Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Are We Ready for Machine-Led Healing Process? AI Vs Human Touch in Addiction Recovery

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

This study examined how an AI chatbot for Cognitive Behavioral Therapy (CBT) can impact Motivation for Change and Self-Efficacy in Alcohol Use Cessation. Participants were divided into two groups, one received standard addiction treatment, while the other received both the standard treatment and intervention from the AI-CBT chatbot. The results showed no significance in readiness to change in the group using the chatbot ($Z = -0.540$, $p = .589$), as well as compared to the control group ($U = 184$, $p = .619$). On the other hand, self-efficacy did see a significant boost over time ($F(1, 38) = 11.09$, $p = .002$). This shows that while both groups improved, the participants did benefit from the treatment, highlighting how helpful structured support can be during recovery. There wasn't a big difference between the time and group ($p = .798$), which suggests that the overall treatment setup might boost self-efficacy more than just the chatbot. Qualitative analysis revealed AI chatbot reliable and helpful in the recovery of the participants especially for people who are apprehensive in seeking treatment for the fear of stigmatization where AI chatbots can be useful in such cases, however they also reported the lack of emotional warmth and personal connection, making it hard to feel fully engaged. The research highlights how AI can be useful in therapy. It's not about replacing human connection rather; it's a tool that helps with recovery while still valuing real relationships. AI can be a great support in places like rehabilitation centres where routines are a big part of healing. This study helps us understand digital mental health better, showing that mixing technology with human care might be the future of Addiction Rehabilitation.

Keywords: *Addiction, Cognitive Behavioral Therapy, Self-Efficacy, Readiness to Change, AI, Structured Support, Chatbot, Qualitative, Addiction Rehabilitation*

INTRODUCTION

Substance use, including alcohol and nicotine, poses significant challenges to individuals attempting cessation. One of the primary concerns in substance use recovery is the level of motivation for change and the individual's self-efficacy in resisting substance use. Motivation for change is essential in initiating and sustaining behavioral modifications, while self-efficacy plays a crucial role in relapse prevention and long-term abstinence.

With advancements in digital interventions, AI-driven Cognitive Behavioral Therapy (CBT) chatbots have emerged as potential tools for enhancing psychological support in substance use cessation. AI chatbots provide immediate, accessible, and structured interventions, helping individuals regulate their thoughts, emotions, and behaviors related to substance use.

This study aims to assess the effectiveness of an AI CBT chatbot in enhancing motivation for change (measured using the Readiness to Change Questionnaire - RCQ) and self-efficacy (measured using the Alcohol Abstinence Self-Efficacy Scale - AASES) among individuals attempting to quit alcohol.

In Sikkim, 45% of males and 19% of women over 15 reported using alcohol in NFHS-3 (2005-06), compared to 32% and 17%, respectively, in NFHS-2 (1998-99) (International Institute for Population Sciences [IIPS] & ORC Macro, 2007). These numbers are significantly higher than the national average, which is 2% for women and 32% for males (IIPS & ORC Macro, 2007). For men, alcohol consumption increased from 32% (NFHS-2) to 45% (NFHS-3) but slightly declined to 41.8% (NFHS-5). For women, alcohol consumption was 17% (NFHS-2), peaked at 19% (NFHS-

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

3), and later dropped to 16.2% (NFHS-5). This data suggests a fluctuating trend, with a peak in NFHS-3, followed by a slight reduction in NFHS-5, though the rates remain much higher than the national average.

Males (93.8%) outweighed females (6.2%), according to a study by Pandey et al. (2015). The majority of the sample fell into one of two groups: those who dropped out of school or those who finished school (36.1%). The majority of the samples were urban dwellers, unemployed in their line of work, Nepali by ethnicity, unmarried, and Hindu (48.5%). The minimum ages to begin using drugs and alcohol were seven and five years old, respectively.

Bandura (1977) used the term self-efficacy to explain in Social Cognitive Theory an individual's faith in his/her ability to perform the behaviors necessary to meet specific goals. Self-efficacy is of central concern in alcoholism treatment because it dictates whether an individual can effectively reduce or abstain from alcohol consumption, resist cravings, and remain abstinent in the long term. Although low self-efficacy often leads to feelings of powerlessness and a greater likelihood of relapsing into alcohol consumption, high self-efficacy is associated with increased resilience against the stimuli for relapse. The most challenging parts of treating alcoholism despite access to treatment programs is maintaining motivation over time.

Relapse is common in alcohol treatment, and individuals may resume old drinking patterns if they are not provided with continued support. Personal motivation, external support, and therapeutic counseling are often necessary for long-term change. Strategies such as contingency management (Higgins et al., 1991), peer support networks (such as Alcoholics Anonymous), and cognitive-behavioral therapy (Marlatt & Donovan, 2005) can supply the framework and encouragement needed to maintain success. Based on the Cognitive-Behavioral Model of Relapse of Marlatt and Gordon (1985), self-efficacy is a significant determinant of an individual's capacity to sustain behavior change.

