Digital Contingency Management for Substance Use Disorder Treatment: A 12-Month Controlled Trial

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Table of Contents

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Abstract

Background: Though contingency management shows its efficacy in substance use disorder treatment, digital contingency management needs more evidence in treating substance use.

Objective: This study aims to evaluate the effectiveness of digital contingency management in treating substance use disorder by examining two key outcome variables: abstinence and appointment attendance.

Methods: A 12-month controlled trial was conducted by enrolling patients into two groups based on the time sequence of program enrollment: one group consenting to participate in the digital contingency management and the other one with no contingency management. Propensity score matching was conducted to match groups on covariates. After matching, t-tests were conducted to examine the difference between groups on urine abstinence and appointment attendance rates.

Results: Two cohorts of propensity-matched patients (66 interventions and 59 controls) were analyzed. Abstinence was significantly higher in the digital contingency management group (mean = 0.92, 95% CI: 0.88–0.96) than in the treatment-as-usual group (mean = 0.85, 95% CI: 0.79–0.90; $p = 0.01$). Appointment attendance also demonstrated significant differences between the groups, with the Digital contingency management group achieving a mean rate of 0.69 (95% CI: 0.65–0.74) compared to 0.50 (95% CI: 0.45–0.55) in the TAU group ($p < 0.001$). This notable increase highlights the role of Digital contingency management in fostering engagement with care, an essential factor for successful treatment outcomes.

Conclusions: The results suggest that digital contingency management can be an effective treatment modality for substance use disorder. Clinical Trial: NA

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Conclusions: The results suggest that digital contingency management can be an effective treatment modality for substance use disorder.

Keywords: digital contingency management; contingency management; substance use disorder; outcome; mobile app; abstinence; appointment attendance

Introduction

Substance Use Disorders (SUDs) are a worldwide public health concern that impacts millions of people and weighs heavily on healthcare systems, families and communities [1,2]. Over the past ten years, substance use problems have been linked to a significant rise in both sickness and death rates globally [3]. Even with the presence of proven treatments, treatment-related attendance and follow-up remain significant barriers to recovery, and the rate of dropout ranges between 20% and 70% for different treatment programs [4,5]. Treatment adherence (i.e., appointment attendance) and continued substance abstinence are two crucial elements that impact the outcome of treatment [6,7]. However, traditional treatment protocols struggle with multiple problems, such as low appointment attendance as well as long-term abstinence and relapse rates [8].

Contingency Management (CM) is one of the most research-validated behavioral treatments to increase abstinence and treatment adherence in SUD treatment [9]. The foundation of CM is operant conditioning, which holds that actions that result in favorable outcomes are more likely to be repeated, whereas actions that result in unfavorable outcomes are less likely to be repeated. CM can be used to address a number of health behaviors, including medication adherence, substance use, weight loss, and quitting smoking. Based on behavioral economics and operant conditioning, this methodology is a systematic offering of material reward or incentive, depending on verified target outcomes like passing drug tests or attending appointments [10]. The efficacy of CM has been consistently shown in meta-analyses for a range of substance use disorders, and in some studies, CM can boost medication adherence, therapy attendance, and abstinence rates [8]. In spite of this solid evidence base, traditional CM implementation has limitations, including excessive administrative overheads, frequent in-person testing of target behavior, cumbersome reward systems, and policy obstacles, such as U.S. federal anti-kickback and beneficiary inducement monetary and criminal sanctions [11].

Prior Work

Digital contingency management (DCM) combines the traditional CM paradigm with digital health tools, which is the next generation of SUD treatment delivery. DCM involves employing remote, technology-based techniques (such as the Internet and smartphones) to track drug status using biochemical sensors (such as breath alcohol and carbon monoxide monitors) and to provide desired outcomes, such as monetary rewards depending on drug abstinence [12,13]. Such online enhancements aren't only efficient at providing contingency management but also offer unparalleled data collection and program optimization.

