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Engagement in substance use disorder treatment after an emergency department visit among persons at high risk of opioid overdose: A prediction analysis

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HIGHLIGHTS

- SUD treatment engagement was high (43 %) for patients after ED behavioral service.
- Time to SUD treatment did not differ by ED behavioral service (CPRS vs. LCSWs).
- A non-parametric prediction algorithm did not identify predictors of SUD treatment.
- ED patients should receive behavioral services to promote SUD treatment.

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ABSTRACT

Background: Certified peer recovery specialists (CPRS) and licensed clinical social workers (LCSWs) can facilitate substance use disorder (SUD) treatment engagement for emergency department (ED) patients at risk for overdose. Predictors of treatment engagement after such behavioral services are unknown.
Methods: This secondary analysis included Rhode Island ED patients at high risk for opioid overdose participating in a randomized controlled trial comparing the effectiveness of CPRS and LCSWs services (2018–2021). SUD treatment engagement within 90 days post-discharge was identified using statewide administrative data. Potential predictors were obtained from baseline questionnaires. Classification and regression trees (CART) were used to identify predictors of treatment engagement.
Results: In the ED, 323 and 325 participants received CPRS and LCSWs services, respectively, among whom 141 (43.7 %) and 137 (42.2 %) engaged in SUD treatment within 90 days post-discharge. For the CPRS group, predictors of treatment engagement included unhealthy alcohol use, prescription opioid or benzodiazepine use in past 6 months, and lifetime history of: unstable housing, barriers to treatment, bipolar disorder diagnosis, addiction treatment, and recovery services. In the LCSW group, predictors included health insurance, current pain, opioid overdose in past year, and lifetime history of anxiety disorder diagnosis and mental illness treatment. However, CART had low predictive accuracy (CPRS: 60.9 %, LCSW: 54.8 %).
Conclusions: Among ED patients at high risk of opioid overdose receiving behavioral services, 90-day SUD treatment engagement was high. Sociobehavioral and clinical patient characteristics did not accurately predict treatment engagement. Behavioral services should be offered to all ED patients at high risk of opioid overdose.

1. Introduction

Opioid overdose-related emergency department (ED) visits in the United States increased by 29 % from 2018 to 2020, despite a decrease in all-cause ED visits during this period (Soares et al., 2022). Many but not all of these visits are among persons with a substance use disorder

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(SUD), for whom the ED is often the first or only point of contact for opioid-related care (Langabeer et al., 2021). The ED has, therefore, been identified as a critical access point for interventions to reduce the risks of drug-related harms and mortality among populations at high risk of overdose (Rodda et al., 2020).

Behavioral services during drug-related ED visits are frequently provided by licensed clinical social workers (LCSWs) and, more recently, by certified peer recovery specialists (CPRS) (Moore et al., 2016; McGuire et al., 2020). LCSWs typically employ patient-centered approaches to provide counseling about substance use and link persons with SUD to community-based treatment (Auerbach and Mason, 2010). CPRS have lived experiences of recovery and typically offer non-clinical support, coaching, mentoring, and education in navigation of treatment and recovery (Serrano and Conley, 2021; Liebling et al., 2021). In addition to ED-based services, CPRS aim to provide ongoing support following discharge.

Recently, a large randomized controlled trial in Rhode Island (RI) evaluated the effectiveness of ED behavioral interventions delivered by CPRS compared to LCSWs among persons at high risk of opioid overdose (Beaudoin et al., 2022). Although no overall difference in SUD treatment engagement within 30 days post-discharge was observed by behavioral service, it remains unknown whether certain subgroups of patients might benefit most from either CPRS or LCSW services. This evidence gap limits implementation of evidence-based, personalized support for ED patients at high risk of opioid overdose. For example, consideration of patients' SUD treatment history and prior experience with healthcare access barriers might aid in connecting them with the appropriate ED behavioral services and increase their likelihood of engaging in SUD treatment post-discharge (Madras et al., 2020; Volkow and Blanco, 2021).

Therefore, the objective of this study was to identify predictors of post-discharge SUD treatment engagement among ED patients at high risk of opioid overdose, separately for those who received CPRS versus LCSW services in the ED. We hypothesized, due to prior experiences with substance use, navigating psychosocial and structural barriers to recovery, and the ability to communicate treatment plans using nonmedical terminology, CPRS services would be more likely to increase treatment engagement for patients with a history of healthcare access barriers, unstable housing, arrests, mental health comorbidities, and use of both prescribed and non-prescribed drugs (Cos et al., 2020; Blakeman et al., 2006; Reblin and Uchino, 2008; Substance Abuse and Mental Health Services Administration SAMHSA, 2024; Sells et al., 2020; Laudet and Humphreys, 2013; Abbott et al., 2019; Davidson et al., 2012; Chinman et al., 2024; Boisvert et al., 2008). On the other hand, LCSW services would be more effective for patients with prior SUD treatment experience due to adherence to a traditional clinical care model (Selby et al.,). A secondary objective was to evaluate whether time to SUD treatment engagement post-discharge differed for ED patients who received CPRS and LCSW services. We hypothesized that patients who received CPRS services would have a shorter time to treatment engagement than those who received LCSW services.

2. Material and methods

2.1. Study population

This study involved secondary analyses of data collected from ED patients at high risk for opioid overdose enrolled in a randomized controlled trial in RI. The trial evaluated the effectiveness of ED-based behavioral interventions delivered by CPRS compared to LCSWs. The trial protocol (ClinicalTrials.gov identifier: NCT03684681) and interventions have previously been described (Beaudoin et al., 2022; Goedel et al., 2019). Briefly, from November 2018 to May 2021, RI residents presenting to one of two study EDs for treatment of an opioid overdose or opioid use disorder (OUD), or who had an opioid overdose within the past year, were enrolled and randomized to receive a behavioral intervention from either a CPRS or LCSW. A baseline questionnaire was administered to obtain sociobehavioral and clinical information. Post ED discharge, participants were followed for 18 months to evaluate health outcomes. Participants provided informed consent and permission for linkage of their study data to statewide administrative data, including SUD treatment. The study sites, Brown University, and RI Department of Health Institutional Review Boards approved the trial protocol.

