



ARTIFICIAL INTELLIGENCE-ENHANCED MINDFULNESS- BASED COGNITIVE BEHAVIOR THERAPY (AI-MB-CBT) FOR ADULT MENTAL HEALTH EFFECTIVENESS, MECHANISMS, AND PERSONALIZATION

Amena Begum Sumi¹;

[1]. Counseling Psychologist, University of Dhaka, Bangladesh
Email: amenasumi007@gmail.com

Doi: [10.63125/s2jeeh43](https://doi.org/10.63125/s2jeeh43)

Received: 12 October 2025; **Revised:** 20 November 2025; **Accepted:** 18 December 2025; **Published:** 12 January 2026

Abstract

This study evaluated the effectiveness, mechanisms, and personalization effects of Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behavior Therapy (AI-MB-CBT) for adult mental health using a quantitative longitudinal design. A total of 312 adults participated (mean age = 34.8 years, SD = 9.6; 56.1% women), drawn from community (62.8%) and outpatient (37.2%) contexts. Outcomes and process variables were assessed at baseline, mid-treatment, post-treatment, and follow-up, alongside platform-logged engagement and AI adaptation indicators. Descriptive results showed clinically meaningful symptom reductions over time. Depression severity decreased from baseline ($M = 15.9$, $SD = 6.2$) to post-treatment ($M = 10.4$, $SD = 5.8$) and remained lower at follow-up ($M = 10.8$, $SD = 6.0$). Anxiety severity declined from baseline ($M = 14.7$, $SD = 5.8$) to post-treatment ($M = 9.8$, $SD = 5.5$) and follow-up ($M = 10.1$, $SD = 5.7$). Stress/distress improved from baseline ($M = 19.8$, $SD = 6.4$) to post-treatment ($M = 14.2$, $SD = 6.1$), with follow-up stability ($M = 14.6$, $SD = 6.3$). Functional impairment improved from baseline ($M = 17.1$, $SD = 6.9$) to post-treatment ($M = 13.4$, $SD = 6.7$) and follow-up ($M = 13.1$, $SD = 6.6$). Mechanisms shifted in theoretically consistent directions, including increases in mindfulness skills (baseline $M = 3.1$, $SD = 0.7$; post-treatment $M = 3.7$, $SD = 0.7$) and decreases in rumination/worry (baseline $M = 3.6$, $SD = 0.8$; post-treatment $M = 3.0$, $SD = 0.8$). Engagement was substantial (module completion $M = 61.4\%$, $SD = 23.6$), and adaptation exposure varied (adaptations $M = 5.2$, $SD = 3.4$; time-to-first adaptation $M = 9.1$ days, $SD = 6.8$). Overall findings supported AI-MB-CBT as an effective, mechanism-linked, and personalization-sensitive intervention for adult mental health.

Keywords

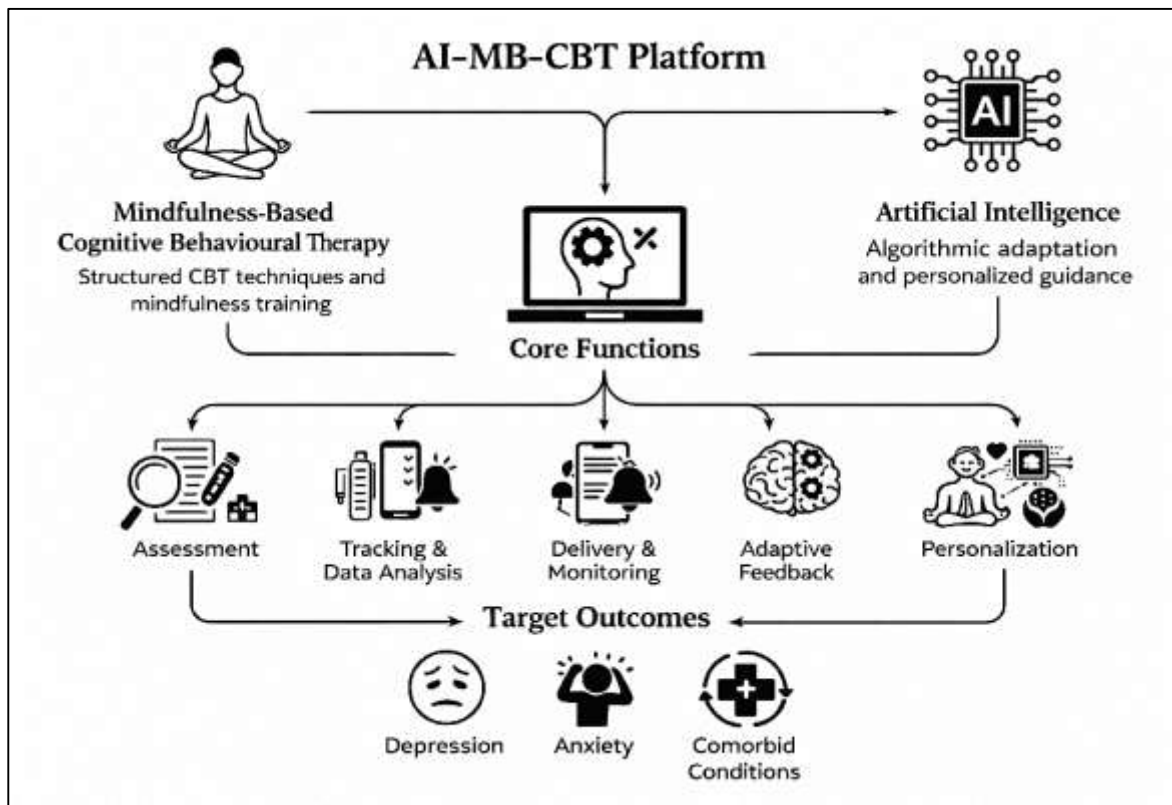
Artificial Intelligence, Mindfulness, Cognitive Behavior Therapy, Personalization, Adult Mental Health.

