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Implementation of Digital Tools Supporting MOUD Treatment Improves Retention: A Stepped-Wedge Cluster Randomized Trial

Jorge E Palacios, Robert Sherrick, Tim Janssen, Elana Deuble, Sara Lorenzen, Mark Shaefer, Jenna Tregarthen

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Abstract

Background: Despite its proven efficacy, Medication for Opioid Use Disorder (MOUD) retention remains low, with structural and systemic barriers such as access to care and treatment setting, together with individual barriers such as personalization and motivation, contributing to high rates of discontinuation. Digital interventions are a promising solution to many of these barriers, however robust evidence for their effectiveness at improving retention and engagement with treatment is scarce.

Objective: To evaluate the impact on patient retention, treatment continuance and medication adherence of Recovery Connect, a digital remote patient monitoring app used as part of a blended treatment model.

Methods: A stepped-wedge cluster randomized trial was conducted across nine outpatient MOUD clinics organized into eight clusters. Clusters were sequentially graduated from usual care to a digitally-enhanced model incorporating Recovery Connect, which provided real-time monitoring, psychoeducational and skill based learning content, and messaging between patients and clinicians. The primary outcome was 30-day retention in treatment following either exposure (implementation of the app into the clinic), linkage (connecting the patient app with the clinician's app), or engagement (levels of usage of the app). Secondary outcomes included treatment continuance and # daily doses within the first 3, 7 and 30 days. Cluster-controlled discrete-time survival analyses were used, adjusting for patient- and clinic-level covariates.

Results: Patients admitted to clinics which had implemented the app saw increased retention (74.8%) compared to those that had not (69.5%; p=.047). Patients who linked with a clinician on Recovery Connect had a 81.3% likelihood of retention, compared to 72.0% (p<.001) among those not linked. Linkage also significantly predicted higher continuance and number of daily doses taken in the first 7 and 30 days. Low, moderate and high engagement levels had progressively higher 30–day retention vs no retention (p<.001).

Conclusions: Recovery Connect significantly enhanced patient retention and treatment continuance in MOUD treatment. Implementing digital interventions can effectively complement traditional care methods, substantially improving clinical outcomes. Clinical Trial: ClinicalTrials.gov ID: NCT07140926

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To evaluate the impact on patient retention, treatment continuance and medication adherence of Recovery Connect, a digital remote patient monitoring app used as part of a blended treatment model.

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Conclusions

Recovery Connect significantly enhanced patient retention and treatment continuance in MOUD treatment. Implementing digital interventions can effectively complement traditional care methods, substantially improving clinical outcomes.

Trial registration

ClinicalTrials.gov ID: NCT07140926

Keywords

Digital Intervention, Opioid Use Disorder, Medication for Opioid Use Disorder, Treatment Retention, Stepped-Wedge Cluster Randomized Trial, Blended Treatment

Introduction

Opioid use disorder (OUD) remains a significant public health challenge, characterized by high morbidity, mortality, and substantial societal costs[1,2]. Medications for opioid use disorder (MOUD) have been shown to reduce opioid use and mortality by more than 50%, while improving social and health outcomes[3,4,5] . Yet, despite this efficacy, MOUD retention remains low, with structural and systemic barriers—such as access to care, treatment setting, and referral source—compounding individual patient factors (availability of treatment, personalization, and motivation) in contributing to high rates of

discontinuation[6,7,8].

Digital interventions hold promise for overcoming common barriers such as stigma, limited clinic access, and resource constraints[9]. A recent systematic review highlights the potential of digital and remote interventions to augment traditional substance use treatment, reducing risk of relapse and offering interactive contact between patients and clinicians[10]. These technologies may not only facilitate improved retention but also foster patient autonomy and continuous engagement with care.

Preliminary findings from a large-scale feasibility study indicate that Recovery Connect (RC), a digital remote patient monitoring app, successfully facilitated patient-clinician interactions, was well-accepted, and was associated with improved 30-day retention[11]. However, robust randomized trial evidence evaluating app-based tools in real-world opioid treatment settings remains limited[10]. The current study addresses this gap by rigorously testing the effectiveness of RC implementation through a stepped-wedge cluster randomized design.

The main objectives of this study were (1) to assess the effect on retention of implementing RC in outpatient OUD clinics, relative to care as usual, (2) to explore the impact on retention of clinician-patient linkage facilitated by the app, and (3) to examine the association between patient engagement levels and treatment retention.

Methods

Study Design

We conducted a stepped-wedge cluster randomized trial[12] to evaluate the impact of RC on retention and treatment continuance among individuals initiating medication for opioid use disorder (MOUD). This design allowed for sequential implementation of the intervention,

such that each cluster transitioned from a control period (usual care) to an intervention period (RC), serving as its own control. Clusters were randomized to crossover into the intervention condition at weekly intervals beginning February 26, 2024, through April 16, 2024. Figure 1 shows the full data collection period alongside dates for crossover at each clinic. The stepped-wedge approach was selected to facilitate pragmatic implementation, reflecting real-world conditions, whilst preserving the ability to evaluate causal effects. This design also allowed us to account for temporal trends and clinic-level variability through staggered rollout.

Ethical considerations

The trial protocol was approved by Sterling Institutional Review Board (IRB) ID: 11629. All collected data, including app usage statistics and clinical outcomes, is stored securely in compliance with applicable data protection regulations. Digital data is encrypted and stored on secure servers with restricted access. Clinicians signed informed consent to participate in the study. Patients give consent for their anonymized data to be used for research purposes as part of their treatment contract and thus a waiver for consent was approved by the IRB. No additional costs were incurred by clinicians or patients participating in the study. The implementation of the Recovery Connect app was part of the rollout at participating clinics and integrated into existing treatment pathways. No compensation was given to clinicians as this was part of their regular duties as members of the clinics and the research did not ask for anything more than what they would otherwise do as normal practice within the clinic.

Setting and Participants

The study was conducted across nine outpatient MOUD clinics operated by Community Medical Services (CMS), a network of Opioid Treatment Programs (OTPs) serving urban

and rural populations across multiple U.S. states. Participating clinics were located in Montana (Billings, Bozeman, Kalispell, Missoula), North Dakota (Fargo, Grand Forks, Minot), and Alaska (Anchorage, Wasilla). Grand Forks and Fargo were grouped into one cluster, as Fargo clinicians often treat Grand Fork patients. All clinics provided methadone and buprenorphine treatment under similar protocols, including same-day admissions, observed daily dosing, routine counseling, regular urine drug screening, and medical follow-ups within 7 days of admission and as needed thereafter. Treatment is delivered by mental health professionals (MHPs), whose education spans from high school diplomas to advanced degrees in social work and counseling. Eligible participants were adults (18+) newly admitted to treatment between January 1st and November 1st, 2024. Patients were excluded if their dosing suggested a transfer from a non-CMS clinic, or if they had previously used RC before their most recent admission during the study. For patients with multiple admissions during the study period, their most recent was selected. Adjusted analyses controlled for presence and number of prior admissions.

