Improving Cognitive Bias Modification through Interaction Design: A Mixed-Method Study with LLM Support

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Abstract

Acknowledgements

Abbreviations

ACB	Apple Banana Carrot

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Chapter 1

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This chapter explains model characteristics and limitations gained from the literature review and interaction with the model. Based on these characteristics and from reviewing the literature, section 5.2 introduces rules to enhance the response when interacting with the model. Most of the rules are gained from [3]. The rules were tested when solving reasoning problems using Python linked with the GPT-3.5-turbo model, and the chapter presents an example of the response before and after applying one rule. Please refer to the Appendix B.4 for the other examples. Then, using these rules, the research proposes three techniques for solving the water jug problem in section 5.3. These techniques are This chapter explains model characteristics and limitations gained from the literature review and in- teraction with the model. Based on these characteristics and from reviewing the literature, section 5.2 introduces rules to enhance the response when interacting with the model. Most of the rules are gained from [3]. The rules were tested when solving reasoning problems using Python linked with the GPT-3.5-turbo model, and the chapter presents an example of the response before and after applying one rule. Please refer to the Appendix B.4 for the other examples. Then, using these rules, the research proposes three techniques for solving the water jug problem in section 5.3. These techniques areThis chapter explains model characteristics and limitations gained from the literature review and in- teraction with the model. Based on these characteristics and from reviewing the literature, section 5.2 introduces rules to enhance the response when interacting with the model. Most of the rules are gained from [3]. The rules were tested when solving reasoning problems using Python linked with the GPT-3.5-turbo model, and the chapter presents an example of the response before and after applying one rule. Please refer to the Appendix B.4 for the other examples. Then, using these rules, the research proposes three techniques for solving the water jug problem in section 5.3. These techniques areThis chapter explains model characteristics and limitations gained from the literature review and in- teraction with the model. Based on these characteristics and from reviewing the literature, section 5.2 introduces rules to enhance the response when interacting with the model. Most of the rules are gained from [3]. The rules were tested when solving reasoning problems using Python linked with the GPT-3.5-turbo model, and the chapter presents an example of the response before and after applying one rule. Please refer to the Appendix B.4 for the other examples. Then, using these rules, the research proposes three techniques for solving the water jug problem in section 5.3. These techniques areThis chapter explains model characteristics and limitations gained from the literature review and in- teraction with the model. Based on these characteristics and from reviewing the literature, section 5.2 introduces rules to enhance the response when interacting with the model. Most of the rules are gained from [3]. The rules were tested when solving reasoning problems using Python linked with the GPT-3.5-turbo model, and the chapter presents an example of the response before and after applying one rule. Please refer to the Appendix B.4 for the other examples. Then, using these rules, the research proposes three techniques for solving the water jug problem in section 5.3. These techniques are

1.1 test

Chapter 2

Literature Review

This chapter explores and discusses the potential of applying Cognitive Bias Modification (CBM) techniques with Large Language Models (LLMs) in smartphone applications from previous research. Section 2.1 introduces the CBM concept; Section 2.2 discusses how CBM can help improve emotional issues; Section 2.3 explores existing CBM-based smartphone applications; Section 2.4 explains the role of LLM in metal health interventions; and Section 2.5 Identifies the limitations of both traditional and digital CBM systems. Finally, section 2.6 summaries the findings and highlights the research gap.

To inform this literature review, I searched academic databases including ACM Digital Library, ScienceDirect, and FindIt@Bham using combinations of keywords such as: "Cognitive Bias Modification ", "CBM mobile app", "CBM anxiety depression", "LLM mental health", and "CBM Large language model". Journals and articles from 2000 to 2025 were considered.

2.1 Cognitive Bias Modification (CBM)

Cognitive bias modification (CBM) as a low-intensity intervention designed to address biases, which are cognitive tendencies associated with anxiety and depression. CBM has been well-established as providing therapeutic benefits in a range of disorders [3]. By experimentally inducing and modifying biases, CBM supports the assumption that cognitive patterns play a causal role in emotional resilience or vulnerability [14][29]. It is a theory-driven treatments that use repetitive word-based tasks to reduce bias and promote adaptive processing and have been applied to improve anxiety and depression[16].

Cognitive Biases refer to the tendency to process negative or threatening information more readily [14]. These unconscious processes are acknowledged as contributing factors in various psychological disorders, including social anxiety disorder, alcohol use disorder, and tobacco use disorder [32]. In general, compared to healthy individuals, people who are prone to anxiety or depression are more likely to pay attention to negative or threatening cues, resolve ambiguity negatively, and tend to selectively remember negative events[2][14].