Digital technologies offer multiple benefits for CM over other forms of implementation. First among these is greater accessibility as digital services transcend geographic boundaries and transportation expenses, especially for patients living in congested urban, rural or underserved communities. Digital platforms remove much of the administrative cost as automated solutions cut staff time compared to manual CM systems while keeping similar verification accuracy rates. In addition, DCM systems' real-time data collection capabilities allow dynamic program optimization: machine learning algorithms can recognize patterns in patient usage and adjust reward schedules to optimize treatment. Data show personalized digital incentives better drive program retention than traditional fixed-schedule solutions [14]. DCM implementations may be affordable, with programs averaging per-patient costs less than CM, with equal or better outcomes.
Even with the promising potential of digital CM, there is still a lack of comprehensive understanding of how it compares to traditional contingency management (CM) methods. Existing literature provides substantial evidence supporting the efficacy of traditional CM in substance use disorder (SUD) treatments, particularly for smoking cessation and alcohol use disorders [15]. However, more research is needed to evaluate its effectiveness in treating drug use. While DCM shows significant potential as an innovative approach, there remains a critical need for robust empirical evidence to validate its efficacy and broader applicability [15].

Study Objectives

CM is underutilized in clinical settings [12]. There is a pressing need to understand the interrelationships between appointment attendance, abstinence outcomes, and DCM interventions [10, 16]. This understanding is crucial for developing more effective, integrated treatment approaches to better support individuals in their recovery journey [17].

In this study, we attempted to fill critical gaps in understanding how well DCM is working in SUD treatment by evaluating its effectiveness on two key outcomes: appointment attendance and abstinence rates. We aimed to identify effective strategies for improving treatment outcomes and provide evidence-based recommendations for enhancing SUD treatment protocols. In particular, we compared a standardized DCM intervention with conventional CM across multiple sites in a time-randomized controlled trial. These results will be part of the scientific evidence base for digital behavioral interventions in SUD treatment and will guide the development of more effective, accessible, and long-term treatment solutions.

Research Questions
1. How does contingency management impact treatment adherence, as measured by appointment attendance?
2. How does contingency management impact treatment outcomes, as measured by substance test abstinence rates?

Methods

Study Design

We ran a 12-month protocol of contingency management in an SUD population seeking treatment in partnership with providers located in the Greater Cincinnati Metropolitan Statistical Area. This experimental design utilized two groups to compare treatment outcomes between a non-CM control group and a CM treatment group. Participants were consented to and assigned to their group based on the time sequence of their enrollment in the program. The study was carried out over a two-year period in 2021 and 2022. DynamiCare Health (Boston, MA) provided the DCM platform. Clients used the DynamiCare Health mobile app on their smartphones to check in to their treatment appointments (verified by GPS) and track the rewards they earned by logging. Rewards were provided on a smart debit card that blocked access to charges in bars, liquor stores, cash withdrawals, and other potential actions that present a risk for relapse.

Procedure

Patients were assigned to groups sequentially. During intake, clinicians described the Digital Contingency Management project. If a patient was interested in participating, they were placed in the treatment group and consented. The next patient would not have the project described to them but would automatically be placed in the control group. This alternating process continued, offering participation in the project to every other patient. The intake coordinator then informed therapists of each patient’s group assignment, and therapists explained the DynamiCare system to those in the experimental group in their second appointment. Participants in the control group were not given any further instructions; they just received treatment as usual. The EHR system documented all treatment events in which the experimental and control groups participated and their medical histories.

Intervention - Digital Contingency Management

Contingency management was delivered via the DynamiCare app. Patients in the treatment group used their own iOS or Android smartphones (or were provided with one if they did not already have one). They were advised to register with DynamiCare and log in to the mobile app. Once in the app, they could access a library of self-guided cognitive behavioral treatment (CBT) lessons. They were assigned tasks to be completed and were issued appointment reminders with directions to the clinic.