Exposure groups were defined by implementation timing and patient app download / linkage to the MHP app, as detailed in the Intervention section. To statistically handle patients whose MHP was trained in the use of RC during their ongoing admission, survival analyses using a time-varying indicator of exposure were used to reflect the day that MHP training in the RC platform occurred; see Analysis Strategy below.

Control Condition: Usual Care

During the control period, all clinics followed standard MOUD protocols. Usual care included in-person dosing as well as take-home dosing per federal guidelines. Counseling was available on-site and included both individual and group therapy sessions. Communication with patients outside the clinic setting was generally limited to phone calls, and no structured digital tools were used to support remote monitoring, messaging, or

check-ins. Documentation was completed via electronic health records, but there was no mechanism for providing real-time intervention or behavioral feedback.

Intervention: Recovery Connect

RC is a white-labelled version of Recovery Path[13], rebranded to allow partner organizations to maintain brand continuity while leveraging its evidence-based digital infrastructure. Recovery Path is a HIPAA-compliant digital remote patient monitoring platform that supports a blended care model for MOUD by combining in-person treatment with continuous digital engagement. It enables daily check-ins, access to evidence-based resources and coping strategies, and secure, real-time communication between patients and their care teams. MHPs gain timely insights through real-time data on patient progress, risks and setbacks, allowing for early intervention and timely containment during periods of heightened distress. Between sessions, MHPs can recommend tailored coping strategies and psychoeducational content, reinforcing accountability and enhancing continuity of care. RC was also integrated into the CMS medical record system to reduce administrative burden on MHPs and improve documentation accuracy through auto-generated case notes. Implementation involved two components: MHP training and patient onboarding. MHPs received live virtual training on app features, linkage procedures, and app-based communication strategies. Materials included step-by-step guides, video tutorials, and ongoing technical support. The training was deliberately designed to accommodate differing levels of prior experience, ensuring every MHP gains the skills to use the app effectively in clinical settings. App rollout began immediately after training, at which point MHPs were instructed to help newly admitted patients download the RC app and link via a QR code during onboarding. MHPs were also asked to show patients key features of RC, including daily check-ins, homework activities, and the messaging feature.

For primary analyses, we operationalized three key constructs:

- Exposure: Patients were considered “exposed” if MHPs at their clinic had completed training in the RC platform prior to or during the patient's ongoing admission.

- Linkage: Patients were considered “linked” if they had downloaded the RC app and were linked to a MHP trained in the use of RC at a given time during the patient’s admission process.

- Engagement: Defined according to app usage patterns during the first week post-linkage, including logins, check-ins, and secure messages sent and received by patients through the app.

These categories allowed us to examine both the impact of clinic-level implementation (exposure) and the patient-level uptake and use of the app (linkage and engagement). A full overview of data transformations and underlying statistical considerations is available in Multimedia Appendix 1, alongside the code syntax for all analyses. Additional details on timing and classification are described in the Analysis Plan.

Measures

Primary Outcome

The primary outcome was treatment retention. In line with federal guidelines, patients who leave care can be readmitted within 30 days without restarting the intake process[14]. Therefore, a patient was considered to have dropped out—and thus not retained—if a 30-

day gap in treatment began within the first 30 days after intake. The first day of that gap was considered the discontinuation date.

Secondary Outcomes

Treatment continuance: A binary measure defined as receiving at least 75% of expected doses within the first 30 days following intake, and at least one dose administered during the final week of that period (i.e. days 24-30 post-intake).

3, 7, and 30 days doses: representing the number of confirmed daily MOUD doses administered during the first 3, 7, and 30 days after intake, respectively. Dose analyses are exclusive to patients retained for at least the matching number of days. These outcomes provide a more granular view of early medication adherence patterns. Confirmed doses included both in-clinic administrations and verified take-home doses, based on standard documentation protocols in place across clinics.

Covariates

All covariates were assessed at time of patient admission, and included age, gender, ethnicity, presence of any fentanyl or amphetamine use, presence of moderate-to-severe depression or anxiety, unemployment or unhoused status, having any prior CMS admissions, number of prior CMS admissions, and primary MOUD medication (methadone or buprenorphine).

Analysis Plan

We used intent-to-treat analyses, in which all enrolled patients whose sites engaged in training activities were included unless previously excluded based on exclusion criteria. The effects of exposure and linkage on odds of retention were tested using cluster-controlled discrete-time survival analyses, controlling for the nested nature of patients across sites. In these analyses, the likelihood of successful client retention on a given day, provided loss to follow-up did not occur earlier, were regressed on prior-day exposure or linkage status, with loss to follow-up defined as the event (1), retention defined as the absence of the event (0),

and days after loss to follow-up defined as missing data[15]. The effects of app engagement on retention, as well as the effects of provider intervention exposure and patient linkage on secondary outcomes were assessed using cluster-controlled logistic and linear regression analyses. Effects of exposure were examined across all patients based on their degree of exposure. Effects of linkage and engagement were examined across all patients, as well as among those fully exposed. This allowed us to study both the pragmatic, system-level impact of linkage and engagement under routine conditions, including partial exposure and implementation variability, as well as analyze the fully exposed subgroup to isolate effects under implementation fidelity.

Main effects analyses were tested across a series of models that estimated the effect of condition unadjusted and adjusted for covariates, following a moderator-first approach to ensure treatment effects were consistent across strata of predictors[16]. The effects of exposure, linkage, and engagement were first modeled as a function of its main effect, as well as its interaction with each covariate in separate models. We did not hypothesize specific interaction effects; therefore, only interactions that were significant at Benjamini-Hochberg-adjusted *p*-values were considered non-spurious, and retained in the final adjusted model that featured all covariates[17].

All MHP- and patient-level analyses were conducted in Mplus 8.9[18] using full-information maximum likelihood (FIML) estimation with a robust sandwich estimator to allow non-parametric adjustment for clustering by site, using a design-based adjustment to estimation of standard errors for nesting and for potential violations of multivariate normality[19]. FIML allows for estimation under the assumption of Missing at Random, meaning that valid inferences can be drawn in the presence of missing data on outcomes, if known predictors

of missing data are included in the model[20].

Results

A CONSORT diagram (Figure 2) shows participant flow, including exclusions, exposure classification, linkage status, as well as retention of eligible patients by condition. A total of N = 1524 patients were allocated to arms. See Table 1 for description of sociodemographic characteristics. On average, among those exposed, those who linked were significantly younger than those who were not linked (T(*df*=1) = 3.69, *p*<.001), and were more likely to encounter unstable housing (χ^2(*df*=1)=15.50, *p*<.001). There were no other significant relations between exposure or linkage and other study covariates. Table 2 shows raw observed means and proportions of study variables, contrasted by condition.