INTRODUCTION

Artificial Intelligence–Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) can be defined as an integrated psychotherapeutic framework that combines mindfulness-based cognitive behaviour therapy with artificial intelligence–driven systems to support assessment, delivery, adaptation, and monitoring of mental health interventions for adults (Więckiewicz et al., 2024). Mindfulness-based cognitive behaviour therapy itself is an integrative clinical approach that unites structured cognitive and behavioural strategies with systematic mindfulness training. Mindfulness refers to a learned capacity for sustained, present-moment awareness characterized by attentional focus, openness, and nonjudgmental observation of internal experiences such as thoughts, emotions, and bodily sensations. Cognitive behaviour therapy is a structured, skills-oriented psychotherapy that addresses emotional distress through identification and modification of maladaptive cognitions, behavioural patterns, and emotional responses. AI-MB-CBT extends this foundation by embedding algorithmic processes that analyze user data, guide intervention pacing, and personalize therapeutic content in real time. Artificial intelligence in this context refers to computational systems capable of recognizing patterns, learning from data, and making adaptive decisions without constant human input. These systems may operate through machine learning models, natural language processing, adaptive feedback mechanisms, or rule-based clinical algorithms. Internationally, AI-MB-CBT is situated within a broader movement toward scalable, data-informed mental health care capable of reaching diverse adult populations across cultural, economic, and healthcare contexts. Adult mental health disorders represent a major contributor to disability worldwide, affecting functioning, productivity, and quality of life across nations (Spytska, 2024). Access to evidence-based psychological treatments remains uneven across regions due to workforce shortages, cost barriers, and structural limitations within healthcare systems. AI-MB-CBT is positioned as a response to these challenges by offering a model that preserves established therapeutic principles while enabling broader reach, continuous monitoring, and individualized support. The definition of AI-MB-CBT therefore encompasses not only a clinical methodology but also a systems-level approach to delivering psychotherapy in ways that are responsive to individual needs while remaining consistent with standardized therapeutic frameworks (Di Fazio et al., 2022).