Two primary cognitive biases are frequently targeted by CBM:

- Attentional Bias: This refers to the tendency to focus more on threat-relevant information [2]. For instance, when an emotionally negative and a neutral cue are replaced by a single target, anxious individuals respond more quickly to the replacement of the threatening cue. The experiment also shows they exhibit slower disengagement from threat stimuli [14]. This bias has been reliably associated with anxiety and depression [2][9].
- Interpretation Bias: This is the tendency to interpret ambiguous or mildly negative information in a more threatening way. In one study, participants read narrative texts with critically ambiguous sentences and were asked to determine the final word. Anxious individuals demonstrated more negatively biased interpretations compared to others. This bias is considered a robust phenomenon linked to anxiety[2][14].

2.2 CBM in the Treatment of Anxiety and Depression

CBM is a cognitive experimental approach that aims to alter biases by exposing participants to a range of stimuli related to psychopathology-linked processing [29]. The fundamental assumption of CBM is the same as that of cognitive therapy: cognitive characteristics contribute to emotional resilience or vulnerability [14]. The goal of CBM procedures is to alter either attention bias (CBM-A) or interpretation bias (CBM-I).

2.2.1 Treatment method of CBM

CBM-A (Attention Bias Modification)

CBM-Attention (CBM-A), also known as Attention Bias Modification (ABM), aims to training anxious individuals to redirect their attention away from threatening cues, potentially reducing anxiety[11] [24]. A number of attention bias assessment tools, such as the Visual Search task, the Dot-Probe task, and the Visual-Probe task, have been developed by experimental psychologists[32]. These tools are commonly used for training as well as evaluation.

In the Dot-Probe task, developed by MacLeod and colleagues [21], participants respond to a probe, such as a dot or letter, that appears in the location previously occupied by either a neutral or threatening stimulus. If participants respond faster to probes replacing threat-related stimuli, it indicates attentional bias[32]. By manipulating the contingency between stimulus valence and probe position, the individuals' attention can be trained to shift away from negative information[2][19]. However, many studies indicate that this type of training suffer from low credibility and acceptability, as participants often report boredom and a lack of clear rationale[4].

A potentially more engaging CBM-A paradigm is the Visual Search training task. Participate are required to find a single smiling face among a grid of emotionally negative faces [32]. This trains individuals to attend to positive stimuli while ignoring negative ones[9]. This method has demonstrated positive effects on self-esteem and stress response in adults, as verified in a series of experiments[7].

CBM-I (Interpretation Bias Modification)

CBM-Interpretation (CBM-I) aims to mitigate negative explanations of ambiguous information and encourage harmless ones[2][19][24][29][30]. A classic CBM-I task is the Mathews and Mackintosh scenario paradigm, in which participants are presented with three-line ambiguous scenarios that can be interpreted in either positive or negative way. Participants might be asked to imagine themselves in these scenarios and reframe their emotional responses accordingly[14][20][25].

The Word Sentence Association Paradigm (WSAP) is another common CBM-I approach[30]. In this task, participants are shown an ambiguous sentence followed by a word representing either a negative, neutral or positive interpretation. They are required to indicate whether the work is related to the sentence. Training involves providing feedback that reinforces positive interpretations and discourages negative ones[2][3][20][30].

2.2.2 Role of CBM in Mental Health Treatment

Research has shown that cognitive biases can be modified through CBM, and these modifications can subsequently affect emotional reaction[14].

According to certain research reports, CBM-A has demonstrated early effectiveness in reducing symptoms of Social Anxiety Disorder (SAD) and Generalized Social Phobia (GSP), performing better than control training[4][6][10][11][14][28]. Similarly, CBM-I has been found to reduce social anxiety, with multi-session interventions producing stronger and longer-lasting effects compared to single-session ones[2][30].

In the treatment of depression, CBM aims to improve processing biases in order to better understand their causal role in depression and eliminate maladaptive processing biase[19]. Studies show that CBM-I approaches are effective at influencing interpretation biases and mood [20]. Positive CBM-I interventions have been shown to diminish depressive intrusions after exposure to stress, modify negative mood states, and improve depressed symptomatology. Moreover, combining CBM-I with online CBT has also shown potential for lowering depressed symptoms[3][19].

2.3 Digital Implementation of CBM: Smartphone-Based Applications

2.3.1 Advantages of Smartphone-Based CBM

Cognitive Bias Modification (CBM) is a theory-based psychological interventions that employ repeated, computerized exercises to systematically address and alter cognitive biases, fostering more adaptive cognitive processing[16][20]. This technique seeks to modify automatic tendencies in attitude, emotion, and behavior[24].

The use of smartphones for delivering CBM has been investigated as a viable and beneficial approach a variety of reasons. First, the portability of mobile devices allows individuals to complete training anytime and anywhere. Smartphones not only remind and prompt users to engage with the program but also facilitate a higher training frequency, which contributes to more lasting changes in attentional habits[1][30].