Individuals with high self-efficacy tend to perceive difficult situations as challenges to be overcome and not as threats, and this makes them more resilient in trying to abstain from alcohol. Conversely, individuals with low self-efficacy will question their capability to cope with stress or pressures from social situations when they are sober, increasing the likelihood of relapse. This indicates the importance of enhancing self-efficacy for alcohol treatment programs. ChatGPT really changed how we interact with AI. Now, we can have natural, everyday conversations with chatbots for fun, help, or just support. These days, millions of people are turning to AI for one of the most personal things out there: therapy. The reason is simple, it is because there just aren't enough therapists to go around, and more people need their help. These AI bots aim to fill that gap by offering affordable or even free mental health support. The reason so many are looking for easy, big-scale solutions is because mental health issues are on the rise worldwide, and there aren't enough trained professionals to meet the demand (WHO, 2021).

Overcoming alcohol is not for the faint of heart and a lot of will power is required to make a change. Internal and external sources, including self-awareness, social support, and strategically planned interventions, can motivate individuals. Behavior change models such as the Self-Determination Theory (Deci & Ryan, 2000) and the Transtheoretical Model (Prochaska & DiClemente, 1983) explain the reasons that people are motivated to reduce or abstain from alcohol consumption.

According to recent research, opinions on the usefulness and appropriateness of AI in therapeutic settings are divided between clients and physicians. While some see AI as a useful supplement to conventional treatment, others worry that it could compromise the fundamentally human aspect of psychotherapy. Exploring professional and public perceptions of AI in therapy is crucial as this discipline develops, especially with regard to its perceived efficacy, reliability and future possibilities.

RELATED WORK

Aggarwal et al. (2023) conducted a meta-analysis over seven bibliographic databases wherein empirical papers published within the time frame of 1980 to 2022 were sourced to explore the efficacy or relevance of AI chatbots in terms of behavioral change. Some of the 15 studies included demonstrated effectiveness on the part of AI chatbots in promoting healthy lifestyles, smoking cessation, adherence with treatment regimen, or medications, and substance abuse reduction. However, the findings expressed inconsistencies in usability, acceptability, and feasibility. Data about preferences and behavioral performance from the real-time interaction of users with chatbot services will be collected into the chatbot platform to find out how to personalize services.

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https://www.jisem-journal.com/ **Research Article**

Fulmer et al. (2018) offered a randomized controlled trial of a sample of 75 subjects selected from 15 colleges across the United States. All participants filled several Web-based questionnaires at baseline and again two-four weeks later (T2): Positive and Negative Affect Scale (PANAS), Generalized Anxiety Disorder Scale (GAD-7) and Patient Health Questionnaire (PHQ-9). The 50 participants were divided into two experimental groups, which were randomized to receive unlimited Tess access for either two weeks (n=24) or four weeks (n=26). In the information-only control condition (n=24), participants were provided with an electronic link to the National Institute of Mental Health (NIMH) eBook on depression among college students and were not given any access to Tess until after the trial was completed. The findings from this study demonstrate the capacity of AI to act as a cost-effective, ever-present treatment. Integrative psychological AI provides a potential alternative for these subjects, though it was never meant to replace the role of a licensed therapist.

Among their study, Lee et al. (2024) performed systematic review by surveying 28 papers on the chatbot-assisted treatment of substance use disorders retrieved from a pool of nearly 1000 references. The review indicated that therapeutic interventions were the design intention of over 85% of the chatbot programs, with much fewer targeting assessment or prevention. Thus, only around 18% of the studies have been implemented specifically targeting alcohol use; the other half has focused primarily on tobacco, and a better concerted effort is warranted across other substances. The other half of the studies assessed was, thus, directed specifically toward smoking cessation; roughly 18% to address alcohol alone; 7% to address methamphetamine alone; while the rest either assessed multiple substances or were simply more generalized in their scope. Another small fraction of these interventions focused on prevention or assessment; more than 85% were designed with a therapeutic purpose. Various researchers have also studied the opportunities and limitations of chatbot interventions. For example, Moberg et al. (2022) conducted pilot research to evaluate the usability of the AI chatbot "Be Well Buddy," designed to support substance use disorder screening and treatment referrals. The study found that users mostly rated the chatbot as easy and useful for SUD information, although the study was more properly described as a feasibility/usability study and not as a full-scale efficacy trial.

Meta-analyses and systematic reviews demonstrate that digital treatment tools such as chatbots and text messaging effectively support substance use treatment by delivering continuous care regardless of time or location constraints. The field needs longer-term follow-ups to assess sustained impacts and relapse prevention while calling for broader study populations and more exacting research methods to progress from its current early development stage. Technical assessments together with in-depth user interaction research and ethical considerations about algorithmic bias and data privacy need to be included for continued advancement in the field of study.

METHODS

Sample

A priori power analysis was performed using G*Power 3.1.9.7 to determine the required sample size for the present study. The analysis was conducted for an ANOVA: Repeated measures, within–between interaction, assuming a medium effect size (f = 0.30), based on Cohen's (1988) guidelines. The standard alpha level was set at .05, and a desired power of .95 was specified to reduce the probability of a Type II error.