Adult mental health conditions such as depression, anxiety disorders, stress-related disorders, and comorbid emotional difficulties occur across cultures and socioeconomic contexts, contributing substantially to global disease burden (Ramón-Arbués et al., 2020). Epidemiological data consistently demonstrate high prevalence rates among adults, with many individuals experiencing chronic or recurrent symptoms that interfere with occupational functioning, interpersonal relationships, and physical health. Mental health treatment gaps persist internationally, with large proportions of adults either receiving no treatment or receiving care that does not align with evidence-based practices. Structural barriers including limited availability of trained clinicians, geographic distance from services, stigma, and financial constraints reduce access even in high-resource settings. Psychological interventions that can be delivered flexibly and at scale are therefore central to global mental health strategies. Digital mental health interventions have emerged as a response to these needs by enabling remote access, self-paced engagement, and standardized delivery of therapeutic content (Cénat et al., 2020). Within this context, mindfulness-based and cognitive behavioural interventions have received substantial attention due to their transdiagnostic applicability and adaptability to digital formats. Adult populations demonstrate varied symptom profiles, coping styles, and motivational levels, which necessitate interventions that can accommodate heterogeneity while maintaining therapeutic integrity. AI-MB-CBT addresses this need by integrating adaptive systems capable of tailoring intervention components based on user engagement, symptom trajectories, and behavioural data. The international significance of AI-MB-CBT lies in its alignment with public health goals emphasizing accessibility, equity, and efficiency in mental health care delivery (Åkesdotter et al., 2020). By combining empirically grounded therapeutic approaches with computational personalization, AI-MB-CBT represents a model through which adult mental health interventions can be systematically delivered across diverse populations while supporting continuous outcome monitoring and quality assurance.

Figure 1: AI-Enhanced Mindfulness CBT Framework



The theoretical foundations of mindfulness-based cognitive behaviour therapy are rooted in cognitive models of emotional disorders and empirical understandings of mindfulness as a modifiable psychological capacity (Jowf et al., 2022). Cognitive behavioural frameworks conceptualize emotional distress as arising from reciprocal interactions among maladaptive thought patterns, dysfunctional beliefs, emotional responses, and reinforcing behaviours. Therapeutic change occurs through structured skill acquisition aimed at modifying these patterns. Mindfulness-based approaches introduce an additional dimension by training individuals to observe internal experiences without habitual reactivity, thereby altering the process through which thoughts and emotions influence behaviour. A central construct in MB-CBT is decentering, which involves recognizing thoughts as transient mental events rather than accurate representations of reality or the self. This metacognitive shift supports disengagement from repetitive negative thinking processes such as rumination and worry, which are strongly associated with adult depression and anxiety. Emotion regulation is another foundational process linking mindfulness and cognitive behavioural approaches (Duby et al., 2021). Mindfulness practices enhance awareness and acceptance of emotional states, while cognitive behavioural techniques provide strategies for reappraisal, problem-solving, and behavioural engagement. These complementary mechanisms support flexible responding to stressors and reduce maladaptive avoidance patterns. From a transdiagnostic perspective, MB-CBT targets shared mechanisms underlying multiple adult mental health conditions, including attentional bias, cognitive inflexibility, experiential avoidance, and deficits in self-regulation. This theoretical orientation supports application across diagnostic categories and cultural contexts, as it focuses on universal psychological processes rather than disorder-specific symptom clusters. AI-MB-CBT builds upon these foundations by embedding systems that can detect changes in these processes through user input and behavioural data, enabling adaptive delivery of therapeutic strategies aligned with individual patterns of response. Artificial intelligence contributes to MB-CBT by enabling continuous assessment, adaptive feedback, and personalized intervention pathways within digital environments. Digital delivery platforms allow therapeutic content to be accessed beyond traditional clinical settings, supporting integration of mindfulness and cognitive behavioural practices into daily life (Colizzi et al., 2020). AI systems can

analyze self-reported symptoms, engagement metrics, linguistic patterns, and behavioural indicators to generate individualized recommendations and prompts. Conversational interfaces, such as digital therapeutic agents, can deliver psychoeducation, mindfulness exercises, and cognitive strategies through structured dialogue that mirrors core therapeutic principles. AI-supported monitoring enables frequent assessment of mood, stress, and behavioural activation, capturing dynamic fluctuations that may not be observed in periodic clinical sessions. This capacity aligns with the practice-intensive nature of mindfulness training and the behavioural focus of CBT. By identifying patterns associated with improvement or deterioration, AI systems can adjust intervention pacing, suggest alternative strategies, or increase support intensity. These adaptive processes are particularly relevant for adult populations, where engagement and adherence vary widely based on motivation, symptom severity, and contextual demands (Ma, 2022). AI-MB-CBT therefore functions as a learning system that continuously refines intervention delivery based on observed data while maintaining alignment with established therapeutic protocols. Internationally, such systems can support multilingual content, culturally adapted exercises, and standardized quality control, contributing to consistency of care across settings.

