	**1.076**	**1.274**	**0.000**	**1.175**	**0.000**	**0.158**	**0.043**	**3.664**
Mental Health Treatment Need	1.053	0.951	1.165	0.320	1.056	0.278	0.051	0.052	0.995
Housing Support Need	1.053	0.919	1.207	0.454	1.061	0.384	0.052	0.069	0.749
Employment Support Need	1.006	0.915	1.107	0.900	1.007	0.894	0.006	0.049	0.126
Primary Medical Support Need	0.972	0.892	1.059	0.511	0.970	0.480	−0.029	0.044	−0.658
Family Relationships Support Need	1.056	0.935	1.193	0.377	1.047	0.440	0.055	0.062	0.883
Other Support Need	0.991	0.846	1.160	0.908	1.003	0.966	−0.009	0.080	−0.115
Experiencing Acute Housing Issue	0.987	0.904	1.078	0.767	0.989	0.815	−0.013	0.045	−0.297
Risk Taking Behaviour	0.894	0.753	1.062	0.203	0.888	0.214	−0.112	0.088	−1.274
CLS Involvement	**0.880**	**0.807**	**0.959**	**0.003**	**0.875**	**0.003**	**−0.128**	**0.044**	**−2.924**
Lack of Meaningful Activities	1.146	0.993	1.322	0.062	1.129	0.108	0.136	0.073	1.867
Substance Use									
Substance Use (90 Days Prior)	**1.208**	**1.020**	**1.430**	**0.028**	**1.214**	**0.018**	**0.189**	**0.086**	**2.192**
History of Alcohol Use	0.856	0.727	1.007	0.061	0.844	0.051	−0.156	0.083	−1.872
History of Cannabis Use	**1.239**	**1.125**	**1.364**	**0.000**	**1.237**	**0.000**	**0.214**	**0.049**	**4.370**
History of Opioid Use	0.955	0.848	1.075	0.442	0.947	0.350	−0.046	0.060	−0.769
History of Stimulant Use	1.000	0.912	1.097	0.993	1.013	0.787	0.000	0.047	0.009

0.014). An unmet need for alcohol treatment also corresponded to longer length of stay (HR = 0.810, $p < 0.005$). CLS involvement reduced the discharge hazard by 12% (HR = 0.879, $p < 0.005$).

Four baseline characteristics associated with shorter length of stay. Recent cannabis use was the strongest single correlate of faster discharge (HR = 1.239, $p < 0.005$), followed by an unmet need for drug treatment (HR = 1.171, $p < 0.005$) and recent substance use within 90 days prior to admission (HR = 1.208, p = 0.028). Personal recovery capital showed a small positive association with the discharge hazard in the primary specification (HR = 1.018, p = 0.004); however, this variable showed strong evidence of non-proportional hazards and is therefore absorbed into the baseline hazards in the sensitivity analysis below. Hispanic ethnicity showed a non-significant association with faster discharge in the primary specification (HR = 1.148, p = 0.082) that reached conventional significance in the sensitivity analysis (HR = 1.174, p = 0.046). All other variables were not significantly associated with length of stay after adjustment.

Schoenfeld residuals assessed the proportional hazards assumption for each predictor. Given the large sample, a stricter significance threshold of $p < 0.01$ applied. Four predictors showed evidence of non-proportionality at this threshold: personal recovery capital ($\chi^2(1)$ = 18.98, $p < 0.001$), Black or African American ethnicity ($\chi^2(1)$ = 11.18, $p < 0.001$), drug treatment need ($\chi^2(1)$ = 8.75, p = 0.003), and social recovery capital ($\chi^2(1)$ = 8.11, p = 0.004). A subsequent sensitivity analysis stratified the model by the two predictors with the strongest evidence of violation, personal recovery capital and Black or African American ethnicity (Kuitunen et al., 2021). This analysis produced substantively similar results across all remaining predictors.

The sensitivity analysis stratified by personal recovery capital and Black or African American ethnicity retained every significant predictor in the primary model with the same direction and similar magnitude. Hispanic ethnicity, which was non-significant in the primary specification (HR = 1.148, p = 0.082), reached conventional significance in the stratified model (HR = 1.174, p = 0.046). We assessed the overall model adequacy of the stratified model via the likelihood-ratio test and the time-dependent concordance index. The likelihood-ratio test result was $\chi^2(25)$ = 148.94, $p < 0.001$, indicating that the variable set significantly improves upon the null model. The concordance index was 0.570, indicating modest discrimination.

3.2. Alternative SurvMixClust model specifications

The evaluation tested cluster solutions ranging from two to ten clusters to identify the most effective representation of retention-trajectory heterogeneity. Three metrics assessed model performance: the time-dependent concordance index (C-index), integrated negative binomial log-likelihood (NBLL), and the integrated Brier score. Each cluster specification ran five random restarts, with the maximum number of EM iterations set to 40. Notably, the selection excluded any cluster solution producing a subgroup smaller than 30 individuals on grounds of interpretability, consistent with simulation-based evidence that mixture modelling applications require a minimum threshold of 20 to 30 observations per subgroup to achieve satisfactory statistical power (Dalmaijer et al., 2022). The final cluster solution was, therefore, the specification producing the highest test-fold C-index among those meeting the minimum subgroup size criterion.

Across all (K, restart) combinations, test-fold C-index values ranged from 0.511 to 0.733. Among the 25 solutions meeting the described criterion, test-fold C-index values ranged from 0.511 to 0.659 (for the full results, see the Supplementary Materials Section C). The nine-cluster solution (K = 9, restart = 3) achieved the highest test-fold C-index (0.659) of any eligible specification, with a validation NBLL of 0.216 and a validation Integrated Brier score of 0.065, and a minimum cluster size of 37 in the test set. Although solutions with superior metrics existed, none met the minimum cluster size criterion when evaluated on the test set. We selected the nine-cluster solution (K = 9, restart = 3) as the optimal balance between model fit and the interpretability of subgroups. We describe the characteristics of these nine clusters below.