2.2. Outcome

The primary outcome was engagement in any SUD treatment within 90 days of ED discharge (yes, no). Treatment engagement was identified through deterministic linkage to statewide administrative data from the Rhode Island Behavioral Health Online Database (BHOLD) and Prescription Drug Monitoring Program (PDMP) (Eddie et al., 2019). BHOLD includes all SUD treatment episodes at publicly-licensed facilities in RI, including methadone, detoxification, outpatient, intensive outpatient, and residential treatment. The PDMP database includes all buprenorphine prescriptions dispensed to RI residents by retail pharmacies in RI and most out-of-state retail pharmacies (State of Rhode Island Department of Health, 2024). SUD treatment engagement within 90 days post-discharge was defined as any: (1) new SUD treatment episode at a publicly-licensed program; or (2) fill of a buprenorphine prescription for OUD. Participants currently or recently (in the two weeks before) engaged in SUD treatment at baseline were included in the study and considered to have the study outcome if they transitioned to a new SUD treatment type, level of care, or provider, or continued buprenorphine via prescription during follow-up.

2.3. Baseline characteristics hypothesized to influence SUD treatment engagement

The Behavioral Model of Healthcare Utilization Framework was used to identify the baseline characteristics considered in the prediction analysis. Within this framework, four overarching factors influence engagement in care: *predisposing* factors (individual characteristics), *enabling* factors (social/structural barriers to care), *need* factors (diagnosed and perceived health conditions), and *health behavior* factors (steps taken to manage substance use or co-morbid conditions) (Heidari et al., 2022). Baseline characteristics hypothesized to influence SUD treatment engagement were selected within this framework based on content expertise (Mauro et al., 2022; Macmadu et al., 2021; Wyse et al., 2022; Ober et al., 2018; Gideon, nd). Most characteristics were obtained from study questionnaires, with a few others based on administrative data.

Predisposing factors included age, race, ethnicity, and sex assigned at birth. *Enabling* factors included baseline health insurance, monthly income (including public assistance or family support), employment (full-time or part-time), receipt of disability benefits, and highest education attained, as well as lifetime history of unstable housing, barriers to treatment access, and arrest. *Need* factors included baseline unhealthy alcohol use, pain, and reason for the ED visit; use of specific substances in the past 6 months (P6M) (prescription opioids, prescription benzodiazepines, marijuana, crystal methamphetamine, cocaine, heroin, and club drugs); previous opioid overdose in past 12 months (P12M); and lifetime history of injecting drugs, any mental health diagnosis, and specific mental health diagnoses (depressive disorder, bipolar disorder, psychosis, and anxiety disorder). *Health behavior* factors included a lifetime history of receiving mental illness treatment, addiction treatment, and recovery services.

Of note, unhealthy alcohol use was measured with the Alcohol Use Disorders Identification Test (AUDIT-C) (U.S., 2024). Opioid overdose as the reason for ED visit was defined as having decreased levels of consciousness or respiratory depression after consuming opioids which resolved after naloxone administration. Prescription opioid and benzodiazepine use in the P6M included use without a prescription or not as prescribed. Club drug use in the P6M included any of the following: molly, MDMA, ecstasy, mushrooms, GHB, or ketamine.

2.4. Statistical methods

Analyses were completed using STATA® Version 16.0 with significance level $p<0.05$, unless otherwise specified (StataCorp, 2021). The time to engagement and the type of SUD treatment received were compared between participants who received CPRS and LCSW services in the ED using *t*-tests and χ^2 tests, respectively. Differences in the time to engagement by behavioral service were also assessed using Kaplan Meier curves and Cox proportional hazards (Cox-PH) models, with and without adjustment for SUD treatment in the two weeks before or at the baseline ED visit. All baseline characteristics hypothesized to influence SUD treatment engagement were compared between participants who did and did not engage in SUD treatment within 90 days post-discharge using χ^2 tests (categorical variables) and *t*-tests (continuous variables), stratified by receipt of CPRS and LCSW services. Any characteristic associated with 90-day SUD treatment engagement ($p\leq0.10$) was considered as a "potential predictor" and included in prediction analyses.

The primary prediction analyses used classification and regression trees (CART) performed in R (v4.2.2). CART is a "decision tree" algorithm that employs a non-parametric approach to create nested trees with binary splits that group participants into increasing homogenous groups based on "risk" of the outcome (Chambers et al., 2018). The recursive nature of CART makes it ideal for considering complex relations between predictors (Morgan, 2014). For binary outcomes, the Gini index and entropy values are used to define each split point (Strobl et al., 2009). Cross-validation with the optimal complexity parameter was used to build the classification tree and split the data into training (90 % for LCSW, 80 % for CPRS) and test (10 % for LCSW, 20 % for CPRS) sets (Bertsimas and Dunn, 2017; Statistical tools for high-throughput data analysis STHDA, 2024). Training and test splits were chosen to yield CART models with highest predictive accuracy, based on best practice guidance (Bertsimas and Dunn, 2017). Training sets were used to create the nested decision trees. To avoid overfitting the data, the decision tree was "pruned" by selecting the tree that minimized cross-validation error (James et al., 2021). The test sets were then used to validate the selected decision tree. Performance of the selected tree was evaluated using: predictive accuracy (difference between observed and predicted values), sensitivity, specificity, positive predictive value, and negative predictive value.

Of note, for categorical variables used in the bivariate and CART analyses, participants with unknown information ("Don't Know/ Refused" or missing responses) were included in the "No" or "Never" group. We assumed this would not considerably impact the findings because $\leq$10 % of participants had unknown information for each variable. To maintain clinically meaningful interpretation, several categorical variables were collapsed into binary variables (Supplemental Table 1), and race was collapsed into fewer categories ("Black, African, Haitian, or Cape Verdean", "White", and "Other").