In the experimental group, cash rewards were promptly provided for attending scheduled appointments, undergoing urine screening, completing surveys, and completing CBT modules. The system automatically assigned CBT modules to the user patients when they created their accounts, and it recorded negative “weeks since onboarded” as an automatic process from the account creation.

Usually, patients downloaded the app shortly after receiving the invitation, but there were occasions when the user did not access the app for weeks (or at all). Four sites implemented the intervention between 10/16/2020 and 9/13/23.

Participants could earn up to $1,290 in rewards over a 12-month period, with incentives front-loaded during the first three months to foster engagement and a pattern of active effort. During this initial period, participants could earn $200 per month, with the rewards tapering down in subsequent months. Specifically, months 4-6 offered $100 per month, months 7-9 provided $80 per month, and months 10-12 offered $50 per month. The reward structure was voucher-based, with the potential for additional "streak" rewards to be earned within each month.
The rewarded behaviors in the program were structured to evolve over time, focusing on different aspects of participation and engagement. During the first six months, rewards were primarily tied to urinalysis results, which participants were expected to complete on-site twice weekly. In the latter half of the program (months 7-12), the focus shifted to rewarding overall engagement. Participants could also earn rewards throughout the program by completing any 36 CBT modules, each providing a reward of $1-$2, encouraging consistent participation in these therapeutic activities.

Outcome variables

The outcome variables were abstinence and appointment attendance. Abstinence was measured using objective methods, e.g., urine drug screening. Urine test success is measured as the number of negative urine test results or medically consistent results divided by the total number of urine tests logged by providers in their EMRs. A test was marked consistent, or abstinent, if it met medical expectations: negative for illicit substances, with positive results for prescribed substances allowed. Appointment attendance was calculated as the number of attended appointments divided by the total number of scheduled appointments.

Propensity score matching

Propensity score matching (PSM) was used to remove confounding bias [18-22] as our experimental study was only randomized based on the time of program entry. To control for selection bias, we used nearest-neighbor 1:1 matching. A binary logistic regression was used to estimate the propensity score. Variables' association with treatment and outcome, as well as both treatment and outcome, were considered and reported. The variables used in the PS model included gender, race, relationship status, and insurance. Covariate selection was based on prior evidence[23]. This study aimed to estimate the effect of DCM on abstinence and appointment attendance. The challenge in estimating these effects is to plausibly separate them from confounders that might affect patients' outcomes and to isolate those associated with digital CM. PSM was performed to design balanced samples. We selected a treatment group for each patient receiving DCM that had similar observed characteristics at intake. PSM was performed using a 1:1 nearest neighbor matching algorithm with replacement with distances determined by logistic regression using the Stata package PSMatch2. Standardized mean differences (SMD) were used to evaluate the balance between treated patients and matched controls. Before and following matching, this measure is employed to balance the variables [18]. SMD less than 0.2 suggested a reasonable balance for group comparison following matching [21]. Standardized differences between the covariates were in the range of 0.01 -0.08, within the recommended value of less than 0.1, except for gender, which has a moderate imbalance.

Results

Statistical Analysis

Group comparison and linear regression were used to assess the average treatment effect of DCMon abstinence and appointment adherence. Statistical analyses were performed in Stata 18, and 2-sided p < 0.05 indicated statistical significance. P-values for continuous values were calculated using a weighted t-test, and a chi-squared test was used for categorical comparisons. We also conducted the Robustness Check by conducting a sensitivity analysis.

Cohort Characteristics

Table 1 presents the demographic and insurance-related characteristics of the treatment group (N=74) and the control group (N=119) in the unmatched sample. The p-values indicate statistical significance, and standardized differences provide a measure of the imbalance between groups. Females were more prevalent in the treatment group (59.5%) compared to the control group (42.86%). Males were more prevalent in the control group (57.14%) compared to the treatment group (40.5%). With p = 0.025 and SMD = -0.31, there is a significant difference between groups in terms of gender. Race and education exhibit comparable characteristics between the unmatched cohorts. Relationship status shows a moderate imbalance (p = 0.05, SMD = -0.58), while insurance type shows a significant imbalance (p = 0.02, SMD = 0.35).