3.3. Cluster composition

Within the test set, the subgroups had cluster sizes ranging from 37 to 107, with median lengths of stay ranging from 29 to 91 days. Kaplan-Meier survival functions on the test set appear in Fig. 1, in addition to an overview of the length of stay descriptive statistics (Table 2). Table 3 further summarises the cluster characteristics of the test set. The cluster solution describes a somewhat graded distribution of length of stay trajectories. C3 had the longest median length of stay (91 days; N = 61) and shows a gradual early decline in the survival function. C1 exhibited a distinct long-tail profile (median 73 days; N = 53), declining more steeply in the early period but maintaining a higher survival probability, which tapers at approximately 100 days and produces the longest observed stays in the sample (maximum 739 days). C8 had the shortest median length of stay (29 days; N = 37), and the remaining six clusters occupy an overlapping intermediate range of 39 to 64 days.

The Cox model and cluster solution align on several baseline characteristics. Older age predicts longer stay in the Cox model (HR = 0.993), and the two clusters with the longest mean stays (C1: 138.6, C2: 115.5 days) have mean ages of 46.7 and 43.4 compared to 32.7 and 33.6 years for the clusters with the shortest average stay. Higher quality of life (HR = 0.993) shows the same effect: C2 exhibited the highest mean quality of life score (80.0), while C8, with the lowest median length of stay and second lowest mean length of stay, exhibited the lowest quality of life score equal to 59.4. With regard to recovery group participation (HR = 0.982), the highest mean score (11.9) appeared in C2 and the lowest (2.88) in C0, which was among the clusters characterised by a shorter stay. The clusters with the shortest median stays (29, 39, and 41 days) corroborate the Cox findings for a history of cannabis use (HR = 1.239), recent substance use (HR = 1.208), and unmet drug treatment need (HR = 1.171), with a concentration of these characteristics among them. CLS involvement (HR = 0.879) is most evident in the cluster with the highest prevalence (0.93) and the longest mean stay (138.6 days).

However, we note that the cluster solution captures patterns that the Cox model does not. Through observing cluster composition, we begin to understand each group holistically and how different circumstances can begin to interact and influence the length of stay. For example, C7 (median: 39 days) demonstrated very high levels of unmet needs (housing support, 0.86; mental health treatment, 0.93; primary medical care, 0.70; employment support, 0.75), and relatively low levels of baseline recovery capital compared to other groups. This cluster had the highest proportion of women and exhibited a range of positive and negative discharge outcomes. C5 demonstrated the highest proportion of abandonment (33%) and the lowest proportion of programme completions (4.8%) with the shortest mean length of stay (74.81 days). This group also had the second-lowest recovery group participation score (4.07) but otherwise scored highly on the other aspects of positive recovery capital.

Our Cox model identified variables that operate across the entire sample, and these variables are broadly corroborated by gradients across the nine clusters. Our cluster solution adds a holistic view of configural groups, their association with length of stay, and an expression of outcomes associated with those groups.

4. Discussion

4.1. Overview of findings

Using a Cox proportional-hazards model and a complementary survival clustering algorithm applied to records from 2534 individuals across 61 recovery residences in the United States, this study identified baseline characteristics associated with length of stay and characterised the heterogeneity of length of stay trajectories across the sample. The