2.5. Sensitivity analyses

To evaluate the robustness of the primary analysis, two sensitivity analyses were conducted. The prediction process was repeated using: (1) the adaptive least absolute shrinkage and selection operator (adaptive LASSO) and (2) stepwise regressions. LASSO is an extension of ordinary least squares regression that selects predictors that minimize mean squared errors and balances bias and variance in prediction models using a penalizing [tuning] parameter (λ) (Columbia University Mailman School of Public Health, 2024). Adaptive LASSO is an improvement of the LASSO variable selection process that uses adaptive penalty weights specific to each predictor, thus avoiding overfitting of large coefficients (Zou, 2006; Courtois et al., 2021). Ten-fold cross-validation was employed during the adaptive LASSO process (95 % training and 5 % test sets for both CPRS and LCSW) to identify the optimal tuning parameter that produced the best-fitting parsimonious model with minimal out-of-sample prediction error (Stata 16, 2024). The model's predictive performance was evaluated using deviance ratios, which are analogous to the R^2 for linear models and measure the relative difference of the likelihoods between the fitted adaptive LASSO models and a fully-saturated abstract model (García-Portugués, 2024; StataCorp, 2023). Deviance ratios between 0 and 1 indicate a good model fit (StataCorp, 2023).

In contrast, stepwise regression uses a stepwise process at pre-specified significance levels to add and remove potential predictors and build a model with a final set of predictors. The significance level was set at $p\leq 0.15$ for potential predictors to be included in the stepwise regression model and $p>0.1$ for removal from the model. These significance levels are the default in most statistical software and have shown reasonable bias-variance trade-off in prior simulation studies (Bursac et al., 2008).

3. Results

3.1. Sample characteristics

In total, 325 and 323 participants at high risk of opioid overdose were randomized to receive ED-based behavioral services from LCSW and CPRS, respectively, after enrollment in the trial. Due to randomization, the characteristics of participants who received LCSW and CPRS services were similar (Supplemental Table 2). In each group, the median age of participants was about 34–35 years, and most participants identified as White (LCSW=69.5 %, CPRS=67.5 %), non-Hispanic/Latino(a) (LCSW=82.8 %, CPRS=80.2 %), and male (LCSW=68.9 %, CPRS=67.5 %). At the time of the ED visit, 26.8 % (n=87) and 27.6 % (n=89) of participants who received LCSW and CPRS services, respectively, were currently or recently in SUD treatment.

Overall, 137 (42.2 %) and 141 (43.7 %) participants who received LCSW and CPRS services, respectively, engaged in SUD treatment within the 90 days post-discharge (Table 1).

Baseline characteristics stratified by 90-day SUD treatment engagement and behavioral service are summarized in Table 2. Among participants who engaged in SUD treatment within 90 days, some baseline characteristics that were prevalent among participants who received CPRS services compared LCSW services included: Hispanic/Latina(o) ethnicity (20.6 % vs. 14.6 %), monthly income between \$1 and \$500 (18.4 % vs. 13.9 %), and a lifetime history of barriers to treatment (46.1 % vs. 40.9 %). Some baseline characteristics that were prevalent among participants who received LCSW services compared to CPRS services, among those who engaged in SUD treatment within 90 days, were: employment (29.2 % vs. 18.4 %), unhealthy alcohol use (40.2 %

Table 1
Characteristics of SUD treatment engagement among Navigator trial participants who engaged in SUD treatment 90 days post ED discharge, stratified by behavioral service (n = 278).

	Licensed clinical social workers (n = 137)	Certified peer recovery specialists (n = 141)	p-value
Time to SUD engagement in days, median (IQR)	30.0 (9.0 – 62.0)	30.0 (7.0 – 63.0)	0.50
Type of SUD treatment, n (%)			0.88
Methadone	25 (18.2)	32 (22.7)	
Buprenorphine	75 (54.7)	73 (51.8)	
Residential	19 (13.9)	20 (14.2)	
Detoxification	11 (8.0)	11 (7.8)	
Intensive outpatient or outpatient	7 (5.1)	5 (3.6)	

Table 2

Baseline characteristics hypothesized to influence SUD treatment engagement among Navigator trial participants, stratified by behavioral service and 90-day SUD treatment engagement post ED discharge (n = 648).