The analysis included 2 groups, 2 measurement points, a correlation among repeated measures of 0.5, and nonsphericity correction set to 1. Based on these parameters, the power analysis indicated that a total sample size of 40 participants would be sufficient to detect a statistically significant interaction effect. This yielded a noncentrality parameter λ of 14.40, critical F value of 4.10, and an actual power of 0.9588.

Sample Inclusion Criteria:

1. Individuals with a history of alcohol abuse, as identified through self-report, family referral, or recommendation by rehabilitation center staff.
2. Individuals who have expressed intent to quit or reduce alcohol consumption.
3. Individuals with basic English reading ability (to interact with the chatbot).

Sample Exclusion Criteria:

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2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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1. Individuals with a clinical diagnosis of substance dependence requiring medical detoxification or intensive inpatient care.
2. Have any other diagnosed mental disorders or co-morbid conditions that could interfere with the intervention.

Hypotheses

• H1: Participants receiving standard addiction treatment along with the AI CBT chatbot intervention will demonstrate significantly greater self-efficacy in resisting substance use compared to those receiving only standard addiction treatment.

• H2: Participants receiving standard addiction treatment along with the AI CBT chatbot intervention will exhibit significantly higher motivation for change compared to those receiving only standard addiction treatment.

Tests and Tools

The study used standardized psychological tools used to assess key variables in the study. As in concordance to the research interests, the samples were assessed with means of the following measures:

Alcohol Abstinence Self-Efficacy Scale (AASE)

Carlo C. DiClemente, Lisa A. Carbonari, Holly A. Montgomery, and Susan O. Hughes created the Alcohol Abstinence Self-Efficacy Scale (AASE) in 1994 to assess a person's confidence in their capacity to withstand the temptation to consume alcohol in a range of high-risk circumstances. The AASE is one of the most popular tools for assessing abstinence self-efficacy in people receiving treatment for alcohol use disorders. It is based on Bandura's theory of self-efficacy and the relapse prevention principles. The scale measures self-efficacy in four major domains: Craving and Urges, Physical and Other Concerns, Social/Positive Situations, and Negative Affect. It comes in both long (40 items) and short (20 items) versions. Respondents are asked to score how confident they are in their ability to refrain from drinking on a likert scale: Not at all confident, Not very confident, Moderately confident, Very confident and Extremely confident. Initial validation research in outpatient populations (n = 266) showed good test-retest reliability and ideal internal consistency, with subscale Cronbach's alpha values exceeding 0.90. Strong relationships between relapse outcomes, temptation ratings, and self-efficacy scores supported concurrent and construct validity.

Readiness to Change Questionnaire

Stephen Rollnick and Nick Heather (1993) created the Readiness to Change Questionnaire (RCQ) using the Transtheoretical Model of behavior change as a guide. This model describes the three stages of change i.e, Precontemplation, Contemplation, and Action, that people usually go through while trying to change behaviors like substance use. Researchers can determine a person's present stage by using the RCQ, which includes of measures that reflect attitudes and intentions toward behavior change. Every item is worded to correspond with a particular stage of change; for instance, the Precontemplation stage is represented by comments like "I don't think I drink too much," while the Action stage is represented by words like "I am trying to stop drinking." The responses are based on a likert scale ranging from Strongly Disagree, Disagree, Unsure, Agree and Strongly Agree. According to a study examining predictive validity among 174 male excessive drinkers, changes in alcohol consumption at 8 weeks and 6 months after discharge were strongly predicted by RCQ stage classification. Even after adjusting for other variables, regression models demonstrated that RCQ scores were still significant predictors. The reliability and factor structure of the RCQ were confirmed by recent psychometric analyses.

Character AI Chatbot

The intervention tool employed in this study was an artificial intelligence (AI)–based chatbot titled CBT Therapist, accessed through the Character.AI platform. Character.AI is an interactive online platform that enables users to engage in human-like conversations with AI-generated characters, ranging from fictional personas to those modeled after professional roles, including therapists and counselors.

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Character.AI was founded in 2021 by Noam Shazeer and Daniel De Freitas, both of whom were previously researchers at Google and co-creators of foundational AI architectures, including the Transformer model, which underpins most contemporary natural language processing systems. The platform leverages large language models (LLMs) to simulate dynamic, responsive, and contextually coherent dialogue, allowing users to receive personalized interaction in real time.

Design and Procedure

The study design adopted a sequential mixed method including both a quantitative and a qualitative research design with quasi-experimental and narrative case study approach. It was done following a pre-test/post-test control-group format. The Readiness to Change Questionnaire (RCQ) and the Alcohol Abstinence Self-Efficacy Scale (AASES) were the standardized instruments used for evaluation of the participants.