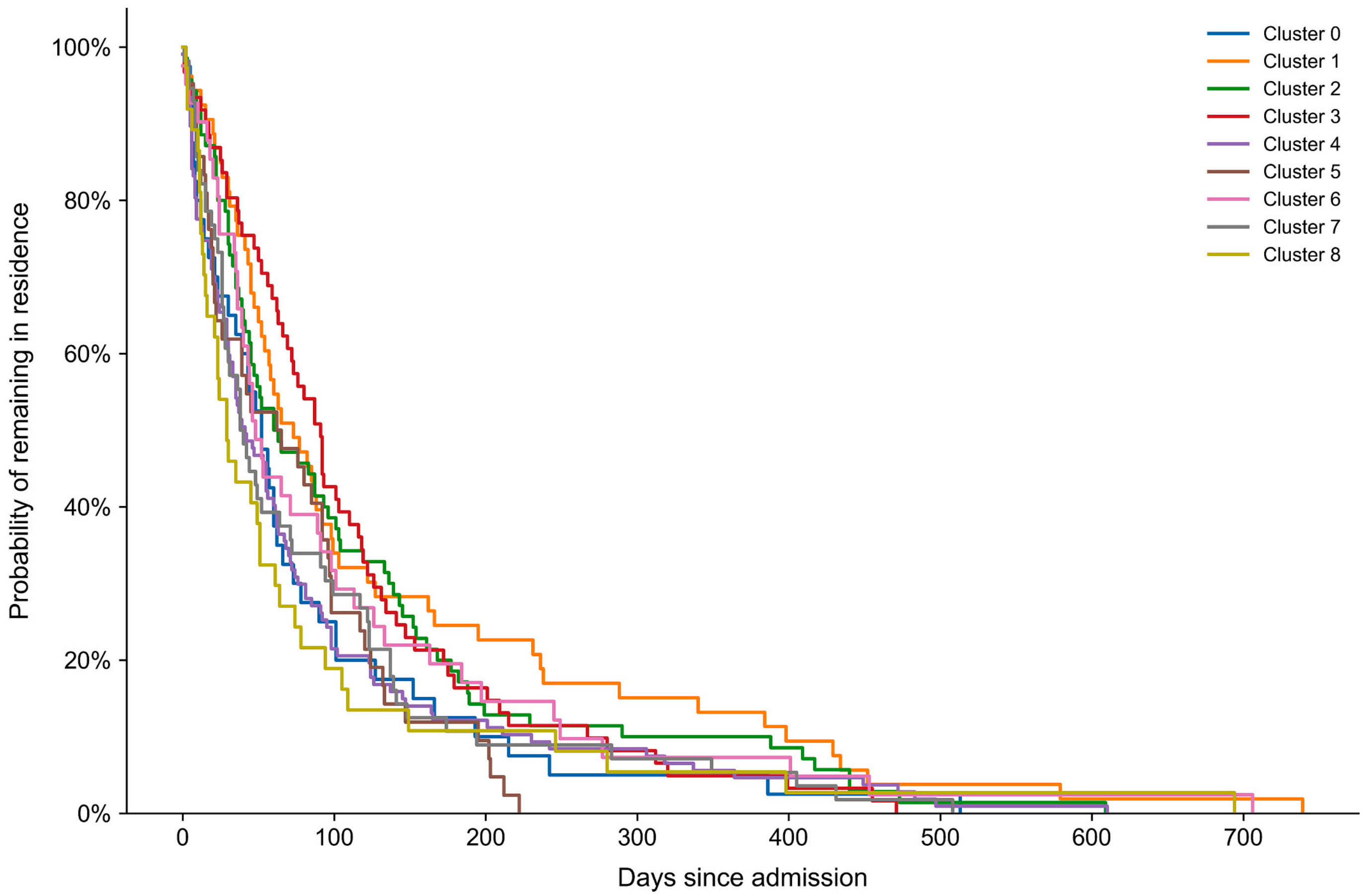

Fig. 1. Kaplan-Meier survival functions stratified by retention trajectory cluster. Kaplan-Meier survival estimates for length of stay across the nine latent trajectory clusters. Survival probability represents the time (in days) in a recovery residence. Differences between clusters illustrate heterogeneity in retention patterns.

Table 2
The length of stay distribution across latent clusters in the test set. For each cluster, the table reports sample size, mean, standard deviation, and percentile-based summaries (minimum, 25th percentile, median, 75th percentile, and maximum).

Cluster	N	Mean	St. Dev.	Min	25%	Median	75%	Max
C0	40.00	81.90	105.18	2.00	16.25	52.00	92.75	513.00
C1	53.00	138.60	161.42	2.00	41.00	73.00	166.00	739.00
C2	70.00	115.47	131.32	2.00	30.25	61.50	150.25	609.00
C3	61.00	115.23	106.04	1.00	47.00	91.00	141.00	471.00
C4	107.00	85.16	119.12	0.00	15.50	41.00	93.50	610.00
C5	42.00	74.81	64.86	2.00	19.25	63.50	112.25	222.00
C6	41.00	108.66	141.13	0.00	34.00	48.00	126.00	706.00
C7	56.00	86.79	111.37	1.00	22.50	39.00	122.25	508.00
C8	37.00	78.11	133.71	2.00	13.00	29.00	74.00	694.00

Cox model identified nine significant baseline characteristics in the primary specification (with a tenth reaching conventional significance in the sensitivity analysis). Five associated with longer length of stay (i.e., older age, higher quality of life, higher recovery group participation, unmet need for alcohol treatment, and CLS involvement) and four with shorter length of stay (i.e., recent cannabis use, substance use within 90 days prior to admission, unmet need for drug treatment, and personal recovery capital). Note that while personal recovery capital was positively associated with the discharge hazard in the primary specification, this predictor showed evidence of non-proportional hazards and is interpreted with caution. Hispanic ethnicity also showed a non-significant association with faster discharge in the primary specification that strengthened to conventional significance in the sensitivity analysis. The survival clustering algorithm identified nine length of stay trajectory subgroups spanning a range of median lengths of stay from 29 to 91 days in the test set, whose baseline characteristics were broadly consistent with the Cox model findings.

Evidence from recovery home residents suggests that categorical involvement in fellowship or other mutual aid recovery activities is associated with significantly higher recovery capital and abstinence-specific social support, indicating that peer-based recovery engagement may contribute to a richer recovery resource base among those pursuing an abstinence-based recovery pathway (Majer et al., 2022). The protective role of quality of life is less straightforward to contextualise, as the existing literature predominantly treats quality of life as an outcome of treatment rather than a determinant of it. Studies consistently demonstrate that SUD treatment improves quality of life over time (Mitchell et al., 2015; Pasareanu et al., 2015) and that continued treatment enrolment is itself associated with higher psychological and environmental quality of life domains (Mitchell et al., 2015).

Table 3
Summary characteristics of the nine trajectory clusters derived from recovery capital, sociodemographic, and substance use characteristics. The table illustrates heterogeneity in both clinical presentation and treatment retention across latent patient subgroups. Note: Age, Quality of Life, Personal Recovery Capital, Social Recovery Capital, Recovery Group Participation Score, and Commitment to Sobriety are reported as means. All other variables are expressed as proportions (0.0 to 1.0), where 1.0 = 100%.