Table 1. Comparison of characteristics of study cohorts in the original unmatched sample.

		Treatment (N= 74)	Control (N= 119)	P value	Standardized differences
Gender	Female	44 (59.50%)	51 (42.86%)	0.025	-0.31
	Male	30 (40.50%)	68 (57.14%)		
Race	Black	16 (21.62%)		0.37	0.11
	Hispanic or Latino	2 (2.7%)	20 (16.8%)		
	Other Race	2 (2.7%)	3 (2.5%)		
	White	54 (72.97%)	96 (80.7%)		
Education	Associate’s degree	3 (4.05%)	3 (11.11%)	0.74	0.02
	Bachelor’s degree	2 (2.70%)	1 (3.7%)		
	High School Diploma/GED	28 (37.84%)	7 (25.93%)		
	Less than high school	19 (25.68%)	6 (22.22%)		
	Master's degree	1 (1.35%)			
	Some College	16 (21.62%)	8 (29.63%)		
	Unknown	5 (6.76%)	2 (7.41%)		
Relationship	Divorced	7 (9.46%)	5 (8.47%)	0.052	
	In a Relationship	4 (5.41%)			-0.58
	Married	11 (14.86%)	7 (11.86%)		
	Single	50 (67.57%)	38 (64.41%)		
	unknown	2 (2.7%)	4 (6.78%)		
	Separated		5 (8.47%)		
Insurance	Commercial	5 (6.76%)	21 (24.14%)	0.02	
	Medicaid	58 (78.38%)	50 (57.47%)		0.35

	Medicare	9 (12.16%)	11 (12.64%)		
	Not Insured	2 (2.7%)	4 (4.6%)		
	Medicaid/Medicare		1 (1.15%)		
UrineRate	Mean:	0.92 [0.77,1.07]	0.86 [0.71,1.02]		.34
ApptRate	Mean:	0.65 [0.44,0.87]	0.62 [0.39,0.84]		0.43

Table 2 shows the characteristics of unmatched cohorts. After matching, the sample size for the treatment was 66, whereas the sample size for the control was 59. All the characteristics are well-balanced between the matched cohorts.

Table 2. Comparison of characteristics between treated and control subjects in the propensity score matched sample.

		Treatment N=66	Control N=59	p-value	Standardized Difference
Gender	Female	37 (56.06%)	29 (49.15%)	0.44	0.23
	Male	29 (43.94%)	30 (50.85%)		
Race	Black	14 (21.21%)	16 (27.12%)	0.4	0.02
	Hispanic or Latino	2 (3.03%)	(0.00)		
	Other Race	1 (1.52%)	3 (5.1%)		
	White	49 (74.24%)	40 (67.8%)		
Education	Associate's degree	3 (4.55%)	3 (11.11%)	0.79	0.06
	Bachelor's degree	2 (3.03%)	1 (3.7%)		
	High School Diploma/GED	25 (37.88%)	7 (25.93%)		
	Less than high school	16 (24.24%)	6 (22.22%)		
	Master's degree	1 (1.52%)	(0.00)		
	Some College	14 (21.21%)	8 (29.63%)		
	Unknown	5 (7.58%)	2 (7.41%)		
Relationship	Divorced	6 (9.09%)	5 (8.47%)	0.15	
	In a Relationship	1 (1.52%)	(0.00)		0.08
	Married	11 (16.67%)	7 (11.86%)		
	Single	46 (69.7%)	38 (64.41%)		
	Unknown	2 (3.03%)	4 (6.78%)		
		(0.00)	5 (8.47%)		
Insurance	Commercial	5 (7.58%)	4 (14.81%)	0.35	0.03
	Medicaid	50 (75.76%)	21 (77.78%)		
	Medicare	9 (13.64%)	2 (7.41%)		
	Not Insured	2 (3.03%)			
UrineRate	Mean	0.92[0.76,1.09]	0.84[0.64,1.05]		0.34