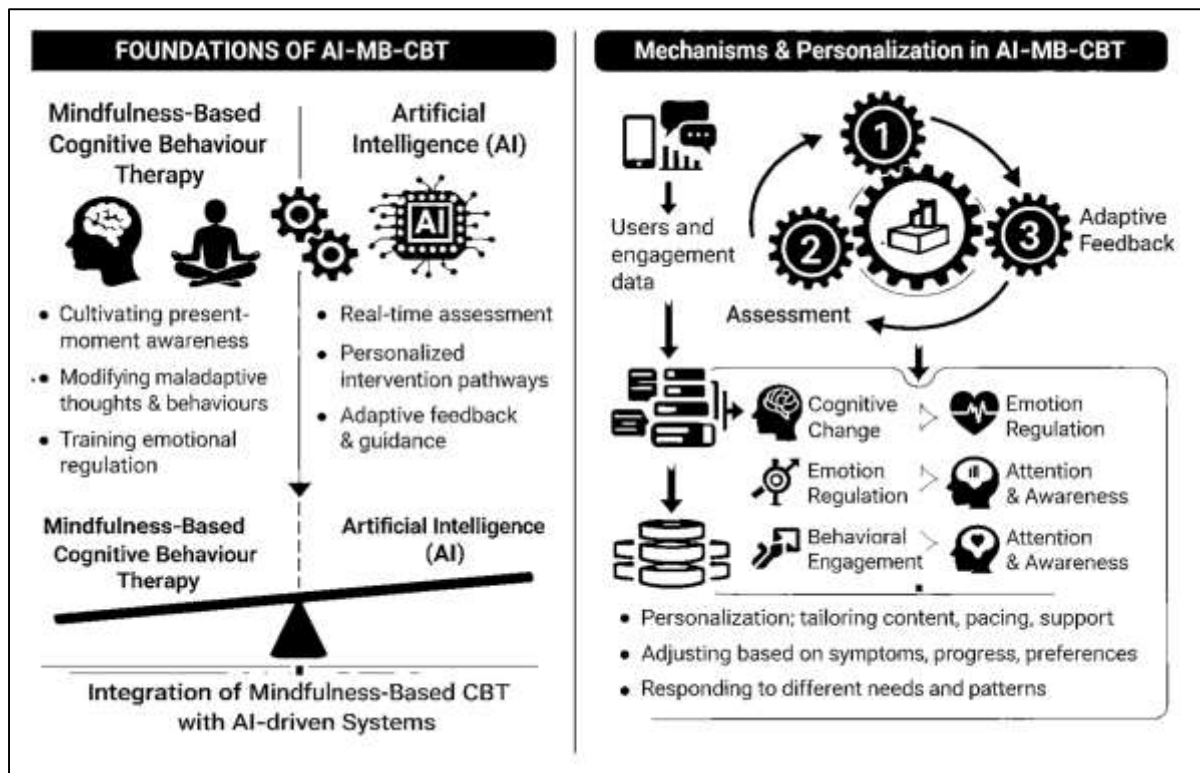
Effectiveness in AI-MB-CBT is conceptualized through measurable changes in adult mental health outcomes, including symptom severity, functional impairment, emotional regulation, and quality of life indicators. Both mindfulness-based and cognitive behavioural interventions have demonstrated effectiveness across adult populations, providing a strong empirical foundation for integrated approaches (Chudzicka-Czupala et al., 2023). Digital adaptations of these interventions have further demonstrated that structured therapeutic content can be delivered remotely with meaningful clinical outcomes. In quantitative evaluation, effectiveness encompasses not only symptom reduction but also engagement, adherence, and skill acquisition. AI augmentation introduces additional dimensions of effectiveness by supporting timely feedback, adaptive sequencing, and individualized dosing of intervention components. Adult mental health outcomes are influenced by the extent to which individuals engage in between-session practice, apply skills in real-world contexts, and maintain consistency over time (Saeed & Gargano, 2022). AI-MB-CBT platforms can reinforce these processes through personalized reminders, progress visualization, and adaptive goal setting. Measurement-based care is central to this framework, as regular outcome tracking enables both users and systems to observe change trajectories and adjust interventions accordingly. Quantitative research on AI-MB-CBT therefore emphasizes longitudinal outcome measurement, comparison across intervention conditions, and analysis of engagement-response relationships (Shalata et al., 2024). Effectiveness is assessed within controlled study designs that isolate the contribution of AI-driven personalization relative to standard digital or non-adaptive interventions.