Cluster	C0	C1	C2	C3	C4	C5	C6	C7	C8
N	40	53	70	61	107	42	41	56	37
Demographics									
Age (years)	31.35	46.736	43.443	31.393	44.178	33.571	42.732	38.929	32.73
Gender (Man)	0.475	0.623	0.871	0.705	0.766	0.405	0.537	0.339	0.892
Black or African American Ethnicity	0.275	0.358	0.057	0.393	0.551	0.238	0.098	0.107	0.0
Caucasian Ethnicity	0.675	0.547	0.886	0.426	0.421	0.69	0.878	0.839	0.919
Hispanic Ethnicity	0.025	0.094	0.029	0.115	0.019	0.048	0.0	0.018	0.054
Other Ethnicity	0.025	0.0	0.029	0.066	0.009	0.024	0.024	0.036	0.027
Measures of Recovery Capital (REC-CAP)									
Quality of Life	62.6	76.623	79.986	71.77	71.421	76.476	63.805	68.125	59.351
Personal Recovery Capital	18.05	19.811	22.257	19.984	19.701	21.214	15.878	14.5	20.514
Social Recovery Capital	19.325	19.83	22.8	21.246	19.682	21.81	14.366	14.911	19.135
Recovery Group Participation Score	2.875	7.321	11.914	10.295	7.421	4.071	8.073	7.268	7.081
Commitment to Sobriety	27.975	29.302	29.786	28.951	29.159	29.452	29.488	27.107	29.297
Alcohol Treatment Need	0.275	0.151	0.029	0.213	0.084	0.024	0.049	0.25	0.297
Drug Treatment Need	0.575	0.075	0.129	0.23	0.449	0.19	0.146	0.625	0.459
Mental Health Treatment Need	0.6	0.321	0.343	0.197	0.477	0.405	0.341	0.929	0.676
Housing Support Need	0.55	0.075	0.271	0.23	0.234	0.119	0.439	0.857	0.216
Employment Support Need	0.825	0.604	0.457	0.311	0.551	0.214	0.146	0.75	0.568
Primary Medical Support Need	0.725	0.642	0.371	0.311	0.533	0.071	0.463	0.696	0.703
Family Relationships Support Need	0.35	0.189	0.143	0.082	0.047	0.19	0.073	0.536	0.243
Other Support Need	0.175	0.057	0.043	0.016	0.056	0.071	0.024	0.357	0.027
Experiencing Acute Housing Issue	0.3	0.245	0.214	0.41	0.374	0.381	0.78	0.893	0.27
Risk Taking Behaviour	0.375	0.019	0.029	0.033	0.206	0.071	0.049	0.25	0.216
CLS Involvement	0.8	0.925	0.229	0.295	0.514	0.786	0.488	0.786	0.757
Lack of Meaningful Activities	1.0	0.943	0.614	0.967	0.916	0.976	0.927	1.0	0.919
Substance Use									
Substance Use (90 Days Prior)	0.925	0.377	0.157	0.607	0.86	0.31	0.78	0.625	0.865
History of Alcohol Use	0.25	0.302	0.114	0.492	0.206	0.19	0.415	0.393	0.541
History of Cannabis Use	0.65	0.075	0.043	0.426	0.374	0.071	0.268	0.339	0.432
History of Opioid Use	0.475	0.075	0.043	0.033	0.561	0.119	0.024	0.304	0.189
History of Stimulant Use	0.7	0.132	0.1	0.279	0.551	0.119	0.366	0.411	0.486
Discharge Reason									
Abandoned	0.275	0.17	0.229	0.197	0.187	0.333	0.171	0.161	0.216
Change Partner	0.05	0.0	0.014	0.0	0.037	0.024	0.0	0.071	0.027
Completed Programme	0.125	0.208	0.157	0.164	0.131	0.048	0.171	0.214	0.108
CLS Discharge	0.05	0.019	0.014	0.016	0.019	0.0	0.073	0.036	0.027
Deceased	0.0	0.0	0.0	0.0	0.009	0.0	0.0	0.0	0.0
Medical	0.0	0.019	0.014	0.0	0.019	0.0	0.049	0.0	0.054
Other	0.025	0.038	0.029	0.082	0.056	0.119	0.049	0.125	0.027
Other Involuntary Discharge	0.225	0.321	0.114	0.082	0.196	0.238	0.073	0.107	0.081
Other Voluntary Discharge	0.175	0.113	0.186	0.344	0.14	0.143	0.244	0.143	0.243
Recurrence of Substance Use	0.075	0.113	0.2	0.082	0.178	0.095	0.171	0.143	0.189
Referred Out	0.0	0.0	0.043	0.033	0.028	0.0	0.0	0.0	0.027

Among people with SUD, social support networks, substance use severity, and co-occurring mental health conditions influence quality of life (Armoon et al., 2022), and low baseline quality of life corresponds to elevated psychiatric symptom burden at admission (Pasareanu et al., 2015). The present finding that higher quality of life at admission associates with a longer length of stay inverts the typical directionality of these constructs, and our results indicate that baseline quality of life could potentially function as a precursor to a resident's capacity to engage with and remain in recovery residences.

The cluster solution reflects heterogeneity at the trajectory level as well: the nine trajectory subgroups span a somewhat graded range of median lengths of stay (29 to 91 days in the test set), and each subgroup's composition of discharge reasons is consistent with a multi-pathway interpretation of exit. The longest-stay subgroup, for example, had among the highest proportion of programme completions of any cluster, which is consistent with residents exiting as a planned step in their recovery rather than disengaging prematurely. Shorter-stay subgroups showed varying mixes of abandonment, recurrence of use, and involuntary discharge. The model's overall discriminative accuracy was modest, and effect magnitudes across individual predictors were similarly modest in absolute terms; we therefore present these findings to guide adaptive support rather than as a basis for individual classification.

4.1.1. *Substance use*

Indicated needs for alcohol or drug treatment were directionally opposed in this analysis. A reported need for drug treatment corresponded to shorter retention, while a reported need for alcohol treatment corresponded to longer retention. This divergence may partly reflect differences in how alcohol and other substance use disorders interact with the recovery residence model. Residents reporting unmet alcohol treatment needs may have already achieved an acute stabilisation phase prior to admission, meaning they would have arrived at a motivational and physiological baseline more conducive to engaging with the peer recovery structures that recovery residences provide. By contrast, residents with more recent substance use before admission may have faced biopsychosocial challenges at the point of entry that could have influenced their engagement with and retention in the residence. This interpretation is speculative, given the cross-sectional nature of the baseline measures. Broader treatment retention literature supports the pattern observed here. Andersson et al. (2018) suggested that both motivational readiness and psychological symptom burden at admission influenced retention independently of substance use profile. Iovine et al. (2020) similarly found that cocaine use increased the likelihood of dropout from outpatient buprenorphine treatment, while secondary alcohol use corresponded to greater retention. Together, these studies suggest that the divergence between alcohol and other drug use profiles as predictors of retention is not idiosyncratic to the present sample.

4.1.2. Personal recovery capital

The positive association between personal recovery capital and the hazard of discharge is counter to the intuitive expectation that higher recovery capital should support a longer length of stay. However, we emphasise that discharge is not necessarily indicative of instability in this analysis, as many individuals completed their respective programmes. Our findings could reflect residents with greater personal recovery capital at baseline exercising more agency over their residential trajectory and perhaps departing earlier once they perceive themselves as sufficiently stable for independent living. Under this assumption, some of the faster discharges among high-capital residents could reflect recovery-readiness exits rather than disengagement under instability. It is also worth noting that personal recovery capital showed a modest but expected correlation with social recovery capital (VIF approximately 3.1), and that in the stratified sensitivity analysis, this predictor was absorbed into the baseline hazard rather than estimated directly, which limits the confidence with which any single interpretation can be made.