After conducting baseline measures, the intervention group received standard treatment for addiction supplemented with group therapy of AI-based Cognitive Behavioral Therapy (CBT) chatbot for eight sessions within four weeks. The control group did not benefit from the AI chatbot and, instead, received only the standard rehabilitation. After four weeks, both groups were reassessed via the same measures (RCQ and AASES) in order to record any changes within self-efficacy and motivation to change. To get a better sense of how participants felt about their experiences, two people from the intervention group were selected for qualitative case study analysis. Their narratives provided valuable insights that numbers alone couldn't show, especially when it came to their emotions and motivations. Mixing these two approaches helped us understand the real benefits of using the AI chatbot in alcohol rehabilitation.

RESULTS AND DISCUSSION

Quantitative Approach

The findings of the statistical analysis of the quantitative data are covered in this section. The data below were analyzed using SPSS version 25.

Descriptive Statistics

The study had 40 individuals who were receiving alcohol treatment at a rehabilitation facility. Pre-test and post-test measures of self-efficacy and readiness to change scores were completed by every participant. Table 1 displays the descriptive statistics.

Table 1 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Self-Efficacy Pre	40	1.00	4.58	3.01	.74
Self-Efficacy Post	40	1.33	3.58	2.53	.47
Readiness to Change Pre	40	1.00	3.00	2.27	.64
Readiness to Change Post	40	1.00	3.00	2.32	.57
Valid N (listwise)	40				

The data indicates that the mean self-efficacy score was 3.01 (SD = 0.75) prior to the intervention and decreased to 2.53 (SD = 0.47), following the intervention. The RCQ Stages of Change scale was also used to record readiness to change scores both before and after the intervention. The pre-test mean score for readiness to change was 2.28 (SD = 0.64), while the post-test mean score increased marginally to 2.33 (SD = 0.57). Before doing inferential statistical analyses, these values offer a summary of the data's central tendencies and dispersion.

Repeated Measures ANOVA

A repeated measures ANOVA was performed using time (pre-test vs. post-test) as the within-subjects component and group (intervention vs. control) as the between-subjects factor in order to assess the impact of the AI-based CBT intervention on participants' self-efficacy over time as shown in Table 2 and 3.

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e-ISSN: 2468-4376
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Table 2 Within-Subjects Effects Summary for Self-Efficacy

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	4.67	1	4.67	11.09	.002
	Greenhouse-Geisser	4.67	1	4.67	11.09	.002
	Huynh-Feldt	4.67	1	4.67	11.09	.002
	Lower-bound	4.67	1	4.67	11.09	.002
time * Group	Sphericity Assumed	.02	1	.02	.06	.798
	Greenhouse-Geisser	.02	1	.02	.06	.798
	Huynh-Feldt	.02	1	.02	.06	.798
	Lower-bound	.02	1	.02	.06	.798
Error(time)	Sphericity Assumed	16	38	.42		
	Greenhouse-Geisser	16	38	.42		
	Huynh-Feldt	16	38	.42		
	Lower-bound	16	38	.42		

Table 3 Between-Subjects Effects for Self-Efficacy

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	615.12	1	615.12	1676.98	.000
Group	.67	1	.67	1.83	.184
Error	13.93	38	.36		

The within-subjects effect tests are shown in Table 2. Time was found to have a statistically significant main effect, $F(1, 38) = 11.09$, $p = .002$. This suggests that all participants' self-efficacy levels, irrespective of group, changed significantly from the pre-test to the post-test. The time × group interaction effect, however, was not statistically significant $F(1, 38) = 0.06$, $p = .798$. This implies that there was no discernible difference between the intervention and control groups' changes in self-efficacy over time. Table 3 indicates that the group's main effect was likewise not significant $F(1, 38) = 1.83$, $p = .184$. This suggests that, when averaged across time, there was no discernible difference in the self-efficacy levels of the intervention and control groups.

H1: Participants receiving standard addiction treatment along with the AI CBT chatbot intervention will demonstrate significantly greater self-efficacy in resisting substance use compared to those receiving only standard addiction treatment.

Compared to those who would get only normal addiction treatment, Hypothesis 1 proposes that those receiving both normal addiction treatment and AI-based CBT chatbot intervention would have higher self-efficacy levels for resisting substance use. The repeated measures ANOVA results showed that there was a significant main effect of time ($F(1, 38) = 11.09$, $p = .002$), indicating that, generally, self-efficacy levels improved prior to and subsequent to the intervention. However, it seems that within-group comparisons of self-efficacy change from pre- to post-intervention occurred in both the intervention and the control group and not to a much greater extent in the intervention group, and because the interaction between time and group was not statistically significant ($p = .798$). With respect to the substantial increase in self-efficacy over time, although the hypothesis was only partially confirmed, this agrees with the theoretical view of self-efficacy as a dynamic construct affected by environmental, behavioral, and cognitive factors (Bandura, 1977, 1986). Participation in a structured rehabilitation environment may itself enhance an individual's sense of control and competence over time. Research shows that such structured treatment settings can inherently promote self-efficacy, particularly through consistent routines, therapeutic guidance, and peer support (Moos, 2007). Moreover, findings from similar digital health studies suggest that AI and web-based CBT programs are more likely to reinforce coping strategies than create motivational breakthroughs on their own (Sundström et al., 2020; Riper et al., 2018).