ApptRate	Mean	0.69[0.5,0.89]	0.49[0.3,0.69]		0.43

Abstinence

After PSM, we conducted t-tests to compare UrineRate between the control and treatment groups for the matched sample of 125 observations (59 controls + 66 treated). Table 3 shows the urine test consistency rate test statistics between the treatment and control cohorts. This suggests that the treatment intervention likely had a positive impact on urine rate outcomes. The urine test abstinence rate, as indicated by the urine rate, was significantly higher in the DCM group (mean = 0.92, 95% CI: 0.88–0.96) than in the CAU group (mean = 0.85, 95% CI: 0.79–0.90; p = 0.01).

Table 3. T-test results after matching

	Group	Obs	Mean	Std.Dev	95% CI	P value
UrineRate	Control	59	0.85	0.21	(0.79 , 0.90)	0.01
	Treatment	66	0.92	0.16	(0.88 , 0.96)	
ApptRate	Control	59	0.50	0.20	(0.45 , 0.55)	0
	Treatment	66	0.69	0.19	(0.65 , 0.74)	

Appointment Attendance Rate

Table 3 shows the appointment attendance rate statistics between the treatment and control cohorts. The appointment adherence rate was substantially higher in the DCM group (Mean = 0.69, 95% CI: 0.65–0.74) than in the TAU group (Mean = 0.50, 95% CI: 0.45–0.55), with an even stronger statistical significance (P < 0.001).

Sensitivity analysis

Stata's mhbounds command implements Rosenbaum bounds for sensitivity analysis. It evaluates how much-unobserved confounding would change the significance of the treatment effect. The treatment effect for UrineRate is robust to unmeasured confounding within the tested range of Γ\GammaΓ (1 to 2). Even with significant hidden bias (Γ=2\Gamma = 2Γ=2), the estimated treatment effect remains statistically significant and consistent.

The treatment effect for both urine rate and appointment attendance rate remains statistically significant (sig+ and sig- near 0) even at high levels of bias (Γ=3\Gamma = 3Γ=3). The treatment effect (t-hat) decreases slightly as bias increases but remains meaningful within the tested range (Γ≤3\Gamma \leq 3Γ≤3). The intervals for the treatment effect remain relatively narrow and meaningful, even under extreme bias assumptions. The treatment group outperformed the control group in both the urine and appointment attendance rates. The differences are statistically significant for both measures (p-values < 0.05), with the treatment group showing better outcomes. This implies that the treatment intervention was likely effective in improving both urine test abstinence and appointment attendance. (See supplement tables S1 and S2.)

Discussion

Principal Results

Our study aimed to evaluate the effectiveness of DCM in comparison to TAU for individuals with

SUD. The findings reveal statistically significant differences in both urine test abstinence and appointment attendance among participants in the DCM group compared to the TAU group. Patients in the DCM group showed higher urine abstinence rates (92% vs 85%, p=0.01) and substantially better appointment attendance rates (69% vs 50%, p<0.001). These results align with a previous study by [24], who found that digital health interventions can effectively enhance medication adherence among individuals with opioid use disorder (SUD). Also, DeFulio et al. [14] found that inner-city SUD patients who were mostly treated with buprenorphine and the DynamiCare app showed significantly higher rates of treatment attendance in study months 2 to 4 (9.6% –18.0% increases) and odds ratio of 4.84 for greater drug abstinence and medication adherence, vs. TAU controls at 120 days (P < 0.05). These results highlight the potential of DCM as an innovative intervention for improving key treatment outcomes in SUD care. Our findings extend the existing literature on traditional contingency management approaches and contribute to the much-needed evidence on the efficacy of DCMon drug treatment, supporting the broader transition toward digital therapeutic interventions in addiction treatment [12].