Second, higher frequency shortens sessions, improving the tolerability of CBM's repetitive tasks[11]. Third, widespread use of smartphone makes users more open to receiving psychological interventions through digital platforms[4][32]. Additionally, smartphone-based CBM avoids the stigma associated with face-to-face treatment[30].

Fourth, smartphones can support reaction-time-based psychological tasks. For instance, attention bias assessments like the dot-probe task have shown reliable performance when delivered on mobile platforms[11].

2.3.2 Types of CBM Implemented on Smartphones

Several types of CBM have been adapted for smartphone delivery. A research used CBM-A to assess the possibility of reducing social anxiety via iPhone and Android devices. Another trial investigated CBM-A efficacy using a dot-probe task on a screen approximately 5 cm by 7.5 cm[11].

CBM-I has also been implemented in many smartphone studies. One study involved an eight-session CBM-I program to reduce interpretation bias and social anxiety among Chinese undergraduates. This training enabled participants make more positive interpretations in ambiguous scenarios and reduced their social anxiety. This intervention was self-administered, without therapist involvement, and demonstrated the effectiveness of multisession treatment delivered via smartphones[30].

The" HabitWorks" app is another example of smartphone-based CBM-I.It was designed to supplement acute psychiatric care and extend therapy into the high-risk period following discharge. It useed the Word-Sentence Association Paradigm (WSAP), which is well-suited for mobile platforms due to its simplicity and built-in gamification[3].

Another study explored incidental CBM, in which CBM training was integrated into smartphone unlock actions. Users made gestures (e.g., checkmark or X) on the screen to accept or reject healthy or unhealthy food stimuli during unlock events. Results showed that even brief, incidental CBM training could influence food-related attitudes. Results showed that CBM can alter food attitudes even just used a short course of incidental smartphone[24].

2.3.3 Efficacy and Feasibility of Smartphone-Delivered CBM

Studies have shown promising results for smartphone-delivered CBM. In a randomized controlled multi-session trial for social anxiety, both the CBM-A and control training groups had considerably larger symptom reductions than the waiting group. The study revealed the viability of providing CBM-A via smartphone in short, frequent sessions[11].

CBM-I training on smartphones has also been demonstrated to successfully promote positive interpretations of ambiguous scenarios and decrease social anxiety[30]. Pilot data from the HabitWorks app indicated strong feasibility and acceptability during acute psychiatric care[3].

2.4 The Role of Large Language Models in Mental Health Interventions

Large Language Models (LLMs) are rapidly emerging as a promising tool for addressing the increasing demand for accessible and scalable mental healthcare globally. They have been proposed to overcome the limitation of traditional mental health therapy, such as time, cost, and accessibility constraints, and to extend available services[17] [31]. This marks a revolutionary trend in which AI is used to reinforce human expertise and solve systemic inefficiencies[26].

2.4.1 Applications of LLMs in Mental Health Interventions

LLMs are being explored and implemented in various ways to support mental health. First, LLMs serve as emotional support and guidance tools. LLM-based chatbots can provide rapid, round-the-clock emotional support to users who are unable to seek or get treatment due to various barriers[26][28]. These models can provide comfort, coping strategies, and individualized responses based on an individual's reported emotional state[17]. Existing chatbots, such as Wysa and Replika, are designed to provide sympathetic conversations and foster long-term, emotionally supportive relationships with users[8][31][26].

Second, LLMs are employed for mental health diagnosis and prediction. They can be fine-tuned to predict mental health conditions using diverse data sources such as text and wearable sensor data, thereby supporting early detection and assessing the severity of disorders[23][27][31].

Third, LLMs promote to mental health literacy and psychoeducation. They can generate personalized educational materials, explain cognitive distortions, and provide insights into stress patterns and self-management techniques[17][26]. Fourth, LLM-based chatbots have been applied to address a range of mental health concerns, including general mental wellbeing, depression, anxiety, and stress. Some have even been developed to support specific depression-related conditions, such as postnatal depression (PND) and postpartum depression (PPS), with models such as ChatGPT (gpt-3.5-turbo) and GPT-3 (text-davinci-003)[31].

Even though LLMs are extensively utilized in mental health care, their integration with CBM therapies is underexplored, giving a great possibility for future research.

2.4.2 Benefits and Potential of LLMs in Mental Health

The use of LLMs provides numerous substantial benefits for mental health interventions. LLMs offer a scalable, cost-effective, and convenient way to deliver psychological support. Users can access instant, on-demand help at any time and from any location using portable devices such as smartphones[3][17][26][28].

Additionally, LLMs can improve personalization by producing context-aware, empathetic and adaptive responses based on users' evolving psychological states and interaction patterns[22][31][33]. Research shows that emotional support from human coaches positively influence app usage and treatment outcomes, and LLM-based agents are now being developed to replicate these effects[17].