Again, this is not a limitation, but a reflection of a core therapeutic truth: the significant increase in self-efficacy among all participants supports the idea that therapeutic progress can occur as a result of being in a structured, substance-free, and professionally guided environment. Bandura (1977, 1986) emphasized that self-efficacy is shaped by experiences, feedback, and the mastery of coping skills, all of which are present in a rehabilitation setting. These results align with previous research indicating that rehabilitation programs themselves can foster increased confidence in one's ability to resist relapse (Moos, 2007). The finding that both groups improved reinforces the effectiveness of such programs, regardless of digital augmentation.

Further, the tool used in this study, the Alcohol Abstinence Self-Efficacy Scale (DiClemente et al., 1994), measures confidence in dealing with different high-risk situations like emotional distress, social pressure, and physical discomfort. It is possible that therapeutic content was presented to participants and regardless of the intervention condition, that exposed them to therapeutic content that was strengthening their perception of their ability to deal with these circumstances. The increase in general self-efficacy supports literature existing on the fact that even short courses or moderate-strength psychological therapies can develop self-efficacy and coping processes, although the findings do not demonstrate significant extra benefits given by the AI-based CBT session. However, Boness et al. (2023) pointed out in the review that higher frequency and greater customization of CBT are aspects that could be limited in a self-guided chatbot model. In conclusion, such results lend some support to Hypothesis 2: over time, self-efficacy, in line with theoretical and empirical approaches, has seen some increase. AI-CBT chatbot might benefit from more time on task, more interaction, or deeper personalization to achieve stronger results than those provided by conventional treatment alone, as evidenced by the similar affect of intervention and control groups.

Non-Parametric Statistics

Since the readiness to change variable was measured on an ordinal scale, non-parametric tests were conducted to assess group differences as shown in Table 4 to 7.

Table 4 Wilcoxon Signed Ranked Test for Readiness to Change

Source	Readiness to Change Post
Mann-Whitney U	184
Wilcoxon W	394
Z	-0.497
Asymp. Sig. (2-tailed)	0.619

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2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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Exact Sig. [2*(1-tailed Sig.)]	.678b

Table 5 Test Statistics for Wilcoxon Signed Ranked Test

Source	Readiness to Change Pre – Readiness to Change Post
Z	-.540b
Asymp. Sig. (2-tailed)	.589

Table 6 Mann Whitney U test for Readiness to Change

Source	Group	N	Mean Rank	Sum of Ranks
Readiness to Change Post	Intervention	20	21.30	426.00
	Control	20	19.70	394.00
	Total	40		

Table 7 Test Statistics for Mann Whitney U Test

Ranks		N	Mean Rank	Sum of Ranks
Readiness to Change Post – Readiness to Change Pre	Negative Ranks	5a	4.50	22.50
	Positive Ranks	5b	6.50	32.50
	Ties	30c		
	Total	40		

The Wilcoxon Signed Ranks Test was used to examine participants' readiness to change scores before and after the test. The findings were not statistically significant, as indicated by Tables 4 and 5 ($Z = -0.54$, $p = .589$). This implies that the readinesses to change scores of the same subjects were not substantially altered by the intervention. A Mann-Whitney U Test was used to evaluate post-test differences in readiness to change between the intervention and control groups. The two groups' differences were not statistically significant ($U = 184$, $p = .619$), as Tables 4 and 5 demonstrate. This suggests that the AI-based intervention did not result in significantly different readiness to change scores when compared to the control group.

- *H2: Participants receiving standard addiction treatment along with the AI CBT chatbot intervention will exhibit significantly higher motivation for change compared to those receiving only standard addiction treatment.*

Participants who would receive both the AI-based CBT intervention and standard treatment for addiction, according to Hypothesis 2, would be significantly more willing to change than those who would only receive standard treatment. These findings contradicted this hypothesis, however. No significant differences existed from pretest to posttest in within-group Wilcoxon Signed Rank Test records of readiness to modify scores from the intervention group ($Z = -0.540$, p .589). After the Mann-Whitney U Test, posttest differences between the intervention and control groups had borne no significant effects: $U= 184$, $p = .619$. Collectively, these findings

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suggest that the AI-CBT chatbot intervention has not led to shifts in motivation toward change compared to standard treatment alone. The results reflect the reality that while CBT is effective in many areas of substance use treatment (Magill et al., 2019), its short-term digital delivery may not be sufficient to induce immediate motivational shifts in complex environments such as residential rehab.

While this may appear to challenge the hypothesis, but these results really shed light on how ready people are to change and the role of digital tools in therapy. The lack of a strong effect is actually important: it suggests that AI-based interventions, especially short and uniform ones, work better as support tools rather than being the main drivers of change.