4.1.3. CLS involvement

CLS involvement was a modest protective factor in the present sample. This pattern was also visible at the trajectory level: C1 exhibited the highest proportion of CLS involvement and the longest median length of stay. Emerging evidence suggests that individuals with recent CLS involvement may exhibit a lower risk of disengagement from recovery housing due to the mandated legal supervision that accompanies parole conditions or court oversight in CLS-linked pathways (Bunaciu et al., 2025; Sondhi et al., 2024). Prior studies indicate that individuals under moderate to high legal pressure are more likely to remain in treatment for 90 days or more compared to those under low pressure (Hiller et al., 1998; Rivera et al., 2021; Young, 2002). Navigation support and structured referral mechanisms (such as housing navigator programmes and intensive support) also enhance motivation and recovery capital among CLS-exposed individuals. The retention benefit of legal involvement may be augmented by co-occurring support structures (Belanger et al., 2024; Dewey et al., 2024). While conventionally understood as a marker of disadvantage, CLS involvement may function as a sociostructural construct that supports continued engagement, at least over the short-to-medium term.

4.1.4. Synthesis

The findings indicate that, based only on baseline characteristics, substance use in the period prior to admission and the degree to which residents engage in external support structures at the point of entry influence discharge from recovery residences. Of the recovery capital measures, quality of life and recovery group participation corresponded to longer lengths of stay, while personal recovery capital corresponded to faster discharge (which may reflect higher-capital residents exercising greater agency over their residential trajectory rather than disengaging under instability). The strongest predictors of an earlier departure (i.e., recent cannabis use, any recent substance use, and unmet drug treatment need) all associate with ongoing or recent substance involvement at the point of entry. By contrast, the factors associated with longer retention (i.e., CLS involvement, alcohol treatment need, recovery group participation, and quality of life) share a common foundation around engagement with external support structures (whether judicial, peer-based, or service-based). Importantly, the modest overall discriminative accuracy of the model further suggests that baseline characteristics alone account for relatively little of the variance in lengths of stay. Dynamic within-stay factors, such as the quality of relationships with staff or the extent to which peer navigators can support and enable recovery within that environment, could be potentially important, albeit unmeasured, determinants in the present study.

4.2. Clinical and policy implications

Implementation science guidance increasingly emphasises the value of personalising interventions to context and iterating rapidly under conditions of uncertainty, particularly where effect sizes are modest, and population heterogeneity is high (Chambers & Emmons, 2024; McCreight et al., 2019; Neuman et al., 2020). Consistent with this, we advocate for a low-regret, equity-conscious operational approach that involves pragmatic adaptations that minimise downside risk if ineffective, while accelerating benefits if effective. The present findings identify two practical points that could inform any such adaptive response: (1) proactively supporting residents who report recent substance use at admission or an unmet drug treatment need and (2) strengthening engagement with external support structures during the stay. Adaptations should explicitly anticipate, measure, and address differential impacts across resident subgroups, with metrics embedded in intervention design to prevent adaptive changes from widening disparities, for example, through stratified and risk-adjusted completion and engagement monitoring, and targeted culturally responsive supports (Cené et al., 2023; Garzón-Orjuela et al., 2020). Operationally, low-regret decisions can be implemented in short cycles, embedding routine subgroup reporting even where absolute differences between groups are modest, given that the potential consequences of inaction in terms of widening disparities are non-trivial (Chambers & Emmons, 2024; Neuman et al., 2020).

Three cautions warrant explicit statement. First, the cluster solution should not be used as an individual triage instrument. The Cox findings are population-level estimates; cluster membership is descriptive of trajectory heterogeneity and should not be operationalised as a label that assigns service intensity to specific residents. Rather, adaptive service responses informed by the Cox findings (i.e., proactive engagement for residents with recent substance use at admission, culturally responsive peer navigation, early linkage to meaningful activities) are appropriate and reversible if needed. Second, structural inequalities affecting minoritised residents can contribute to who appears in shorter-stay subgroups in ways that reflect upstream system biases rather than person-level risk. Any operational use of these findings should therefore pair with prospective external validation and routine subgroup monitoring of completion and engagement to ensure that adaptive responses do not widen existing disparities. Lastly, we caveat that exit from a recovery residence is a heterogeneous event. The discharge reasons in Table 3 illustrate that many individuals across clusters engaged in planned exits, while some shorter-stay clusters showed varying mixes of abandonment, voluntary disengagement, recurrence of use, and involuntary discharge. This heterogeneity of exit types means that shorter stays cannot be straightforwardly interpreted as treatment failure; some voluntary departures may reflect residents choosing to transition to independent living before programme completion, though the administrative records do not permit this distinction to be made with confidence.

4.3. Limitations

Despite this study's strengths, we acknowledge some limitations. First, the study relies on baseline measures of recovery capital and does not capture how these factors evolve over the course of a stay. Future work examining how recovery capital accrual in the earliest days of residence influences retention beyond admission would meaningfully extend these findings. Although the proportional-hazards assumption was tested via Schoenfeld residuals and a sensitivity analysis stratifying on the two strongest violators produced substantively similar results, several predictors showed some degree of non-proportionality. In a sample of this size, the test is highly sensitive, and for the majority of these predictors, the evidence of violation was marginal. Nevertheless, estimates for the two predictors with the strongest evidence of non-proportional hazards (i.e., personal recovery capital and Black or African American ethnicity) should be interpreted as average effects across the observation period rather than constant hazard ratios. Third, although the sample includes 61 residences across the United States, regional variation in recovery residence practices and population characteristics may limit the generalisability of findings. Lastly, our study overlooks individuals with multiple recovery attempts. The REC-CAP instrument does not record the diverse information about prior recovery attempts. These unmeasured features are plausibly associated with both baseline recovery capital and length of stay in some individuals, and their omission is a major limitation in understanding the individuals holistically. We identify the incorporation of treatment episode records as a priority avenue for future work.