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Table 1. Sociodemographics for eligible participants (n=1524)

									Among exposed				Control/Intervention	
	Eligible		Exposed (n = 1205)		Control (n = 319)		Pearson χ2 / F	*p**	Linked (n = 363)		Not linked (n = 842)		Pearson χ2 / F	*p**
	N	**%**	**N**	**%**	**N**	**%**			**N**	**%**	**N**	**%**		
Fentanyl-positive on admission							χ2(df=1)=4.79	.029					χ2(df=1)=3.27	.071
No	365	24	304	25.2	61	19.1			105	28.9	199	23.6		
Yes	1115	73.2	869	72.1	246	77.1			252	69.4	617	73.3		
Unknown	44	2.9	32	2.7	12	3.8			6	1.7	26	3.1		
Amphetamine-positive on admission							χ2(df=1)=1.58	.209					χ2(df=1)=0.30	.585
No	535	35.1	443	36.8	104	32.6			139	38.3	304	36.1		
Yes	993	61.2	730	60.6	203	63.6			218	60.1	512	60.8		
Unknown	56	3.7	32	2.7	12	3.8			6	1.7	26	3.1		
Moderate-to-severe depression							χ2(df=1)=1.94	.164					χ2(df=1)=0.23	.631
No	1327	88.9	1045	86.7	289	90.6			313	86.2	732	86.9		
Yes	165	10.8	137	11.4	28	8.8			44	12.1	93	11		
Unknown	32	2.1	23	1.9	2	0.6			6	1.7	17	2		
Moderate-to-severe anxiety							χ2(df=1)=7.36	.007					χ2(df=1)=0.27	.604
No	1263	82.9	986	81.8	284	89			297	81.8	689	81.8		
Yes	229	15	196	16.3	33	10.3			60	16.5	136	16.2		
Unknown	32	2.1	23	1.9	2	0.6			6	1.7	17	2		
Unemployed on admission							χ2(df=1)=4.83	.028					χ2(df=1)=7.61	.006
No	507	33.3	421	34.9	92	28.8			148	40.8	273	32.4		
Yes	985	64.6	761	63.2	225	70.5			209	57.6	552	65.6		
Unknown	32	2.1	23	1.9	2	0.6			6	1.7	17	2		
Had Unstable Housing on admission							χ2(df=1)=0.45	.503					χ2(df=1)=15.74	**<.001**

No	1084	71.1	865	71.8	226	70.8			289	79.6	576	68.4		
Yes	408	26.8	317	26.3	91	28.5			68	18.7	249	29.6		
Unknown	32	2.1	23	1.9	2	0.6			6	1.7	17	2		
Gender							χ2(df=1)=0.63	.429					χ2(df=1)=8.92	**.003**
Male	805	52.8	630	52.3	175	54.9			166	45.7	464	55.1		
Female	712	46.7	569	47.2	143	44.8			195	53.7	374	44.4		
Unknown/Other	7	0.5	6	0.5	1	0.3			2	0.6	4	0.5		
Race							χ2(df=4)=8.16	.086					χ2(df=4)=6.32	.177
Black	32	2.1	30	2.5	2	0.6			5	1.4	25	3		
Hispanic/Latino	58	3.8	46	3.8	12	3.8			18	5	28	3.3		
Native American/Pacific Islander	329	21.6	249	20.7	80	25.1			69	19	180	21.4		
Unknown	219	14.4	181	15	38	11.9			50	13.8	131	15.6		
non-Hispanic White	886	58.1	699	58	187	58.6			221	60.9	478	56.8		
Medication Type							χ2(df=1)=1.05	.306					χ2(df=1)=1.81	.179
Methadone	1384	90.8	1099	91.2	285	89.3			325	89.5	774	91.9		
Buprenorphine	140	9.2	106	8.8	34	10.7			38	10.5	68	8.1		
	M	**SD**	**M**	**SD**	**M**	**SD**			**M**	**SD**	**M**	**SD**		
Age (Years) on admission (n=1521)	37.88	12.4	37.6	10.5	37.7	10.2	t(df=1524)=0.162	.872	35.88	9.193	38.39	10.909	t(df=1197)=3.82	**<.001**

Table 2. Study variables for eligible participants (*n* = 1524)

	Eligible		Exposed (n = 1205)		Control (n = 319)		Pearson χ2 / T	*p*
	N	**%**	**N**	**%**	**N**	**%**		
Retained at 30 days (Days30)							21.64	<.001
No	399	26.2	283	23.5	116	36.4		
Yes	1125	73.8	922	76.5	203	63.6		
Retained at 30 days (TC30)							30.3	<.001

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No	723	47.4	528	43.8	195	61.1		
Yes	801	52.6	677	56.2	124	38.9		
Linked with app at 30 days							-	-
No	1305	85.6	363	30.1	-	-		
Yes	219	14.4	842	69.9	-	-		
	M	**SD**	**M**	**SD**	**M**	**SD**		
Time to loss to follow-up (among lost at 30 days)	11.15	8.5	11.27	8.52	10.84	8.4	-0.466	.642
Time to linkage (among linked at 30 days)	13.1	8.3	7.74	9.06	-	-	1.461	.145
Confirmed doses at 3 days	2.69	0.6	2.73	0.59	2.56	0.73	-4.394	<.001
Confirmed doses at 7 days	5.71	1.7	5.84	1.63	5.22	1.93	-5.755	<.001
Confirmed doses at 30 days	20.42	9.3	21.19	1.63	17.51	9.8	-6.373	<.001

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Exposure

Results of exposure analyses are shown in Table 3 and Figure 3. In separate moderator-first analyses, there were no significant interactions between exposure and the eleven (11) covariates (*p*s .09 - .93) after correction. This means that exposure effects appear consistent across individual differences in the study cohort. In unadjusted analysis, compared to no exposure, patients of MHPs trained in app usage were more likely to be retained at 30 days (HR (Hazard Ratio of loss to follow-up) = 0.80, 95% CI= 0.64 - <1.00, *p* = .047; 74.8% 30-day retention likelihood compared to 69.5% likelihood among unexposed). Effects of exposure were of equal valence but non-significant following covariate-adjustment (HR: 0.81, 95% CI: 0.65- 1.01, *p*=.059).

Linkage

Results of linkage analyses are shown in Table 3 and Figure 4a-b.

Across full sample (*N* = 1524). There were no significant interactions between linkage and covariates (*p*s .09 - .91). In unadjusted analyses, compared to no linkage, patients who linked were more likely to be subsequently retained at 30 days (HR (loss) = 0.63, 95% CI= 0.48 - 0.83, *p*<.001; 81.3% 30-day retention among those who linked compared to 72.0% retention among those unlinked). Adjusted effects of linkage were of equal valence and were significant (HR: 0.65, 95% CI: 0.48- 0.87, *p*=.004).