Particularly relevant to that effect might be the theoretical background of the Readiness to Change Questionnaire (RCQ), which has a foundation in the Transtheoretical Model of Change by Prochaska & Diclemente in the year 1983. It describes that there are certain stages an individual travels through during the time they make a change regarding addictive behavior: precontemplation, contemplation, and action. Short-term interventions can mobilize awareness and reflection but it usually takes a while, repetitional support, and much more substantial cognitive restructuring before movement across those stages becomes a reality. Although the RCQ has been demonstrated as valid measure of these stages (Heather & Rollnick, 1993), it is sensitive to situational factors including perceived expectations and external motivation, especially within institutions. In rehabilitation settings where participation in treatment may be mandated or encouraged, motivational states may already seem more heightened at baseline and hence less sensitive to observation of changes from a brief intervention period.

This shows a key point of this study. It points out the real limits of AI in tough situations like substance use recovery. Instead of thinking of this as a setback, it shows how important it is to have emotional support and human connection, which AI can't really offer right now. So, AI shouldn't be seen as a replacement for therapy, but rather as an extra tool that can help make support more available and organized.

Most cognitive behavior therapy (CBT), recognized worldwide as widely effective in treating substance use, mainly work through coping skills, cognitive restructuring, and relapse prevention techniques (Magill et al., 2019; Witkiewitz et al., 2019). Although general and common in the literature, cognitive behavioral therapy (CBT) efficacy mainly focused on psychological and emotional development; direct evidence toward readiness to change rarely appeared, not to mention in brief therapies. Techniques like MI might be closer to the main test regarding inducing and cultivating intrinsic motivation, which improves thereby the readiness to change.

Rather than disproving the hypothesis entirely, this study clarifies the conditions under which AI interventions are effective. The lack of significant improvement in reflects the importance of relational depth, emotional timing, and therapeutic context. This reinforces the growing consensus in digital mental health research that AI tools function best alongside and not as not substitutes for human connection (Bickmore et al., 2010; Topol, 2019).

Qualitative Approach

The quantitative analysis didn't find strong evidence of changes in participants' readiness to change or self-efficacy after the AI therapy, however the qualitative findings dig deeper into their experiences which reveals more. Two people came from different places and had different reasons, but they both showed up for the same intervention. What they took away from it was completely different, and their thoughts tell us much more than the stats ever could. This case study shares detailed stories from two participants, giving us insight into their thoughts and feelings. Their accounts show how the AI therapy worked for them and why it might not always reach the deeper benefits that often come with traditional therapy.

Participant A

Background: Participant A is a female in her early 20s from a small town. She had struggled with alcohol addiction for two years, bouncing in and out of rehab. She talked about her tough family life, which included feeling neglected and losing family members at a young age. She felt like she learned to cope with loneliness early on. She had tried individual therapy before and appreciated the personal bond she built with her therapist. When she checked into the rehab center, it was actually her third time trying to get better. When she found out she would be using a new AI therapy chatbot, she was very interested.

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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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She reached out to the chatbot, hoping it would make her feel understood, but what she got was a system that communicated well enough, just not in a way that resonated with her. She felt the chat was technically right, but it lacked any real emotional touch.

When asked whether she felt the AI chatbot understood her, Participant A responded positively. *"Yes, it did,"* she confirmed, emphasizing that the answers she received were logical and often matched those given by her past therapist. On the surface however, this might suggest a successful intervention. But when probed deeper, her motivations revealed something else entirely: she was not using the AI to change, she was using it to compare.

"I just wanted to make sure if it does give me the right answer... the answers that I'd gotten before."

She was not emotionally invested in change during her interactions but rather, she was testing the chatbot's accuracy and consistency by anticipating its responses, comparing them to those previously given by her human therapist. She wasn't using the chatbot like everyone else. She had seen a real therapist before and still remembered how those sessions felt. With the chatbot, she wasn't after any big change. She just wanted something that reflected her own feelings, a way to see if a machine could mimic understanding. This is similar to what Fitzpatrick et al. (2017) found showing that people often treat AI chatbots more like information machines rather than helpful therapists when they don't feel emotionally connected.

"We do need that human touch... sometimes feelings are so intense, and when you don't get that emotional response back... it does make a difference."

She really wants that emotional give-and-take in conversations, which AI just can't provide, no matter how smart it is. It leaves things feeling pretty dull and lacking warmth, especially when she's feeling vulnerable. In the end, she thinks AI therapy can be helpful, but she still prefers talking to a real person. Emotional attunement and empathy are central elements in effective therapy, areas where AI falls short (Wachter & Mittelstadt, 2019). Reena's dissatisfaction likely stemmed from the chatbot's inability to mirror emotional cues or provide empathetic warmth, which prior research identifies as crucial for client engagement and motivation (Elliott et al., 2011).

When asked if the chatbot made her feel more motivated to change, her answer was clear:

"No, because that's not what I came for. I came to see if it could understand me. But it didn't ask the right questions. A therapist... they would've noticed that I wasn't really ready."