These results suggest that integrating digital tools into contingency management can enhance both treatment abstinence and engagement in care, consistent with prior studies highlighting the promise of digital interventions in substance use treatment [10,14]. This finding suggests that DCM interventions are effective in promoting abstinence, a critical metric in SUD treatment. Digital networks could be more accessible, timely, and individualized; therefore, they are more likely to be adhered to for urine testing. Such gains align with previous findings on contingency management's efficacy in motivating behavior change. Mobile apps can better communicate between the care team and the patients, and could potentially save lives [25].

A 19% increase in appointment attendance with DCM is clinically meaningful, consistent with prior findings on digital interventions on treatment adherence [26]. This increase highlights the role of DCM in fostering engagement with care, an essential factor for successful treatment outcomes. By leveraging digital tools to deliver incentives and reminders, DCM may reduce barriers such as forgetfulness or logistical challenges, thus encouraging consistent participation in scheduled appointments [27]. Compared to patients who chose SUD alone, those who selected SUD with app-based CM had a noticeably higher chance of remaining in treatment for longer [28]. These results corroborate earlier research concluding that receiving rewards motivates patients to maintain treatment compliance [10].

The digital platform's prompt reinforcement, lower obstacles to incentive receipt, and fewer infrastructure barriers may benefit attendance rates. Urban-rural disparities exist in CM availability [29]). Digital interventions expand access to a broader patient population [30, 31], suggesting DCM could help reduce this disparity. DCM interventions align with behavioral reinforcement principles, for example, by providing timely rewards for desirable behaviors, enhancing adherence, and reducing substance use [10]. Furthermore, the convenience and accessibility of digital platforms likely played a role in maintaining higher engagement rates. According to earlier studies, digital interventions lessen logistical obstacles to participation, like schedule conflicts and travel time, which are frequent problems in conventional therapy settings. The results support these views, which highlight digital CM's capacity to remove important obstacles and encourage long-lasting behavioral improvements in SUD populations [14].

Limitations

Despite these promising findings, certain limitations warrant consideration. First, the study did not explore differences in outcomes across social determinants of health. Future studies will explore the efficacy of DCMon SUD treatment relative to educational level, economic stability, transportation availability, etc. Nevertheless, our sample's high proportion of Medicaid and non-commercial insureds suggests that patients at risk from SDOH challenges may benefit. Second, the study may have excluded individuals less familiar with digital technology. This digital divide may disproportionately affect certain demographic groups, such as older adults or those from lower socioeconomic backgrounds, potentially limiting the generalizability of the findings to all individuals with SUD. However, the front-loading of rewards is designed to motivate patients to overcome tech unfamiliarity. Third, the study focused on outcomes, specifically drug abstinence and appointment adherence, during the intervention. While these measures are critical indicators of treatment success, the study did not assess the sustainability of behavior changes following the conclusion of the intervention. The 12-month duration of the study, however, exceeds that of many prior trials. Future studies should incorporate extended follow-up periods to evaluate the durability of the observed effects and explore the need for continued reinforcement strategies to maintain engagement and adherence over time. Additionally, the variability observed within the appointment and urine rates suggests that individual differences, including socioeconomic status, comorbid conditions, and digital literacy, may affect treatment outcomes. Future research should explore these contextual factors to identify and address potential barriers to successful implementation.

Conclusions

This article supports the validity of digital contingency management as an intervention to improve treatment adherence and outcomes for people with SUD. For the DCM group, urine test abstinence and appointment attendance were significantly higher than in TAU recipients. These results also show that technology-enabled interventions can improve patient engagement. The findings could provide additional support for policymakers in making policies that reimburse digital contingency management as a viable treatment option.

Abbreviations

CM: contingency management
DCM: contingency management
SUD: substance use disorder
TAU:treatment-as-usual
PSM: Propensity score matching
CBT: cognitive behavioral treatment

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