Among Exposed (*n* = 1209). There were no significant interactions between linkage and covariates (*p*s .09 - .99) after correction. In unadjusted analyses, compared to no linkage, patients who linked were more likely to be subsequently retained at 30 days (HR (loss) = 0.69, 95% CI= 0.50 - 0.95, *p*=.021; 80.9% 30-day retention compared to 73.5% retention among unlinked). Adjusted effects of linkage were of equal valence

and significant (HR: 0.70, 95% CI: 0.51- 0.97, *p*=.032).

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	Provider training				Patient linkage							
	All Eligibles (n = 1524)				All Eligibles (n = 1524)				Therapist-exposed Only (n = 1209)			
	HR	95% CI		*p*	HR	95% CI		*p*	HR	95% CI		*p*
Unadjusted Linkage (0: not linked; 1: linked with app)	0.80	0.64	<1.00	.047	0.63	0.48	0.83	.001	0.69	0.50	0.95	.021
Adjusted Linkage (0: not linked; 1: linked with app)	0.81	0.65	1.01	.059	0.65	0.48	0.87	.004	0.70	0.51	0.97	.032
Fentanyl-positive on admission (0=Yes, 1=No)	0.91	0.68	1.23	.554	0.92	0.68	1.25	.601	0.87	0.59	1.27	.457
Amphetamine-positive on admission	1.51	1.20	1.89	<.001	1.51	1.19	1.90	.001	1.44	1.07	1.94	.015
Moderate-to-severe depression	1.28	0.96	1.70	.088	1.28	0.95	1.71	.100	1.26	0.87	1.84	.216
Moderate-to-severe anxiety	1.04	0.91	1.18	.557	1.04	0.93	1.16	.471	1.18	0.91	1.53	.201
Financial stress	1.37	1.08	1.74	.009	1.35	1.06	1.72	.015	1.46	1.14	1.87	.003
Gender	0.96	0.81	1.14	.664	0.98	0.82	1.16	.796	0.92	0.78	1.09	.337
Age (1=>37years; 0=<38years)	0.81	0.60	1.09	.167	0.80	0.60	1.06	.124	0.74	0.57	0.96	.024
Has had prior admissions (1=yes, 0=no)	0.93	0.67	1.29	.669	0.92	0.66	1.28	.616	0.94	0.58	1.54	.817
Number of prior admissions	1.13	0.99	1.28	.063	1.12	0.99	1.27	.064	1.11	0.94	1.30	.217
Race/Ethnicity (ref: Non-Hispanic white)												
Black or African American	2.34	1.67	3.29	<.001	2.20	1.55	3.14	<.001	2.36	1.51	3.69	<.001
Hispanic/Latino	1.05	0.67	1.64	.836	1.06	0.66	1.71	.805	0.84	0.63	1.13	.260
Native American/Pacific Islander	1.37	0.92	2.03	.117	1.36	0.90	2.06	.147	1.40	0.91	2.15	.122
Unknown	0.96	0.68	1.36	.815	0.95	0.67	1.34	.763	0.94	0.61	1.45	.778
Buprenorphine as MOUD (ref: Methadone)	2.52	2.00	3.19	<.001	2.55	2.02	3.24	<.001	2.78	2.24	3.45	<.001

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Table 3. Survival model effects of Exposure and Linkage on subsequent retention

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Engagement

Results of engagement analyses are shown in Table 4. There were no significant interactions between linkage and covariates (*p*s .04 - .89) after correction. Among those retained at 1 week (*n*=1366), minimal, moderate, and high engagement during that first week were each linked to greater 30-day retention compared to no engagement (unadjusted ORs=2.79-7.15, *p*s<.001; adjusted ORs=2.75-6.35, *p*s=.003 - <001). Further, unadjusted high engagement was linked to greater 30-day retention compared to minimal engagement (b = -0.941, *p* = .04, adjusted: b = -0.844, *p* = .069). Among those exposed and retained at 1 week (*n* = 977), minimal, moderate, and high engagement were each linked to greater retention compared to no engagement (unadjusted ORs= 2.39-6.44, *p*s<.001).

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Table 4. Links between Week-1 patient/clinician engagement and subsequent retention

	Retained at 1 week (n = 1366)					Exposed; retained at 1 week (n = 977)				
	b	*p*	OR	95% CI		b	*p*	OR	95% CI	
Unadjusted engagement (ref: 0-1 messages; welcome-message only)	1.05					1.22				
Minimal engagement (2-4 messages)	1.03	<.001	2.79	1.86	4.18	0.87	<.001	2.39	1.50	3.81
Moderate engagement (5-9 messages)	1.52	<.001	4.58	2.68	7.82	1.30	<.001	3.65	1.95	6.82
High engagement (10+ messages)	1.97	<.001	7.15	3.10	16.51	1.86	<.001	6.44	2.32	17.92
Adjusted engagement (ref: 0-1 messages; welcome-message only)										
Minimal engagement (2-4 messages)	1.01	.003	2.75	1.41	5.34	0.83	.004	2.30	1.31	4.06
Moderate engagement (5-9 messages)	1.47	<.001	4.36	2.79	6.82	1.24	<.001	3.45	2.00	5.94
High engagement (10+ messages)	1.85	<.001	6.35	3.08	13.10	1.70	.003	5.45	1.81	16.40
Fentanyl-positive on admission (0=Yes, 1=No)	0.00	.994	1.00	0.66	1.53	0.06	.814	1.06	0.67	1.66
Amphetamine-positive on admission	-0.46	.001	0.63	0.48	0.84	-0.33	.147	0.72	0.46	1.12
Moderate-to-severe depression	-0.32	.149	0.73	0.48	1.12	-0.22	.385	0.81	0.49	1.31
Moderate-to-severe anxiety	0.13	.415	1.13	0.84	1.54	-0.10	.357	0.90	0.72	1.12
Financial stress	-0.20	.392	0.82	0.52	1.29	-0.35	.169	0.71	0.43	1.16
Gender	0.05	.770	1.05	0.77	1.42	0.14	.368	1.15	0.84	1.58
Age (1=>37years; 0=<38years)	0.29	.059	1.34	0.99	1.81	0.44	.015	1.55	1.09	2.20
Has had prior admissions (1=yes, 0=no)	0.06	.791	1.06	0.68	1.66	-0.08	.792	0.92	0.50	1.69

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Number of prior admissions	-0.15	.099	0.86	0.72	1.03	-0.13	.191	0.88	0.72	1.07
Race/Ethnicity (ref: Non-Hispanic white)										
Black or African American	-1.00	<.001	0.37	0.25	0.55	-1.20	<.001	0.30	0.20	0.46
Hispanic/Latino	0.13	.721	1.14	0.56	2.31	0.30	.200	1.35	0.85	2.15
Native American/Pacific Islander	-0.30	.321	0.74	0.42	1.33	-0.40	.212	0.67	0.35	1.26
Unknown	0.25	.251	1.28	0.84	1.96	0.42	.194	1.52	0.81	2.85
Buprenorphine as MOUD (ref: Methadone)	-0.33	<.001	0.72	0.66	0.78	-0.38	<.001	0.68	0.62	0.75

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Secondary outcomes

Results are shown in Supplementary Tables S1-S3 (Multimedia Appendix 2). In unadjusted and adjusted models, exposure predicted greater likelihood of treatment continuance, and a greater number of MOUD doses taken at 3, 7, and 30 days post intake (unadjusted *p*s: .007-.037; adjusted *p*s: .004-.047), among those retained for at least the same number of days.