Her case shows that you can't rely just on logic, especially when it comes to addiction recovery. Emotions play a huge role, and often it's emotional pain that leads to harmful habits. A chatbot, no matter how advanced, just can't read those subtle cues.

Participant B

Participant B was chosen for the qualitative research purely because of the data. Out of the forty participants, his scores showed the biggest change in both Readiness to Change and Self-Efficacy. That shift led for a deeper into his journey, which turned out to be quite meaningful.

Background: Participant B is a male in his early 30s and comes from a village near Gangtok. This was his first stay at a rehab center. As the oldest son, he had always felt the weight of responsibility, sometimes it was too much. He started drinking as a way to cope, as a way to push back against the pressure and the expectations that made him feel stuck when everything went wrong. He had no previous experience with therapy, and when introduced to the AI chatbot, he was neutral.

"It was just another part of the schedule. I didn't expect anything from it."

Participant B didn't have a big revelation all at once. His growth happened gradually. He found the chatbot "interesting" but pointed out that it didn't really change things dramatically. He never thought of it as a therapist, but he started to think about its questions long after they talked.

"It was... different. Not like talking to someone, but also not totally useless,"

Journal of Information Systems Engineering and Management
2025, 10(59s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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At first glance, these little moments might not seem like much, but they actually matched a real boost in his overall questionnaire scores. He felt more confident in his ability to avoid slipping back into old habits. He also became more ready to change, moving from just thinking about it to actively wanting to make an effort.

"I don't think the chatbot changed me. But maybe it helped me hear myself a bit more. Along with everything else here, I think it only added."

What caused that change?

When asked directly, he didn't name the chatbot first. Instead, he credited the environment of rehab, like waking up on time, eating real meals, attending group therapy, sitting with himself.

"I think everything helped a little. Not just one thing. But the chatbot was always there. I could talk to it when I wanted. No pressure."

That absence of pressure became its own kind of safety. The chatbot didn't push. It didn't judge. It didn't expect him to confess or perform. And over time, that non-threatening consistency gave him permission to try. This supports research by Bickmore et al. (2005), who suggest that consistent, low-pressure AI agents may support behavior change, especially for users who are emotionally reserved or new to therapy.

Participant B's story shows a kind of recovery that often gets overlooked: the small, steady changes that might not make for exciting tales but really do stick.

His experience wasn't filled with tears or big revelations. Instead, it was about building new habits, realizing certain questions mattered, and slowly learning to trust himself again. The chatbot played a role here though not as a therapist, but as a helpful buddy who asked just the right questions and let him respond when he felt ready. In the field of therapy, Participant B's story hints that digital tools might be better as supportive companions rather than quick fixes, especially for people who are new to therapy or feel nervous about being judged. This contextual influence is consistent with findings from DiClemente et al. (2004), who argue that readiness is not static and can be enhanced through supportive, consistent environments.

Emerging Themes

The participants shared their stories, and a few common themes came up that give us a look into their experiences with the AI-based chatbot.

Superficial Engagement Driven by Curiosity

Participant A interacted with the AI chatbot in a way that was more about thinking critically than feeling. She didn't see it as a tool for personal growth but as something to analyze. Having been in therapy before, she compared the chatbot's responses to what she'd learned in her sessions. Her approach was more about observation than emotional sharing, showing that she was curious intellectually but wasn't really open to looking at her own behavior. This suggests that if people aren't interested in change or aren't emotionally involved, digital tools like this might not make a real difference.

Absence of Emotional Connection

Participant A shared that for many people, therapy is more about feeling understood than just getting information. She pointed out that while the chatbot gave logical answers, it didn't offer the emotional support that comes from a real conversation. Without facial expressions, changes in tone, or genuine human reactions, it felt flat. For someone like her, who has been through therapy before and links healing to human interaction, the chatbot just didn't cut it.

This shows how important the relationship in therapy is: things like empathy, being present, and non-verbal support are key to making real changes. For those dealing with emotional pain rooted in relationships, AI solutions might not fully meet what they need.

Transformation Through Routine and Non-Intrusive Support

Participant B's experience was pretty different. It was more about what was going on inside him. At first, he wasn't really engaged and seemed closed off. His change didn't start from feeling curious or motivated like some others

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did. But being in a structured setting at the rehab center, along with the chatbot's steady way of interacting, gave him a chance to think things over. Over four weeks, he reported better scores for his readiness to change and believing he could do it which is the most improvement seen in the intervention group. This shows that for some people, especially those who aren't used to sharing feelings or come from tough backgrounds, you don't need deep emotions to grow. Instead, having a stable, repeated routine can help shift behaviors and thoughts.

Internal Readiness as a Determinant of Change

A shared, though contrasting, theme across both narratives was the decisive role of emotional readiness. Participant A possessed therapeutic knowledge and cognitive clarity but was emotionally disengaged. As a result, the intervention did not lead to internal change. Participant B, despite being emotionally restrained and initially passive, was in a phase of gradual openness, supported by the therapeutic structure around him and thus demonstrated measurable progress. This theme reinforces a central tenet of behavior change models such as the Transtheoretical Model of Change: individuals must reach a certain threshold of internal readiness before external tools can be effective. Without readiness, even accurate, well-designed interventions may fall short.