Moreover, LLMs help to lessening the stigma associated with mental healthcare. By offering private and accepting platforms, LLM-based applications can make it easier for individuals to seek help[5][8][15][26].

2.5 Identified Limitations in Existing Digital CBM Systems

According to studies, limited interaction, a lack of real-time feedback, and insufficient personalization are major barriers to user engagement and the effectiveness of mental health applications (MHAs), including those powered by Large Language Models (LLMs)[3][5][12][13][17][18][19][22].

2.5.1 Low Interaction and Less Engaging Functions[17]

Many MHAs struggle with unengaging functions, leading to reduced motivation and concentration, which further hinder continuous use. These apps usually feature monotonous designs with limited options and tedious processes, causing users to disengage. For instance, participants in one study showed low user engagement due to the lack of meaningful responses. This aligns with other research indicating that insufficient personalized and context-appropriate replies lower user satisfaction and interest. One study observed that mental health support systems had a high dropout rate with approximately 95%. Participants reported forgetting to use the app or losing interest over time.

Furthermore, the repetitive activities used in CBM, such as daily mood logging, regular meditation sessions, or ongoing symptom monitoring, create psychological and temporal pressure. Even with improvements like auto-completion features, some participants still found it difficult to maintain interest due to the demand for continuous data entry.

Studies also suggest that the absence of emotional support and practical assistance contributes to disengagement. If users feel an app fails to give emotional support or assist them manage distress, they may lose trust and stop using it.

2.5.2 Lack of Real-time Feedback

A notable shortcoming of many digital mental health interventions is the failure to deliver timely, real-time feedback. In several cases, applications required users to submit multiple entries before any feedback was generated, which was commonly perceived as unpleasant[12]. Users often seek immediate responses for emotional support; however, delays, particularly those requiring human therapist intervention, can intensify distress and lead to abandonment of the service[13].

Moreover, chatbot-driven systems frequently read user input incorrectly, resulting in irrelevant, repetitive, or incongruent responses. These kinds of interactions can be deeply frustrating and may erode trust. For instance, a chatbot that continuously asks, 'Why do you say that?'—even after a user has plainly expressed their feelings. It can come across as dismissive, leaving the user feeling unheard or emotionally sidelined[8][13].

2.5.3 No Personalization and Less Adaptive Functions

Another critical limitation is that many MHAs fail to accommodate users' evolving needs and preferences. Most current systems rely on generic, static content that does not adapt to individual user backgrounds or behavioral shifts. Studies have found that when apps fail to adjust to users' changing conditions, such as new goals or emotional states, users are more likely to disengage[17].

Moreover, existing chatbots face challenges in maintaining consistent personalization. Their responses often lack continuity and situational awareness, resulting in encounters that appear mechanical, impersonal, and divorced from continuing user demands[22].

Overall, these limitations contribute to decreased utility, diminished trust, user fatigue, and high attrition rates. They highlight the urgent need for more personalized, responsive, and emotionally supportive CBM systems. Integrating advanced LLM-based skills shows potential for overcoming these difficulties and improving the overall effectiveness of digital mental health solutions.

2.6 Summary and Research Gap

Despite the effectiveness of CBM techniques in resolving anxiety and depression has been proven, their digital implementation, particularly via smartphone applications, still faces considerable challenges. Existing digital CBM systems usually struggle with low engagement, repetitive and non-personalized interfaces, lack of emotional support, and instant real-time feedback. These problems lead to reduced user retention, limited long-term effectiveness, and a high dropout rate, eventually undermining the treatment potential of CBM interventions.

In addition, while recent advances in Large Language Models (LLMs) have shown new opportunities for scalable and intelligent mental health support, their integration with CBM remains largely unexplored. Current literature has largely focused on the treatment mechanism of CBM or the role of LLM in emotional support chatbots, yet obviously lacks the research at the intersection of these areas, especially regarding how interface design and LLM-driven interaction work together to improve engagement and training consistency in CBM.

This project aims to address this gap by exploring the possibility of digital strategies and large language model (LLM)-based feedback systems to enhance cognitive bias modification (CBM) training experiences. It specifically outlines the design of a mobile CBM training application that integrates an LLM as an intelligent coaching agent, offering context-sensitive guidance and motivational support throughout the training process. The app is designed to alleviate the limitations of the existing CBM system through:

- Increase interactivity via game-like visual interpretation tasks.
- Real-time motivational feedback from the LLM agents.
- More attractive, emotional responsive user interface.

By concentrating on the design and interaction style of the CBM application and empirically analyzing their impact user engagement and behavior performance, this study contributes to the ongoing development of more effective, personalized, and accessible digital mental health interventions.

Chapter 3

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