5. Conclusion

This study identifies baseline characteristics associated with retention in recovery residences and characterises the underlying heterogeneity of retention trajectories. The Cox proportional-hazards model identifies higher age, baseline quality of life, recovery group participation, reported alcohol-treatment need, and CLS involvement as predictors of longer lengths of stay, and a history of cannabis use, recent substance use within 90 days before admission, and a reported drug-treatment need as predictors of shorter retention. Effect magnitudes are modest in absolute terms, and we therefore interpret them as guidance to inform adaptive service responses at admission rather than as a basis for individual classification. Concretely, recovery residences may consider proactive engagement with residents reporting recent substance use prior to admission or those reporting an unmet drug treatment need, while monitoring subgroup outcomes to ensure that adaptive responses do not widen existing disparities. Assessment tools such as the REC-CAP can be used to personalise intake support, but cluster membership should not be used as a triage instrument. Future work should validate these results in other samples and retrospectively audit individual cases to disaggregate disengagement from recovery-readiness exits.

CRediT authorship contribution statement

Matthew J. Belanger: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Kurt D. Lebeck:** Writing – review & editing, Writing – original draft, Methodology. **Adela Bunaciu:** Writing – review & editing. **Arun Sondhi:** Writing – review & editing, Writing – original draft, Formal analysis. **David W. Best:** Writing – review & editing, Supervision, Resources, Data curation.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.josat.2026.210067.

References

Alegría, M., Alvarez, K., Cheng, M., & Falgas-Bague, I. (2023). Recent advances on social determinants of mental health: Looking fast forward. *American Journal of Psychiatry, 180*(7), 473–482. https://doi.org/10.1176/appi.ajp.20230371

Altekruse, S. F., Cosgrove, C. M., Altekruse, W. C., Jenkins, R. A., & Blanco, C. (2020). Socioeconomic risk factors for fatal opioid overdoses in the United States: Findings from the Mortality Disparities in American Communities Study (MDAC). *PLoS ONE, 15*(1), Article e0227966. https://doi.org/10.1371/journal.pone.0227966

Andersson, H. W., Steinsbekk, A., Walderhaug, E., Otterholt, E., & Nordfjærn, T. (2018). Predictors of dropout from inpatient substance use treatment: A prospective cohort study. *Substance Abuse: Research and Treatment, 12*, Article 1178221818760551. https://doi.org/10.1177/1178221818760551

Armoon, B., Fleury, M.-J., Bayat, A.-H., Bayani, A., Mohammadi, R., & Griffiths, M. D. (2022). Quality of life and its correlated factors among patients with substance use disorders: A systematic review and meta-analysis. *Archives of Public Health, 80*(1), Article 179. https://doi.org/10.1186/s13690-022-00940-0

Belanger, M. J., Sondhi, A., Mericle, A. A., Leidi, A., Klein, M., Collinson, B., … Best, D. (2024). Assessing a pilot scheme of intensive support and assertive linkage in levels of engagement, retention, and recovery capital for people in recovery housing using quasi-experimental methods. *Journal of Substance Use and Addiction Treatment, 158*, Article 209283. https://doi.org/10.1016/j.josat.2023.209283

Best, D., Sondhi, A., Best, J., Lehman, J., Grimes, A., Conner, M., & DeTriquet, R. (2023). Using recovery capital to predict retention and change in recovery residences in Virginia, USA. *Alcoholism Treatment Quarterly*, 1–13. https://doi.org/10.1080/07347324.2023.2182246

Borkman, T. J., Kaskutas, L. A., Room, J., Bryan, K., & Barrows, D. (1998). An historical and developmental analysis of social model programs. *Journal of Substance Abuse Treatment, 15*(1), 7–17. https://doi.org/10.1016/S0740-5472(97)00244-4

Buginga, G., & de Souza e Silva, E. *Clustering survival data using a mixture of non-parametric experts*. (2024). https://arxiv.org/abs/2405.15934.

Bunaciu, A., Sondhi, A., Best, D., Hennessy, E. A., Best, J., Belanger, M. J., … White, W. (2025). Longitudinal changes in recovery capital among recovery house residents with and without criminal legal system involvement: A marginal structural modeling analysis. *Criminal Justice and Behavior, 52*(12), 1832–1848. https://doi.org/10.1177/00938548251359584

Cano, I., Best, D., Edwards, M., & Lehman, J. (2017). Recovery capital pathways: Modelling the components of recovery wellbeing. *Drug and Alcohol Dependence, 181*, 11–19. https://doi.org/10.1016/j.drugalcdep.2017.09.002

Cené, C. W., Viswanathan, M., Fichtenberg, C. M., Sathe, N. A., Kennedy, S. M., Gottlieb, L. M., … Peek, M. E. (2023). Racial health equity and social needs interventions: A review of a scoping review. *JAMA Network Open, 6*(1), Article e2250654. https://doi.org/10.1001/jamanetworkopen.2022.50654

Chambers, D. A., & Emmons, K. M. (2024). Navigating the field of implementation science towards maturity: Challenges and opportunities. *Implementation Science, 19*(1), 26. s13012-024-01352–0 https://doi.org/10.1186/s13012-024-01352-0.

Cloud, W., & Granfield, R. (2008). Conceptualizing recovery capital: Expansion of a theoretical construct. *Substance Use & Misuse, 43*(12–13), 1971–1986. https://doi.org/10.1080/10826080802289762

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B, Statistical Methodology, 34*(2), 187–202. https://doi.org/10.1111/j.2517-6161.1972.tb00899.x

Dalmaijer, E. S., Nord, C. L., & Astle, D. E. (2022). Statistical power for cluster analysis. *BMC Bioinformatics, 23*(1), 205. https://doi.org/10.1186/s12859-022-04675-1

Delgadillo, J., Payne, S., Gilbody, S., & Godfrey, C. (2013). Psychometric properties of the Treatment Outcomes Profile (TOP) psychological health scale. *Mental Health and Substance Use, 6*(2), 140–149. https://doi.org/10.1080/17523281.2012.693521

Dennis, M. L., Foss, M. A., & Scott, C. K. (2007). An eight-year perspective on the relationship between the duration of abstinence and other aspects of recovery. *Evaluation Review, 31*(6), 585–612. https://doi.org/10.1177/0193841X07307771