Among all eligibles (*n*=1378, with those whose MHP was trained in the use of RC during their ongoing admission removed), unadjusted prior linkage predicted greater likelihood of treatment continuance and a greater number of doses at 3, 7, and 30 days (*p*s: <.001-.007). Adjusted for covariates, prior linkage predicted greater likelihood of treatment continuance, 7-day doses, and 30-day doses (ps <.001), but not in 3-day doses (*p*=.116).

Among those exposed (*n*=1089), unadjusted prior linkage predicted greater likelihood of treatment continuance and a greater number of doses at 7 and 30 days (*p*s: <.001-.002), but not in number of doses taken at 3 days (*p*=.115). Adjusted for covariates, prior linkage predicted improvement in likelihood of treatment continuance, number of 7-day doses, and 30-day doses (*p*s <.001-.008), but not in number of doses taken at 3-days (*p*=.306).

Discussion

The improvements in 30-day retention and treatment continuance among exposed

patients indicate that implementation of RC (Recovery Path) can meaningfully enhance standard MOUD care. Based on adjusted model estimates, MHP training provided a 23% (HR of covariate-adjusted non-survival = 0.81) decrease in treatment discontinuation.

In the context of MOUD care, this is clinically significant, as retention rates have remained stagnant amongst the almost 2.3 million people who are on MOUD care across the US[21]. Further, among patients whose clinicians were trained, those who linked early on via RC showed even higher retention, showing that downloading the app and linking with their MHP is associated with greater benefit beyond exposure alone. In addition, minimal to high engagement during the first week emerged as a strong and consistent predictor of positive outcomes, underscoring the critical importance of early and active engagement. Digital tools like RC may thus enable proactive, data-informed support during this crucial window, offering a new avenue for sustaining treatment momentum and preventing early discontinuation.

Our findings align with and extend the work of Kwan et al. (2025)[10], who conducted a comprehensive meta-analysis evaluating the effectiveness of remote interventions in conjunction with in-person substance use treatment. Supplementing in-person care with remote interventions led to a 39% reduction in the odds of relapse compared to in-person care alone (OR = 0.61; 95% CI = 0.46–0.81; p = 0.001) . Building upon this, our study found that patients who linked with a MHP on RC, engaging in a blended care model, had significantly higher treatment retention (81.3%) compared to those not

linked (72.0%, p < .001). While Kwan et al.'s study focused primarily on relapse outcomes, our data shows that this synergistic model can also enhance continuity of care in real-world substance use treatment settings. Together, these results underscore the critical role of integrated digital tools in augmenting treatment engagement and supporting sustained recovery.

Our findings have important implications for clinical practice and health system policy. First, they highlight the value of integrating digital tools not as standalone solutions, but as MHP-augmented enhancements to care delivery. Implementation efforts should prioritize not only MHP training, but also workflow and medical record integration, linkage protocols, and patient onboarding early in the admission process to maximize impact. Second, early engagement data may serve as a practical signal for MHPs and program administrators to identify patients at risk of early treatment discontinuation—offering a basis for real-time, data and human driven intervention. At a health system policy level, our findings bolster the case for reimbursement mechanisms and quality metrics that acknowledge the role of digital patient monitoring in OUD treatment. The Centers for Medicare & Medicaid Services have recognized this need by introducing new Healthcare Common Procedure Coding System (HCPCS) codes that facilitate reimbursement for treatment management services related to the patient's therapeutic use of digital mental health treatment (DMHT) devices[22]. By establishing these codes, the Centers for Medicare & Medicaid Services acknowledges the therapeutic value of integrating digital tools into behavioral health care plans. This policy shift aligns with our study's demonstration that digitally-enhanced blended care models, such as MHP

linkage via RC, can significantly improve treatment retention. As MOUD programs work to improve retention and address treatment gaps, these reimbursement pathways may enable the scalable deployment of digital tools that expand care capacity and promote long-term recovery across broader populations.

Additionally, given the legitimate concerns recently raised by Stoltman and Terplan (2025)[23] regarding privacy violations and the use of surveillance technologies in digital health tools for substance use disorders, our study offers an important counterexample. The intervention examined here was deployed within an IRB-approved protocol, and Recovery Path was developed in alignment with established privacy-by-design principles. Recovery Path strictly avoids third-party surveillance technologies, does not collect or share sensitive health data for commercial purposes, and maintains full compliance with relevant privacy laws, including 42 CFR Part 2 and HIPAA. These practices help to mitigate the ethical concerns associated with digital interventions and support the continued development of trustworthy, patient-centered technologies for addiction treatment.

Importantly, to date, adoption of digital tools in OUD treatment has not reached a scale sufficient to meet the needs of many individuals requiring care. Much of the existing research has centered on feasibility or efficacy in ideal conditions, leaving a critical gap in understanding how such tools can be effectively deployed into real world MOUD treatment settings. One national survey found that only 34% of U.S. healthcare organizations reported using any category of digital health technology for OUD treatment[24]. This study contributes to bridging that gap, demonstrating that a blended care model, where digital tools integrate into existing clinical workflows and medical

record systems, can be implemented across multiple outpatient MOUD settings with measurable improvements in patient retention. Future studies should also explore cost-effectiveness, equity of access, and patient-centered outcomes to further define this impact.

While the study's multiple-site stepped wedge design yields many strengths in terms of power, strength of inference, and generalizability, there are limitations that should be considered. First, due to the nature of the app (facilitating interaction between MHP and patient) there was no obvious method of including an attention-matched control app to be used as control. The baseline standard of care at each site served as comparator for the effect of app training and usage on retention, linkage, and engagement, as per usual stepped-wedge crossover design[25]. Furthermore, for feasibility reasons, the stepped-wedge design featured site transition into the experimental condition within short time frames: each site was inducted into the experimental condition with one week difference relative to each other. This raises the concern that there were unobserved consequences or correlates of the passage of time that may have affected app adoption. However, in exploratory analyses, we found no indication of any secular trends of change over time in any of our outcome measures, following either parametric or non-parametric definitions of change. We also focused on short-term outcomes (30 days); future work will examine sustained retention, relapse, and recovery indicators over longer time horizons.