	Licensed clinical social workers		Certified peer recovery specialists	
Baseline characteristics, n (%)	Not engaged (n = 188)	Engaged (n =137)	Not engaged (n = 182)	Engaged (n =141)
Predisposing factors				
Age, median (IQR)	35 (29 – 46)	34.5 (30 – 44.5)	35.0 (29 – 44)	34 (29 – 41)
Race				
American Indian or Alaska Native	6 (3.2)	3 (2.2)	4 (2.2)	4 (2.8)
Asian	1 (0.5)	1 (0.7)	0 (0.0)	1 (0.7)
Black, African, Haitian, or Cape Verdean	11 (5.9)	9 (6.6)	12 (6.6)	7 (5.0)
Native Hawaiian or other Pacific Islander	1 (0.5)	1 (0.7)	1 (0.6)	0 (0.0)
White	132 (71.0)	94 (68.6)	126 (69.2)	92 (65.3)
Mixed, bi-racial, or multi-racial	16 (8.5)	11 (8.0)	20 (11.0)	14 (9.9)
Other	13 (6.9)	16 (11.7)	14 (7.7)	19 (13.5)
Don't Know/Refused	6 (3.2)	1 (0.7)	2 (1.1)	4 (2.8)
Missing	2 (1.1)	1 (0.7)	3 (1.7)	0 (0.0)
Hispanic/Latina(o)				
Yes	29 (15.4)	20 (14.6)	29 (15.9)	29 (20.6)
No	156 (83.0)	113 (82.5)	149 (81.9)	110 (78.0)
Don't Know/Refused	1 (0.5)	4 (2.9)	1 (0.6)	1 (0.7)
Missing	2 (1.1)	0 (0.0)	3 (1.7)	1 (0.7)
Female sex at birth	60 (31.9)	41 (29.9)	60 (33.0)	45 (31.9)
Enabling factors				
Baseline health insurance				
Yes	164 (87.2)	125 (91.2)	157 (86.3)	130 (92.2)
No	17 (9.0)	8 (5.8)	19 (10.4)	4 (2.8)
Don't Know/Refused	3 (1.6)	2 (1.5)	3 (1.7)	4 (2.8)
Missing	4 (2.1)	2 (1.5)	3 (1.7)	3 (2.1)
Baseline monthly income				
$0	41 (21.8)	40 (29.2)	36 (19.8)	41 (29.1)
$1 - $500	23 (12.2)	19 (13.9)	20 (11.0)	26 (18.4)
$501 - $1500	61 (32.5)	42 (30.7)	60 (33.0)	30 (21.3)
$1501 - $3000	26 (13.8)	23 (16.8)	32 (17.6)	18 (12.8)
> $3000	17 (9.0)	7 (5.1)	22 (12.1)	9 (6.4)
Don't Know/Refused	16 (8.5)	6 (4.4)	7 (3.9)	15 (10.6)
Missing	4 (2.1)	0 (0.0)	5 (2.8)	2 (1.4)
Baseline employment				
Yes	55 (29.3)	40 (29.2)	60 (33.0)	26 (18.4)
No	127 (67.6)	97 (70.8)	116 (63.7)	110 (78.0)
Don't know/Refused	2 (1.1)	0 (0.0)	2 (1.1)	2 (1.4)
Missing	4 (2.1)	0 (0.0)	4 (2.2)	3 (2.1)
Baseline highest education attained				
Elementary or grade school	8 (4.3)	7 (5.1)	6 (3.3)	6 (4.3)
Some high school	46 (24.5)	41 (29.9)	38 (20.9)	33 (23.4)
Finished high school or GED	70 (37.2)	47 (34.3)	62 (34.1)	52 (36.9)
Some college	49 (26.1)	28 (20.4)	42 (23.1)	29 (20.6)
Trade or technical school	4 (2.1)	2 (1.5)	7 (3.9)	5 (3.6)
College or university degree or higher	8 (4.3)	12 (8.8)	23 (12.6)	13 (9.2)
Don't Know/Refused	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.7)
Missing	3 (1.6)	0 (0.0)	4 (2.2)	2 (1.4)
Lifetime history of unstable housing	121 (64.4)	103 (75.2)	113 (62.1)	104 (73.8)
Lifetime history of barriers to treatment access				
Yes	57 (30.2)	56 (40.9)	48 (26.4)	65 (46.1)
No	124 (66.0)	79 (57.7)	126 (69.2)	72 (51.1)
Don't know/Refused	3 (1.6)	2 (1.5)	5 (2.8)	2 (1.4)
Missing	4 (2.1)	0 (0.0)	3 (1.7)	2 (1.4)
Lifetime history of arrest	154 (81.9)	117 (85.4)	149 (81.9)	117 (83.0)

Table 2 (*continued*)

	Licensed clinical social workers		Certified peer recovery specialists	
Baseline receipt of disability benefits				
Yes	51 (27.1)	30 (21.9)	47 (25.8)	31 (22.0)
No	132 (70.2)	107 (78.1)	130 (71.4)	107 (75.9)
Don't know/Refused	1 (0.5)	0 (0.0)	1 (0.6)	1 (0.7)
Missing	4 (2.1)	0 (0.0)	4 (2.2)	2 (1.4)
Need factors				
Baseline unhealthy alcohol use				
Yes	85 (45.2)	55 (40.2)	78 (42.9)	42 (29.8)
No	85 (45.2)	72 (52.6)	79 (43.4)	77 (54.6)
Don't know/Refused	1 (0.5)	2 (1.5)	1 (0.6)	4 (2.8)
Missing	17 (9.0)	8 (5.8)	24 (13.2)	18 (12.8)
Reason for ED visit				
Opioid overdose	95 (50.5)	53 (38.7)	90 (49.5)	59 (41.8)
Infectious complication of OUD	5 (2.7)	10 (7.3)	12 (6.6)	9 (6.4)
Opioid withdrawal	6 (3.2)	8 (5.8)	9 (5.0)	11 (7.8)
Seeking treatment/detox for opioids	17 (9.0)	15 (11.0)	9 (5.0)	20 (14.2)
Other	16 (8.5)	12 (8.8)	14 (7.7)	13 (9.2)
Not opioid related	49 (26.1)	38 (27.7)	47 (25.8)	29 (20.6)
Missing	0 (0.0)	1 (0.7)	1 (0.6)	0 (0.0)
Baseline pain	108 (57.5)	93 (67.9)	115 (63.2)	89 (63.1)
Prescription opioid or benzodiazepine use in P6M[b]	120 (63.8)	99 (72.3)	109 (59.9)	94 (66.7)
Marijuana use in P6M	121 (64.4)	86 (62.8)	114 (62.6)	82 (58.2)
Illicit substance use in P6M[c]	144 (76.6)	112 (81.8)	128 (70.3)	107 (75.9)
Previous opioid overdose in P12M[a]				
Yes	17 (9.0)	21 (15.3)	15 (8.2)	19 (13.5)
No	171 (91.0)	115 (83.9)	166 (91.2)	122 (86.5)
Missing	0 (0.0)	1 (0.7)	1 (0.6)	0 (0.0)
Lifetime history of depressive disorder diagnosis	89 (47.3)	77 (56.2)	90 (49.5)	81 (57.5)
Lifetime history of anxiety disorder diagnosis	88 (46.8)	81 (59.1)	97 (53.3)	85 (60.3)
Lifetime history of bipolar disorder diagnosis	42 (22.3)	45 (32.9)	46 (25.3)	44 (31.2)
Lifetime history of psychosis diagnosis	21 (11.2)	17 (12.4)	13 (7.1)	14 (9.9)
Lifetime history of injecting drugs	89 (47.3)	75 (54.7)	82 (45.1)	76 (53.9)
Lifetime history of any mental health diagnosis	133 (70.7)	105 (76.6)	133 (73.1)	100 (70.9)
Health behavior factors				
Lifetime history of mental illness treatment				
Yes	83 (44.2)	74 (54.0)	67 (36.8)	70 (49.7)
No	85 (45.2)	48 (35.0)	87 (47.8)	55 (39.0)
Don't know/Refused	3 (1.6)	2 (1.5)	3 (1.7)	3 (2.1)
Missing	17 (9.0)	13 (9.5)	25 (13.7)	13 (9.2)
Lifetime history of addiction treatment	138 (73.4)	114 (83.2)	125 (68.7)	115 (81.6)
Lifetime history of recovery services				
Yes	54 (28.7)	55 (40.2)	60 (33.0)	52 (36.9)
No	129 (68.6)	80 (58.4)	119 (65.4)	87 (61.7)
Don't know/Refused	1 (0.5)	2 (1.5)	0 (0.0)	0 (0.0)
Missing	4 (2.1)	0 (0.0)	3 (1.7)	2 (1.4)