Dewey, J. M., Bell, J. S., Konchak, J. N., Hinami, K., & Watson, D. P. (2024). "A lot of moving parts": Recovery home challenges linking and housing individuals with criminal legal system involvement. *Journal of Substance Use and Addiction Treatment, 166*, Article 209473. https://doi.org/10.1016/j.josat.2024.209473

Feld, H., Elswick, A., Goodin, A., & Fallin-Bennett, A. (2023). Partnering with recovery community centers to build recovery capital by improving access to reproductive health. *Journal of Nursing Scholarship, 55*(3), 692–700. https://doi.org/10.1111/jnu.12836

Garzón-Orjuela, N., Samacá-Samacá, D. F., Luque Angulo, S. C., Mendes Abdala, C. V., Reveiz, L., & Eslava-Schmalbach, J. (2020). An overview of reviews on strategies to reduce health inequalities. *International Journal for Equity in Health, 19*(1), Article 192. https://doi.org/10.1186/s12939-020-01299-w

Granfield, R., & Cloud, W. (1999). *Coming clean: Overcoming addiction without treatment.* NYU Press.

Groshkova, T., Best, D., & White, W. (2013a). *Recovery Group Participation Scale (RGPS): Factor structure in alcohol and heroin recovery populations*. Routledge.

Groshkova, T., Best, D., & White, W. (2013b). The assessment of recovery capital: Properties and psychometrics of a measure of addiction recovery strengths: Assessment of recovery capital. *Drug and Alcohol Review, 32*(2), 187–194. https://doi.org/10.1111/j.1465-3362.2012.00489.x

Härd, S., Best, D., Sondhi, A., Lehman, J., & Riccardi, R. (2022). The growth of recovery capital in clients of recovery residences in Florida, USA: A quantitative pilot study of changes in REC-CAP profile scores. *Substance Abuse Treatment, Prevention, and Policy, 17*(1), Article 58.

Hiller, M. L., Knight, K., Broome, K. M., & Simpson, D. D. (1998). Legal pressure and treatment retention in a national sample of long-term residential programs. *Criminal Justice and Behavior, 25*(4), 463–481. https://doi.org/10.1177/0093854898025004004

Iovine, P. A., Drachman, D., & Kirane, H. (2020). Risk factors for treatment drop-out: Implications for adverse outcomes when treating opioid use disorder. *Journal of Social Work Practice in the Addictions, 20*(4), 292–301. https://doi.org/10.1080/1533256X.2020.1838859

Ishwaran, H., Kogalur, U. B., Blackstone, E. H., & Lauer, M. S. (2008). Random survival forests. *The Annals of Applied Statistics, 2*(3). https://doi.org/10.1214/08-AOAS169

Jason. (2021). The emergence, role, and impact of recovery support services. *Alcohol Research: Current Reviews, 41*(1), Article 04. https://doi.org/10.35946/arcr.v41.1.04

Jason, L. A., Davis, M. I., & Ferrari, J. R. (2007). The need for substance abuse after-care: Longitudinal analysis of Oxford House. *Addictive Behaviors, 32*(4), 803–818. https://doi.org/10.1016/j.addbeh.2006.06.014

Johnson, K., Pinchuk, I., Melgar, M. I. E., Agwogie, M. O., & Salazar Silva, F. (2022). The global movement towards a public health approach to substance use disorders. *Annals of Medicine, 54*(1), 1797–1808. https://doi.org/10.1080/07853890.2022.2079150

Kelly, J. F., & Greene, M. C. (2014). Beyond motivation: Initial validation of the commitment to sobriety scale. *Journal of Substance Abuse Treatment, 46*(2), 257–263. https://doi.org/10.1016/j.jsat.2013.06.010

Kuitunen, I., Ponkilainen, V. T., Uimonen, M. M., Eskelinen, A., & Reito, A. (2021). Testing the proportional hazards assumption in cox regression and dealing with possible non-proportionality in total joint arthroplasty research: Methodological perspectives and review. *BMC Musculoskeletal Disorders, 22*(1), Article 489. https://doi.org/10.1186/s12891-021-04379-2

Lewis, C., Fischer, I. C., Tsai, J., Harpaz-Rotem, I., & Pietrzak, R. H. (2024). Barriers to mental health care in US military veterans. *Psychiatric Quarterly, 95*(3), 367–383. https://doi.org/10.1007/s11126-024-10078-7

Majer, J. M., Jason, L. A., & Bobak, T. J. (2022). Understanding recovery capital in relation to categorical 12-step involvement and abstinence social support. *Addiction Research & Theory, 30*(3), 207–212. https://doi.org/10.1080/16066359.2021.1999935

McCreight, M. S., Rabin, B. A., Glasgow, R. E., Ayele, R. A., Leonard, C. A., Gilmartin, H. M., … Battaglia, C. T. (2019). Using the Practical, Robust Implementation and Sustainability Model (PRISM) to qualitatively assess multilevel contextual factors to help plan, implement, evaluate, and disseminate health services programs. *Translational Behavioral Medicine, 9*(6), 1002–1011. https://doi.org/10.1093/tbm/ibz085

Mejia, M. C., Kowalchuk, A., Gonzalez, S., Sunny, A., & Scamp, N. (2024). Expanding treatment, recovery, and reentry services for female offenders: Improving outcomes through client-centered interventions. *Community Mental Health Journal, 60*(4), 713–721. https://doi.org/10.1007/s10597-023-01223-w

Mericle, A. A., Patterson, D., Howell, J., Subbaraman, M. S., Faxio, A., & Karriker-Jaffe, K. J. (2022). Identifying the availability of recovery housing in the U.S.: The NSTARR project. *Drug and Alcohol Dependence, 230*, Article 109188. https://doi.org/10.1016/j.drugalcdep.2021.109188

Mericle, A. A., Polcin, D. L., Hemberg, J., & Miles, J. (2017). Recovery housing: Evolving models to address resident needs. *Journal of Psychoactive Drugs, 49*(4), 352–361. https://doi.org/10.1080/02791072.2017.1342154