Patients were identified using a global identifier, so that if they were to transfer among any of the clinics at CMS their dosing records would be continuous. The data records do

not include an indication of whether a patient newly entering treatment transferred from an outside clinic and would therefore already be established on methadone at entry. The maximum allowable first day dose (30 mg before April 2024 and 50 mg afterwards) was used to classify patients as either newly started on methadone or as transfers, since most transfer patients are at doses above these levels. Some patients may be misclassified using this technique, however, this would not be expected to create bias in this stepped-wedge study design. For new patients started on buprenorphine, there was no way to determine if they had been taking it outside of CMS prior to admission. Nevertheless, patients taking buprenorphine were accounted for statistically, and represented a minority of the total sample.

Conclusions

This study demonstrates that implementing RC—a digital remote patient monitoring app—within real-world outpatient OUD treatment settings can significantly improve patient retention and treatment continuance. The stepped-wedge cluster randomized design adds robust evidence to the growing literature on digital interventions in substance use treatment, moving beyond feasibility to demonstrate measurable clinical impact.

Our findings have direct relevance for health systems and policymakers seeking practical, cost-effective strategies to improve MOUD delivery at scale. As national and local governments continue to confront high overdose rates[26,27] and strained treatment infrastructure, evidence-based digital interventions such as RC present a timely and impactful opportunity.

Sustained investment in digital infrastructure, implementation science, reimbursement

mechanisms and equitable access will be essential to ensure these tools reach their full potential. Future research should extend this work to examine long-term outcomes, differential effectiveness across populations, and cost effectiveness of implementing digital care models in routine practice.

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Conflicts of interest

Authors JP, SL and JT are employees of Bright Therapeutics, developers of Recovery Path and Recovery Connect.

Data availability

The datasets generated and analyzed during this study are not publicly available due to data confidentiality agreements in place between Bright Therapeutics and Community Medical Services, but select de-identified data are available from the corresponding author on reasonable request.

Authors' contributions

JP: Conceptualization, Methodology, Data curation, Project administration, Supervision, Validation, Writing – original draft; RS: Conceptualization, Methodology, Data curation,

Resources, Writing – review & editing TJ: Methodology, Formal analysis, Investigation, Writing – review & editing; ED: Project administration, Writing – review & editing ; SL: Project administration, Writing – review & editing; MS: Writing – review & editing; JT: Conceptualization, Funding acquisition, Resources, SupervisionWriting – review & editing.