[a] P12M: past 12 months.
[b] P6M: past 6 months.
[c] Crystal methamphetamine, cocaine, heroin, or club drugs in the P6M.

vs. 29.8 %), ED visit unrelated to opioids (27.7 % vs. 20.6 %), and pain (67.9 % vs. 63.1 %).

3.2. *Time to SUD treatment engagement*

Median time to SUD treatment engagement post ED discharge was similar for participants who received LCSW and CPRS services (median=30 days, interquartile range [IQR]=9.0–62.0 days for LCSW, and median=30 days, IQR=7.0–63.0 days for CPRS; p-value=0.50). In Cox-PH analyses, likelihood of SUD treatment engagement was also similar for participants who received CPRS compared to LCSW services, without (hazard ratio [HR]=1.06, 95 % confidence interval [CI]= 0.84–1.34) and with (HR=1.08, 95 %CI=0.85–1.37) adjustment for SUD treatment engagement in the two weeks before or at the ED visit. Fig. 1 depicts the cumulative incidence of SUD treatment engagement within 90 days post-discharge by behavioral service. SUD treatment engagement occurred at a similar rate over time in the CPRS and LCSW groups, with higher engagement by participants who received CPRS services between 30 and 60 days post-discharge. After 75 days, there was no difference in the percentage of participants who had engaged in SUD treatment between the groups.

3.3. *Baseline predictors of SUD treatment engagement*

In bivariate analyses, 16 baseline characteristics met our pre-specified criteria for inclusion in prediction analyses as potential predictors (Table 3). For participants who received CPRS services, of these 16 variables, the CART analyses selected no lifetime history of bipolar disorder, having unhealthy alcohol use at baseline, not using prescription opioid or benzodiazepine use in the P6M, no lifetime history of unstable housing, no lifetime history of barriers to treatment access, no lifetime history of addiction treatment, and lifetime history of recovery services as predictors of 90-day SUD treatment engagement (Table 3 and Fig. 2; bottom panel). However, the predictive performance of the optimal CART decision tree was poor, as it accurately predicted 90-day treatment engagement for only 60.9 % of participants who received CPRS services, and its sensitivity and specificity were 65.7 % and 55.2 %, respectively (Supplemental Table 3). For participants who received LCSW services, CART analysis identified the following predictors of 90-day SUD treatment engagement: having health insurance at baseline, no lifetime history of anxiety disorder, no pain at baseline, no previous opioid overdose in the P12M, and no lifetime history of mental illness treatment (Table 3 and Fig. 2; top panel). The performance of the optimal CART decision tree for the LCSW group was also poor; it had low predictive accuracy (54.8 %), sensitivity (58.3 %), and specificity (42.9 %).

In sensitivity analyses, the LASSO and stepwise regression identified nine and six predictors, respectively, for 90-day SUD treatment engagement among participants who received CPRS services (Table 3). Four predictors from these sensitivity analyses overlapped with the predictors identified by CART analyses. However, the performance of these two predictive methods was also poor (Supplemental Table 3). For participants who received LCSW services, the LASSO model did not identify any predictors of 90-day SUD treatment engagement, while stepwise regression identified three predictors, only one of which overlapped with the predictors identified by CART.

4. Discussion

Among ED patients at high risk of opioid overdose who were randomized to receive ED-based behavioral services from either a CPRS or LCSW, a similar percentage engaged in SUD treatment within 90 days post-discharge (42–44 %). Time to SUD treatment engagement was also similar across the two groups (median=30 days). Prediction analysis using a non-parametric algorithm identified that, for patients who received LCSW services, not having social/structural barriers to care