Mitchell, S. G., Gryczynski, J., Schwartz, R. P., Myers, C. P., O'Grady, K. E., Olsen, Y. K., & Jaffe, J. H. (2015). Changes in quality of life following buprenorphine treatment: Relationship with treatment retention and illicit opioid use. *Journal of Psychoactive Drugs, 47*(2), 149–157. https://doi.org/10.1080/02791072.2015.1014948

Neuman, H. B., Kaji, A. H., & Haut, E. R. (2020). Practical guide to implementation science. *JAMA Surgery, 155*(5), 434. https://doi.org/10.1001/jamasurg.2019.5149

Pasareanu, A. R., Opsal, A., Vederhus, J.-K., Kristensen, Ø., & Clausen, T. (2015). Quality of life improved following in-patient substance use disorder treatment. *Health and Quality of Life Outcomes, 13*(1), Article 35. https://doi.org/10.1186/s12955-015-0231-7

Patton, D., Best, D., & Brown, L. (2022). Overcoming the pains of recovery: The management of negative recovery capital during addiction recovery pathways. *Addiction Research & Theory, 0*(0), 1–11. https://doi.org/10.1080/16066359.2022.2039912

Polcin, D. (2015). How should we study residential recovery homes? *Therapeutic Communities: The International Journal of Therapeutic Communities, 36*(3), 163–172. https://doi.org/10.1108/TC-07-2014-0027

Polcin, D. L., Korcha, R., Bond, J., & Galloway, G. (2010). What did we learn from our study on sober living houses and where do we go from here? *Journal of Psychoactive Drugs, 42*(4), 425–433. https://doi.org/10.1080/02791072.2010.10400705

Reif, S., George, P., Braude, L., Dougherty, R. H., Daniels, A. S., Ghose, S. S., & Delphin-Rittmon, M. E. (2014). Recovery housing: Assessing the evidence. *Psychiatric Services, 65*(3), 295–300. https://doi.org/10.1176/appi.ps.201300243

Rivera, D., Dueker, D., & Amaro, H. (2021). Examination of referral source and retention among women in residential substance use disorder treatment: A prospective follow-up study. *Substance Abuse Treatment, Prevention, and Policy, 16*(1), Article 21. https://doi.org/10.1186/s13011-021-00357-y

SAMHSA. (2012). SAMHSA's working definition of recovery: 10 guiding principles of recovery. https://library.samhsa.gov/sites/default/files/pep12-recdef.pdf.

SAMHSA. (2019). Recovery housing: Best practices and suggested guidelines. https://samhsa.gov/resource/ebp/best-practices-recovery-housing.

Sánchez, J., Sahker, E., & Arndt, S. (2020). The assessment of recovery capital (ARC) predicts substance abuse treatment completion. *Addictive Behaviors, 102*, Article 106189. https://doi.org/10.1016/j.addbeh.2019.106189

Schoenfeld, D. (1982). Partial residuals for the proportional hazards regression model. *Biometrika, 69*(1), 239–241. https://doi.org/10.1093/biomet/69.1.239

Sondhi, A., Bunaciu, A., Best, D., Hennessy, E. A., Best, J., Leidi, A., … White, W. (2024). Modeling recovery housing retention and program outcomes by justice involvement among residents in Virginia, USA: An observational study. *International Journal of Offender Therapy and Comparative Criminology, 68*(15), 1579–1597. https://doi.org/10.1177/0306624X241254691

Subbaraman, M. S., Mahoney, E., Mericle, A., & Polcin, D. (2023). Six-month length of stay associated with better recovery outcomes among residents of sober living houses. *The American Journal of Drug and Alcohol Abuse, 49*(5), 675–683. https://doi.org/10.1080/00952990.2023.2245123

The Betty Ford Institute Consensus Panel. (2007). What is recovery? A working definition from the Betty Ford Institute. *Journal of Substance Abuse Treatment, 33*(3), 221–228. https://doi.org/10.1016/j.jsat.2007.06.001

Tuten, M., DeFulio, A., Jones, H. E., & Stitzer, M. (2012). Abstinence-contingent recovery housing and reinforcement-based treatment following opioid detoxification. *Addiction, 107*(5), 973–982. https://doi.org/10.1111/j.1360-0443.2011.03750.x

Tuten, M., Shadur, J. M., Stitzer, M., & Jones, H. E. (2017). A comparison of reinforcement based treatment (RBT) versus RBT plus recovery housing (RBTRH). *Journal of Substance Abuse Treatment, 72*, 48–55. https://doi.org/10.1016/j.jsat.2016.09.001

Vilsaint, C. L., Tansey, A. G., Hennessy, E. A., Eddie, D., Hoffman, L. A., & Kelly, J. F. (2025). Recovery housing for substance use disorder: A systematic review. *Frontiers in Public Health, 13*, Article 1506412. https://doi.org/10.3389/fpubh.2025.1506412

White, W., & Mojer-Torres, L. (2010). *Recovery-orientated methadone maintenance*. Great Lakes Addiction Technology Transfer Center, the Philadelphia Department of Behavioral Health and Mental Retardation Services, and the Northeast Addiction Technology Transfer Cente.

Wilson, A. D., Bravo, A. J., Pearson, M. R., & Witkiewitz, K. (2016). Finding success in failure: Using latent profile analysis to examine heterogeneity in psychosocial functioning among heavy drinkers following treatment. *Addiction, 111*(12), 2145–2154. https://doi.org/10.1111/add.13518

Witkiewitz, K., Wilson, A. D., Pearson, M. R., Montes, K. S., Kirouac, M., Roos, C. R., … Maisto, S. A. (2019). Profiles of recovery from alcohol use disorder at three years following treatment: Can the definition of recovery be extended to include high functioning heavy drinkers? *Addiction, 114*(1), 69–80. https://doi.org/10.1111/add.14403

Wittman, F., Polcin, D., & Sheridan, D. (2017). The architecture of recovery: Two kinds of housing assistance for chronic homeless persons with substance use disorders. *Drugs and Alcohol Today, 17*(3), 157–167. https://doi.org/10.1108/DAT-12-2016-0032

Young, D. (2002). Impacts of perceived legal pressure on retention in drug treatment. *Criminal Justice and Behavior, 29*(1), 27–55. https://doi.org/10.1177/0093854802029001003