Abbreviations

CFR: Code of Federal Regulations

CMS: Community Medical Services

DMHT: Digital Mental Health Treatment

HCPCS: Healthcare Common Procedure Coding System

HIPAA: Health Insurance Portability and Accountability Act

MHP: Mental Health Professional

MOUD: Medication for Opioid Use Disorder

OUD: Opioid Use Disorder

RC: Recovery Connect

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Supplementary Files

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Figures

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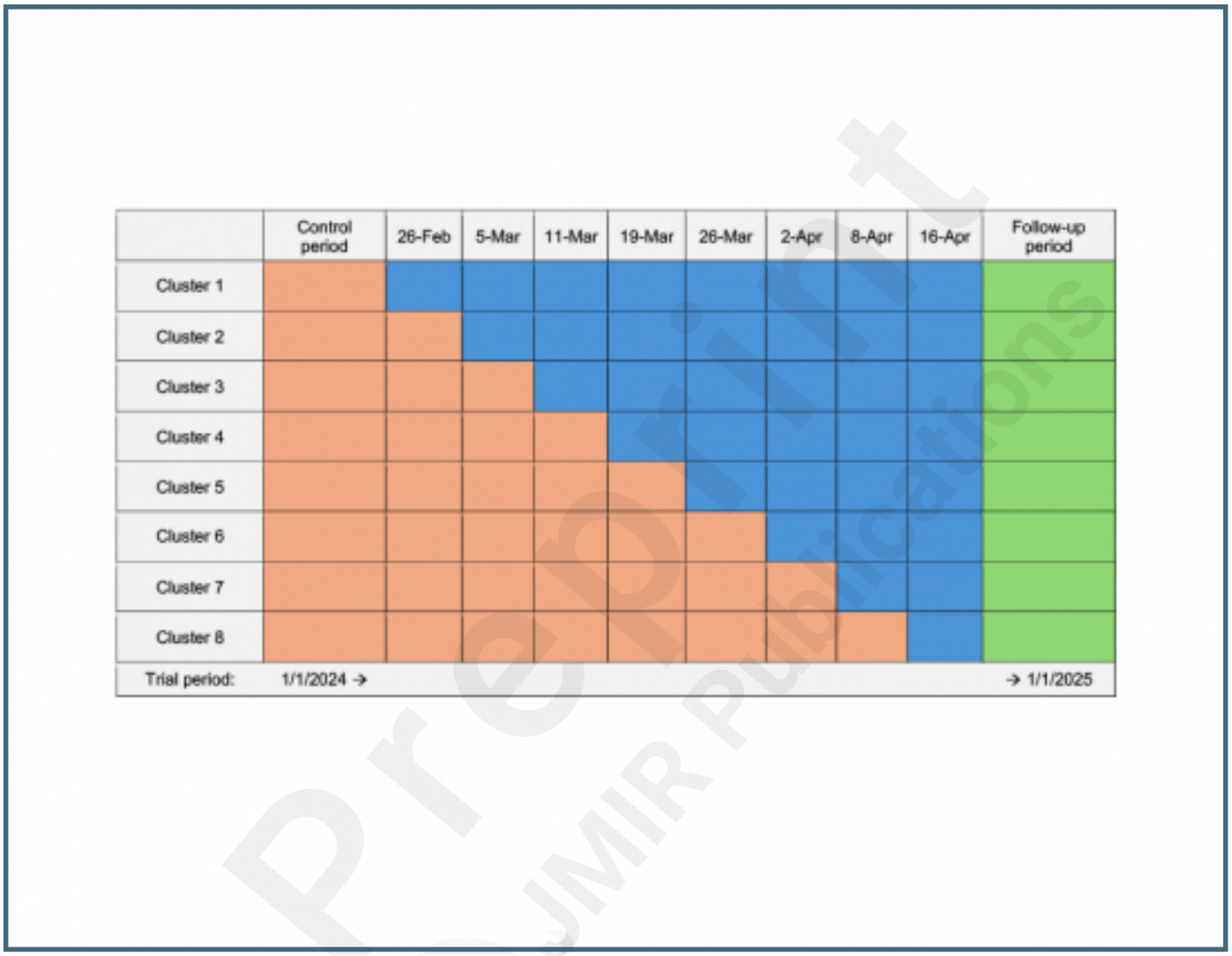
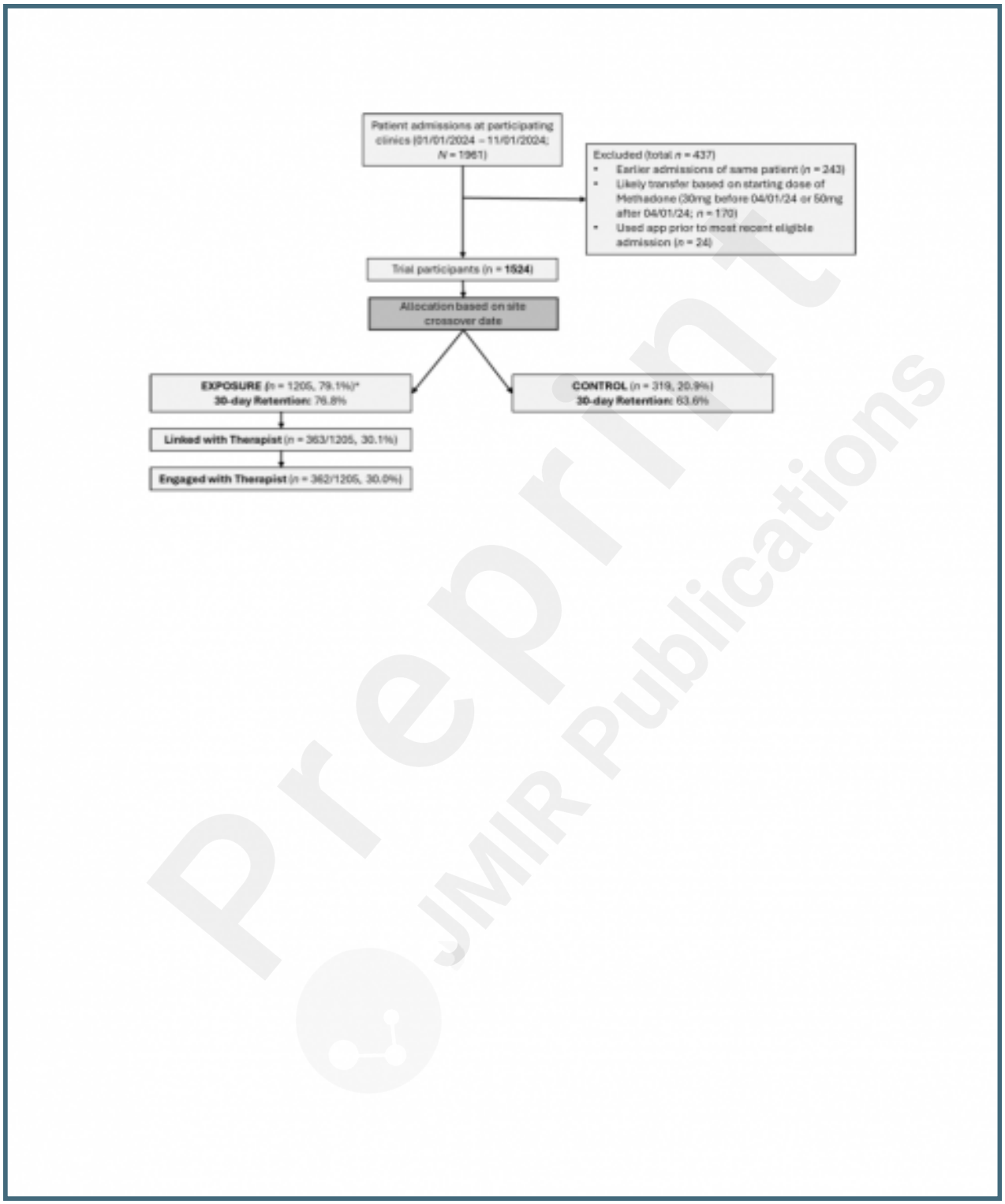
Stepped-wedge crossover design for current study. Colors indicate timed cross-overs within clusters, denoting when MHPs were instructed on app usage and client linkage. Light-orange color indicates Usual Care for MOUD; blue indicates periods following when MHPs were instructed. Note: Follow-up period (green) ended 60 days after the last day of recruitment period (1-Nov-2024) so as to be able to quantify 30-day retention metric for all patients (did a patient begin a 30 day gap in treatment in the first 30 days of admission).



CONSORT diagram. Note: Patients whose clinic crossed over while they were still in treatment were included in the “exposure” allocation.



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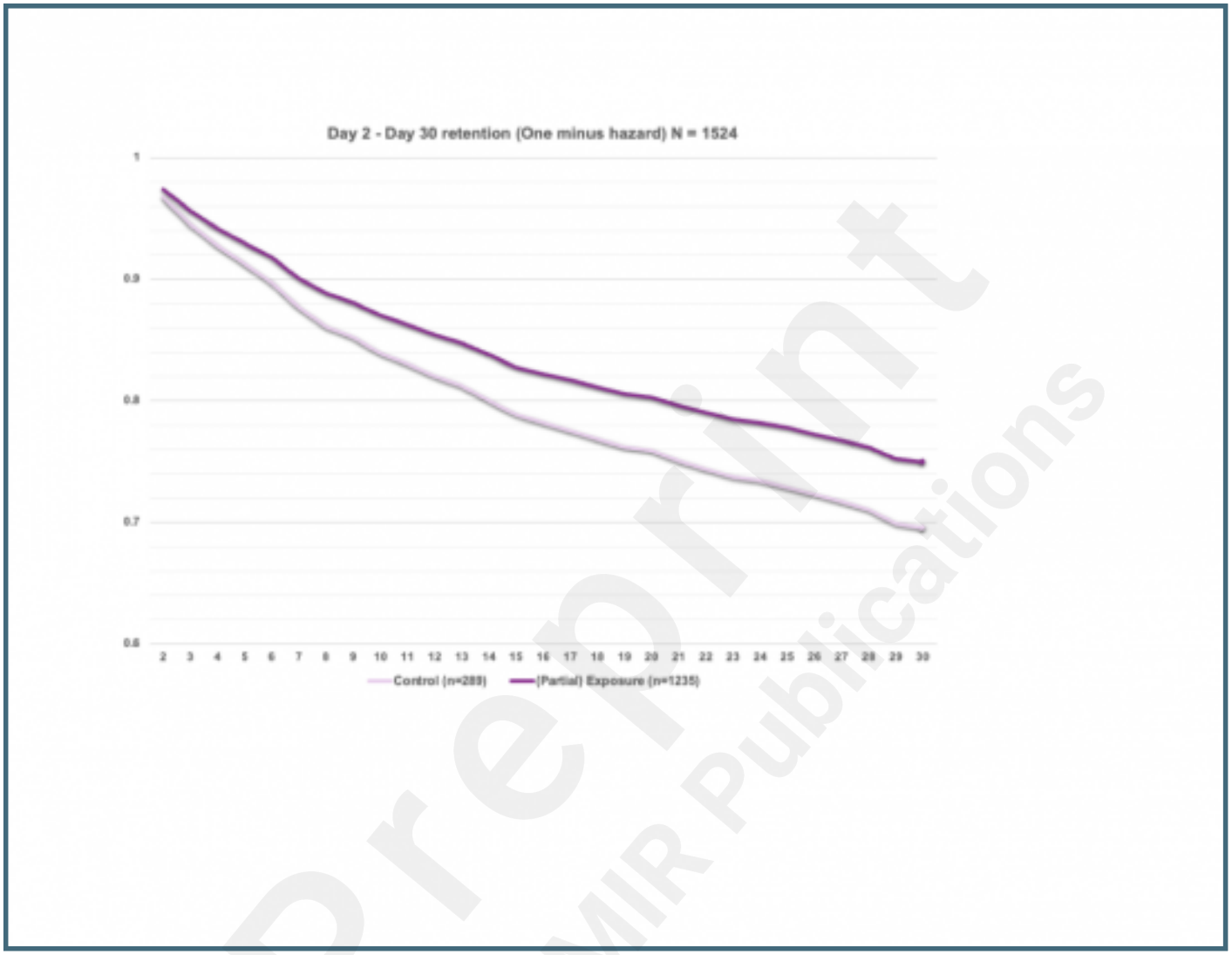
Probability of Retention based on Exposure. Note: Results of Cluster-Controlled Discrete-Time Survival Model predicting probability of loss to follow-up based on prior-day exposure. The absolute difference in estimated 30-day retention is 74.8% (Exposure) - 69.5% (Control) = 5.3%.