The Role of Environment

Participant B's progress was not solely the result of the chatbot intervention. His responses suggested that the combination of routine, social support, therapeutic containment, and sobriety created the conditions for internal change. The chatbot was part of a larger therapeutic ecosystem, functioning more as a reinforcement tool than a stand-alone driver. This theme is essential in the discussion of digital mental health: AI-based therapy may be most effective when embedded in a supportive environment, where users are also receiving human contact, structured routines, and opportunities for real-world feedback. This integrated model may be especially important in treating complex issues such as addiction.

AI as a Supplementary Tool, not a Standalone Solution

Both narratives reinforce the idea that AI-based CBT tools are best viewed as complementary supports. They can extend care, provide structure, offer reminders, and reinforce coping strategies but they cannot yet replace the relational, intuitive, and emotionally responsive components of human therapy. Particularly in areas like substance use, where motivation, shame, ambivalence, and trauma are deeply intertwined, human connection remains irreplaceable. Participant B benefitted from the chatbot because it worked with the broader therapeutic environment. Participant B disengaged because nothing in the AI intervention mirrored the emotional resonance she associated with real therapy. Thus, AI's utility lies not in replication, but in reinforcement.

This study aimed to examine whether the integration of an AI CBT chatbot into conventional addiction therapy would enhance self-efficacy and readiness to change, two important psychological dimensions for substance use recovery. Fast gaining grounds for being scalable and accessible AI's capabilities in mental health care had been the focus here in studying its workings in an institutional setting where social, structural, and personal issues often act against recovery. These findings suggest that while technology can assist in rehabilitation, it does not yet seem to fully replicate the context-sensitive, relational, and motivating aspects of face-to-face therapy. Perhaps the AI-based CBT tools work best in adjunctive roles, as reminders to extend support beyond therapy sessions and reinforce techniques learned in therapy. They are perhaps that steady voice accompanying the individual after the spark has ignited.

The qualitative narratives shed light on this finding. Many participants said that while the AI chatbot seemed logical, it lacked emotional depth. A few even mentioned they used it mainly for answers rather than to make real changes. One person specifically said she checked the chatbot's responses against what her former therapist suggested, instead of really reflecting on herself. Some people, like Participant B, said that at first, they talked to the chatbot more out of habit or because they felt they had to, rather than thinking about it deeply. Because of this, even though they used the chatbot, they didn't really connect with it or trust it. This is particularly important in rehab, where outside pressures like family expectations or routines might make someone seem like they're following along, but they're not really motivated inside. These findings align with research by Fitzpatrick et al.

(2017), who observed that users often perceive AI therapy agents as more educational or informational than emotionally supportive.

From their narratives, it was obvious that the chatbot didn't make them feel more confident or empowered. Most users didn't see it as a source of motivation. They found it useful, but said it felt a bit bland, like a tool that offered good advice, but didn't connect with them on an emotional level to boost their self-belief. Some responses pointed out the gap between just giving advice and really connecting. The chatbot had the right strategies for dealing with things, like tips for coping, reminders to rethink situations, and ways to avoid relapse, but it didn't really feel personal or encouraging. This is important when you think about the Alcohol Abstinence Self-Efficacy Scale (AASES), which measures how confident people are in resisting alcohol when they're stressed, facing conflicts, or under social pressure. In those tough moments, how support is given matters just as much as the advice itself. Participants noted that while the chatbot was organized and informative, it didn't provide much emotional support or adapt to their feelings. When it comes to recovery from addiction, a person's confidence in staying sober usually comes from feeling understood and supported emotionally. The chatbot had some solutions, but it lacked that human touch that makes those solutions feel possible, especially when doubts creep in.

One participant, Participant B, did show some improvement on the AASES scale. However, his story suggests that this progress had more to do with the whole therapy setup, things like daily routines, group support, personal reflection, and being away from alcohol. The chatbot might have helped a bit, but it wasn't the main factor. According to Sundström et al. (2020), therapist-guided internet-based cognitive-behavioral therapy (CBT) resulted in advances in coping abilities and decreased intake of alcohol when accompanied by an AI chatbot. There may be instances when some AI interventions do not show any effect, but the accessibility and format of these interventions might help clients with self-control and self-monitoring, two skills that are paramount for increasing self-efficacy. The gains in self-efficacy seen in this study across both groups may be due to the therapeutic effects of structured treatment settings and the time that passes in a rehabilitation setting with a constant reinforcement of coping skills and abstinence goals.

In conclusion, this research lends to the growing discussion on the responsible integration of digital mental health in clinical care. It acknowledges both the power and limits of AI to influence behavior change. Future research may benefit from extending the intervention, creating a more engaging chatbot interface, or establishing a hybrid form where AI complements rather than replaces therapeutic relationships.

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