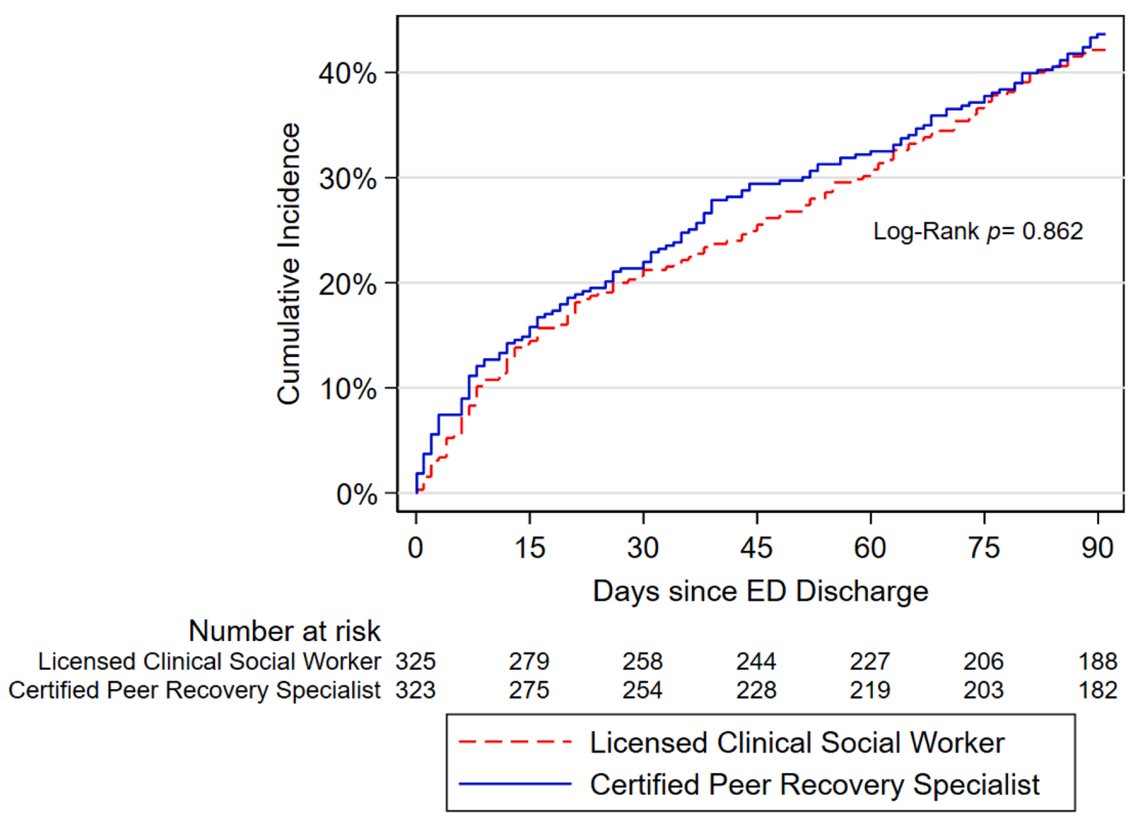

Fig. 1. Cumulative incidence curve for time to engagement in SUD treatment 90 days post ED discharge by behavioral service among Navigator trial participants (n = 648).

Table 3
Predictors selected using CART, LASSO, and stepwise regression algorithms by behavioral service among Navigator trial participants (n = 648)[a].

Predictors	CART		Adaptive LASSO		Stepwise Regression	
	LCSW	*CPRS*	*LCSW*	*CPRS*	*LCSW*	*CPRS*
Enabling factors						
Baseline health insurance	O			X		
Baseline monthly income				X		
Baseline employment				X		X
Lifetime history of unstable housing		X			O	
Lifetime history of barriers to treatment access		X		X		X
Need factors						
Baseline unhealthy alcohol use		X		X		X
Baseline pain	O					
Prescription opioid or benzodiazepine use in P6M[c]		X		X		X
Previous opioid overdose in P12M[b]	O					
Lifetime history of anxiety disorder diagnosis	O				O	
Lifetime history of bipolar disorder diagnosis		X				
Lifetime history of injecting drugs				X		
Health behavior factors						
Lifetime history of mental illness treatment	O			X		X
Lifetime history of addiction treatment		X		X		X
Lifetime history of recovery services		X			O	

[a] The table only lists 15 of the 16 baseline characteristics that met the pre-specified criteria for inclusion in prediction analyses from bivariate analyses; lifetime history of depressive disorder was omitted from the table as it was not selected by any of the three prediction methods.
[b] P12M: past 12 months.
[c] P6M: past 6months.

access (e.g., having health insurance), no diagnosed/perceived health conditions (e.g., no lifetime history of anxiety disorder), and not having co-morbid conditions (e.g., no lifetime history of mental illness treatment) predicted 90-day SUD treatment engagement. Similarly, for participants who received CPRS services, not having social/structural barriers to care access (e.g., no lifetime history unstable housing) and no diagnosed/perceived health conditions (e.g., no lifetime history of bipolar disorder) predicted treatment engagement. However, given the low predictive accuracy and the variation in predictors identified in sensitivity analyses, the current analysis cannot draw firm conclusions about the ability of these predictors to distinguish between patients more likely to benefit from ED-based behavioral services provided by a CPRS versus LCSW. Nonetheless, the predictors clustered within common overarching themes of the Behavioral Model of Healthcare Utilization Framework and may inform future efforts to identify barriers to treatment access.

Social/structural barriers (*enabling* factors) such as lack of health insurance and unstable housing are markers of economic instability that greatly influence SUD treatment engagement and treatment of other co-morbid conditions (Bell et al., 2023). Individuals experiencing economic instability may not be able to prioritize SUD treatment due to more critical needs of housing or due to limited insurance coverage and high deductibles (Acevedo et al., 2020). Medicaid expansion has significantly enhanced coverage of SUD care and decreased the uninsured rates of individuals with opioid-related hospital visits (Bailey et al., 2024). RI is among the few states that offer the full continuum of SUD care in the state's Medicaid program; however, the present study suggests that further provisions in housing support services may be needed (Executive Office of Health and Human Services State of Rhode Island, 2024a, 2024b, 2024c, 2024d). For example, resources for and linkage to residential aftercare programs for patients receiving ED-based behavioral services may increase SUD treatment engagement for those who are homeless (Jason and Harvey, 2022).