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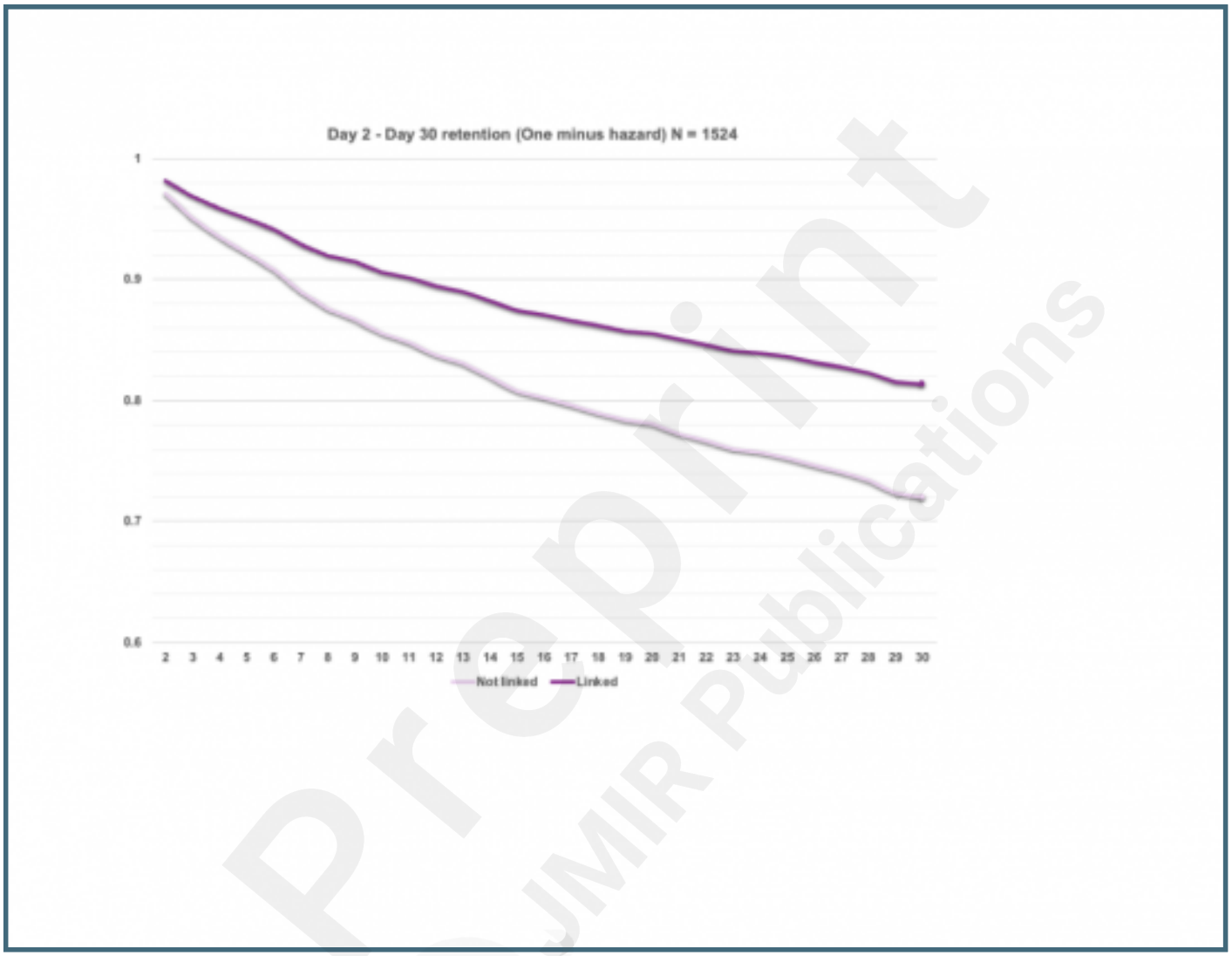
Probability of Retention based on Linkage. Note: Results of Cluster-Controlled Discrete-Time Survival Models predicting probability of loss to follow-up based on prior-day linkage status, among the full sample and among those in the intervention arm. The absolute difference in estimated 30-day retention is 81.3% (Linked) - 72.0% (Not Linked) = 9.3% for the full sample, and 80.9% (Linked) - 73.5 (Not Linked) = 7.4% for the intervention arm. HRs: .63 (loss to follow-up, full sample) and .69 (loss to follow-up, intervention arm).



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Multimedia Appendixes

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Overview of data transformations and statistical considerations for analysis; full code syntax for analyses.
URL: http://asset.jmir.pub/assets/19f0c25877728407c4492e0f7a10f262.docx

Supplementary Tables 1-3.
URL: http://asset.jmir.pub/assets/90b0c36e62ede85940f998dc7650c692.docx

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