The presence (*need* factors) and management (*health behavior* factors) of comorbidities, especially mental health conditions, are integral to successful linkage to SUD care (National Institute on Drug Abuse NIDA, 2024a). Mental health conditions and substance use often co-occur due to shared risk factors (e.g., environmental stressors, genetic vulnerabilities, trauma/stress) (Nestler, 2014; Cerdá et al., 2010; Pelayo-Teran et al., 2012; Kelly and Daley, 2013). In the current study, 73 % of ED patients at high risk of opioid overdose also reported a prior mental health diagnosis. Individuals with co-occurring mental health conditions and SUD experience significant barriers to treatment for both conditions, due to a fragmented healthcare system that is unable to provide comprehensive care suitable to their complex needs (Jones and McCance-Katz, 2019; Novak et al., 2019; Iturralde et al., 2021). The absence of prior mental illness treatment and mental health diagnoses (e.g., anxiety, bipolar disorder) predicted SUD treatment engagement and may indicate that those without these co-morbid conditions experienced fewer barriers to treatment. However, a prior study among the current study population identified that prior hospitalization for mental illness was associated with increased treatment access (Rosenfield et al., 2023). Pain and prior overdose have been identified as health conditions associated with decreased treatment engagement (Mutter et al., 2022; Naeger et al., 2016). Others have suggested that patients may be hesitant to seek SUD treatment for pain relief as they perceive it as a pathway to opioid dependence, and patients who experienced a recent opioid overdose may have complex and distinctive treatment needs post-discharge compared those without a recent overdose (Naeger et al., 2016; Stumbo et al., 2017). While individuals who experience life-threatening events may exhibit behavioral changes towards an increased willingness of recovery, it is possible that the behavioral interventions in the current study are not sufficiently engaging ED patients with a prior overdose to access treatment (Langabeer et al., 2020). Prescriptions for opioids or benzodiazepines was also associated with decreased treatment engagement. Due to the considerable health risks associated with co-prescribing benzodiazepines and opioids, patients receiving SUD treatment, which includes opioid agonist treatment, are less likely to use benzodiazepines (National Institute on Drug Abuse NIDA, 2024b). In contrast, unhealthy alcohol use predicted SUD treatment engagement, possibly owing to ease of identifying symptoms of alcohol misuse within the ED context. Lastly, prior experience with recovery services unsurprisingly increased SUD engagement.

Compared to prior studies of ED behavioral interventions, the percentage of patients who engaged in SUD treatment differed in the current study. Chambers et al. found that 60 % of ED patients treated for opioid overdose and who received ED behavioral counseling (including psychiatry, social work, and/or peer support consultations) engaged in OUD treatment within 30 days (Chambers et al., 2023). Similarly, among ED patients with SUD, 50 % engaged in outpatient addiction treatment within 30 days following an ED behavioral intervention administered by a community health worker (Anderson et al., 2023). However, the latter study may have included some lower risk ED patients with SUD, and the ED behavioral interventions differed across studies. Lower treatment engagement in the current study may also reflect the additional barriers that influence SUD treatment engagement among ED patients at high risk of overdose, (Collins et al., 2023) including housing needs or lack of employment (Hawk et al., 2021). Of note, 35 % of participants in the current study had previously experienced barriers to treatment access. Finally, experiences of poor provider communication, stigma, and negative perceived attitudes on drug use in the ED may have also reduced treatment engagement (Hawk et al., 2021; Carusone et al., 2019).

Although accurate prediction models of SUD treatment engagement

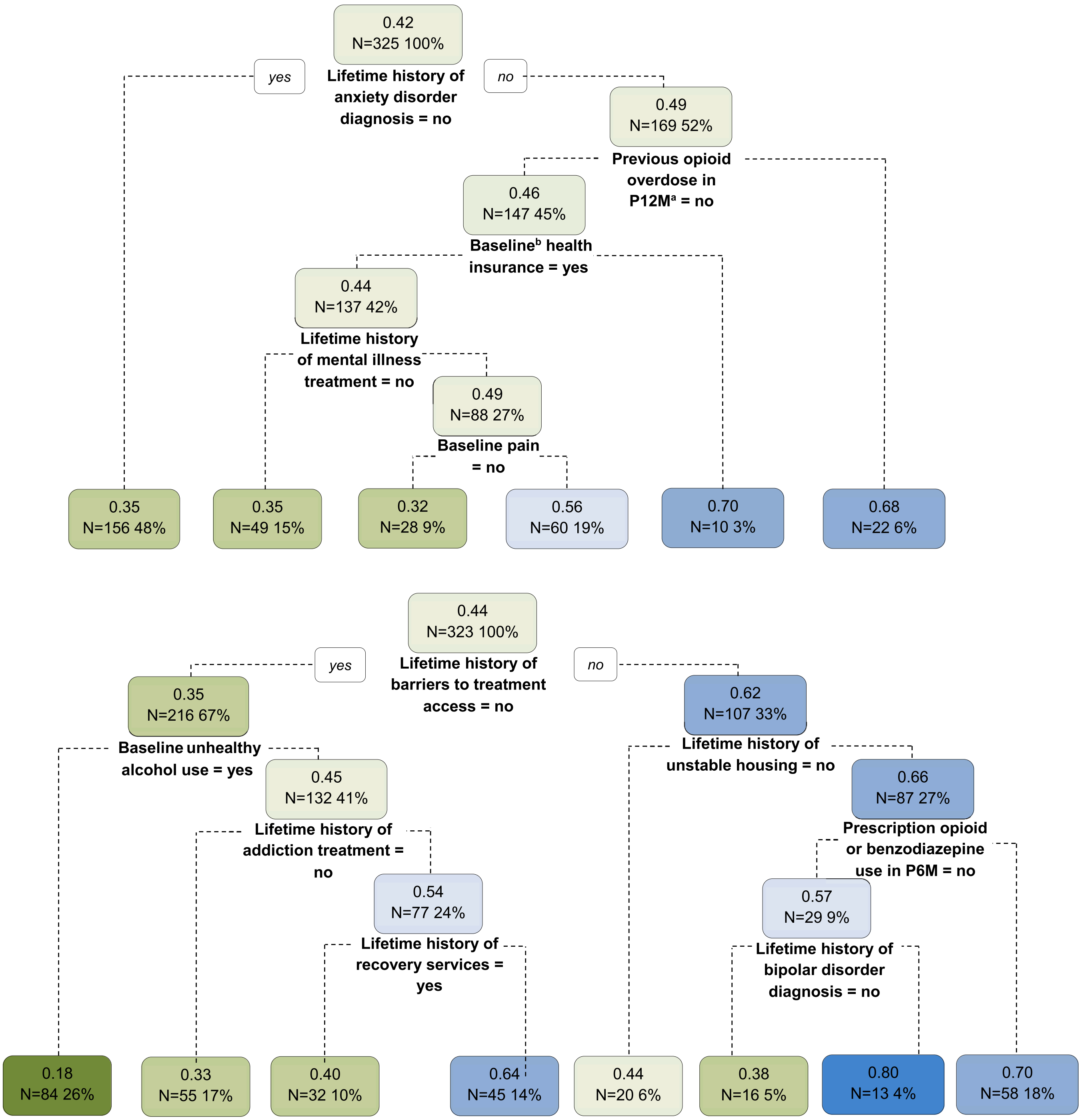

Fig. 2. Classification and regression trees predicting engagement in SUD treatment 90 days post ED discharge for Navigator trial participants randomized to LCSW (top; n = 325) or CPRS (bottom; n = 323). A round square box represents a node. Within each node, the number on the first line is the probability of engagement in SUD treatment within 90 days post-discharge. Green nodes indicate probabilities of engagement in SUD treatment <50 % (the lower the probability, the greener the node), and blue nodes indicate probabilities of engagement in SUD treatment ≥50 % (the higher the probability, the bluer the node). The text on the second line shows the sample size in that node. [a]P12M = past 12 months. [b]Baseline = ED visit.

following an ED visit with LCSW and CPRS services were not identified, these ED services nonetheless have an important role. LCSWs are the largest group of behavioral and mental health providers trained in recovery-oriented practices (Serrano and Conley, 2021; Lombardi et al., 2019). Although they cannot prescribe medications for OUD, they partake in clinical decisions on SUD treatment programs and have a considerable understanding of the community setting that promotes engagement and retention in care (Lundgren and Krull, 2018; Bride et al., 2013). On the other hand, CPRS services are unique non-clinical mentoring and coaching services provided by individuals with lived experiences navigating addiction and recovery, including ongoing support following ED discharge (Liebling et al., 2021; Executive Office of Health and Human Services State of Rhode Island, 2024b). Both LCSW and CPRS operate within the acute-crisis setting of the ED to assess, engage, and link patients to SUD treatment services at a critical point in time, thus, preventing future ED visits and hospitalizations (Ashford et al., 2019). Studies have found that these behavioral services are effective in improving the health and recovery of patients with SUD within both inpatient and outpatient settings (Anderson et al., 2023; Lintzeris et al., 2020; Magidson et al., 2021; Shumway et al., 2008). However, the current study is unique in its evaluation of predictors of treatment engagement following both LCSW and CPRS services in the ED using a non-parametric algorithm. Of note, prior work has found that interventions to improve linkage to SUD treatments in the ED were most successful when a multidisciplinary team of LCSW, CPRS, psychiatrists, addiction specialists, and pharmacists coordinated to provide patients with a customized treatment plan of psychosocial support as well as inpatient, outpatient, and community-based recovery services (Lintzeris et al., 2020; Wakeman et al., 2017). The effectiveness of care coordination efforts started in the ED likely depends on continued connections with both clinical and community resources capable of providing inclusive, person-centered, relationship-based, tailored care.

4.1. Strengths and limitations

This study has some limitations. First, the analysis included a high-risk ED patient population receiving treatment within RI, which may limit generalizability to other clinical and geographic settings. Second, the study was conducted in a relatively small sample size with limited power to detect small differences in SUD treatment engagement by LCSW and CPRS services. Third, most of the covariates from the baseline questionnaire were self-reported and subject to recall and social desirability bias. While missingness was <10 % overall, there is still a chance of misclassification bias as categorical variables were collapsed. Fourth, there may have been other important predictors of SUD treatment engagement that were not available in the baseline questionnaire. Fifth, participants currently or recently engaged in SUD treatment at the time of the ED visit were not excluded. Preliminary analyses showed this variable to be a near-perfect predictor of the outcome, and it was therefore not included as a potential predictor. Findings might therefore differ if the sample was limited to those without prior SUD treatment. Lastly, the current study did not aim to differentiate the effectiveness of ED-based behavioral interventions delivered by CPRS compared to LCSWs among subgroups of ED patients at high risk of opioid overdose. Instead, it sought to identify whether the patient subgroups engaging in SUD treatment following each service type were similar or distinctive. However, the study was strengthened by its use of multiple prediction methods, with the primary method using a non-parametric strategy. CART is a useful method for identifying complex relationships in the data and displaying those associations in easy-to-interpret visualizations (Morgan, 2014). The Behavioral Model of Healthcare Utilization Framework provided a structured approach to identifying relevant predictors informed by clinical expertise. Finally, the exposure was well-defined, and the outcome of SUD treatment engagement was obtained using statewide administrative data which circumvented loss to follow-up.

5. Conclusion

While engagement in SUD treatment was observed for about 43 % of ED patients at high risk of opioid overdose following an ED behavioral intervention with either a LCSW or CPRS, there were no strong predictors of treatment engagement in either group. These findings underscore the importance of providing behavioral counseling services for all patients in the ED at high risk of opioid overdose.

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CRediT authorship contribution statement

Brandon David Lewis Marshall: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Francesca Beaudoin:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Laura Chambers:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Data curation. **Mackenzie Daly:** Writing – review & editing, Resources, Data curation. **Jamieson Goulet:** Writing – review & editing, Resources, Data curation. **Benjamin Hallowell:** Writing – review & editing, Resources, Data curation. **Linda Mahoney:** Writing – review & editing, Resources, Data curation. **Fiona Bhondoekhan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Yu Li:** Writing – review & editing, Software, Resources, Methodology, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Brandon Marshall reports financial support was provided by Arnold Ventures LLC. Brandon Marshall reports financial support was provided by Cigna Foundation. Dr. Brandon Marshall was partially supported by the National Institute of General Medical Sciences of the NIH [grant number: P20GM125507] and the National Institute on Allergy and Infectious Disease of the NIH [grant number: 3P30AI042853]. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dadr.2024.100287.

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