Mechanisms of action in AI-MB-CBT can be examined across cognitive, emotional, attentional, and behavioural domains, with AI functioning as a facilitator of process-level change. Cognitive mechanisms include reductions in maladaptive beliefs, increased cognitive flexibility, and enhanced metacognitive awareness (Heanoy & Brown, 2024). Mindfulness-related mechanisms involve improvements in attentional stability, nonreactivity, and awareness of internal experiences. Behavioural mechanisms include increased engagement in valued activities, reduced avoidance, and consistent practice of therapeutic skills. Emotional mechanisms encompass improved regulation, reduced emotional reactivity, and increased tolerance of distress (McDaniels et al., 2023). AI systems contribute by identifying when these mechanisms are activated or disrupted and delivering targeted interventions accordingly. For example, increased indicators of rumination may prompt mindfulness-based decentering exercises, while behavioural inactivity may trigger activation strategies. Ecological data collection enables examination of within-person variability and temporal relationships among mechanisms and outcomes (Cooray et al., 2022). Quantitative models can test mediation pathways linking AI-supported engagement with changes in mindfulness, cognition, and behaviour to symptom improvement. These analyses provide insight into how AI-MB-CBT produces effects at the process level rather than solely at the outcome level.

Personalization is a defining feature of AI-MB-CBT and addresses the heterogeneity inherent in adult mental health populations (O'Connor et al., 2020). Adults vary widely in symptom presentation, comorbidity patterns, learning preferences, cultural background, and responsiveness to specific

therapeutic techniques. Personalization within AI-MB-CBT refers to systematic adaptation of intervention content, sequencing, intensity, and support based on individual data. This includes tailoring mindfulness practices, cognitive exercises, behavioural tasks, and feedback modalities to align with user needs and preferences. AI-driven personalization operates through predictive modeling and adaptive algorithms that learn from user responses over time. Measurement-based feedback loops allow continuous refinement of intervention pathways, supporting alignment between therapeutic strategies and individual progress (Majnarić et al., 2021). From a quantitative research perspective, personalization is evaluated through moderation analyses, individual growth modeling, and adaptive trial designs that capture differential response patterns. Personalization also supports engagement by reducing mismatch between intervention demands and user capacity. In adult mental health care, where dropout and nonresponse are common challenges, adaptive systems offer a structured approach to sustaining participation while maintaining therapeutic fidelity (Mehta et al., 2023). AI-MB-CBT thus represents a model in which personalization is operationalized as a measurable, testable component of intervention delivery, grounded in data and aligned with established psychotherapeutic principles.

Figure 2: AI-Enhanced Mindfulness CBT Framework



The objective of this quantitative study is to evaluate Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) for adult mental health by systematically examining its effectiveness, core mechanisms of change, and the role of personalization in optimizing outcomes across heterogeneous adult populations. Specifically, the study aims to measure the degree to which AI-MB-CBT reduces symptom severity associated with common adult mental health conditions such as depression, anxiety, and stress-related difficulties through standardized pre-post outcome indicators, repeated-measures symptom tracking, and functional impairment assessments. In addition to outcome effectiveness, the study seeks to identify and quantify mechanism-related pathways through which AI-MB-CBT produces change, focusing on measurable process variables that reflect mindfulness capacity, attentional regulation, cognitive flexibility, decentering, repetitive negative thinking, emotion regulation, behavioural activation, and avoidance reduction. The study also aims to test whether changes in these process variables statistically mediate the relationship between intervention exposure and mental health outcomes using mediation modeling and longitudinal process-outcome mapping. A further objective is to assess personalization as an active component of

AI-MB-CBT by determining whether algorithmically tailored intervention pathways lead to higher engagement, improved adherence, stronger skill acquisition, and superior clinical outcomes relative to standardized non-adaptive delivery. This includes evaluating adaptive sequencing of modules, individualized dosing of mindfulness and CBT exercises, timing of prompts and feedback, and responsiveness of the system to user progress patterns. The study also aims to explore variability in treatment response through subgroup comparisons and moderation analyses, examining whether baseline severity, comorbidity levels, demographic factors, and engagement profiles influence outcomes and interact with personalization effects. Finally, the research objective includes establishing a quantitative evidence base for AI-MB-CBT as a structured, measurable, and scalable intervention model by integrating outcome evaluation with mechanism testing and personalization analytics within a unified statistical framework, thereby generating empirically grounded estimates of how AI-enabled adaptations relate to adult mental health improvement across diverse user trajectories.

LITERATURE REVIEW

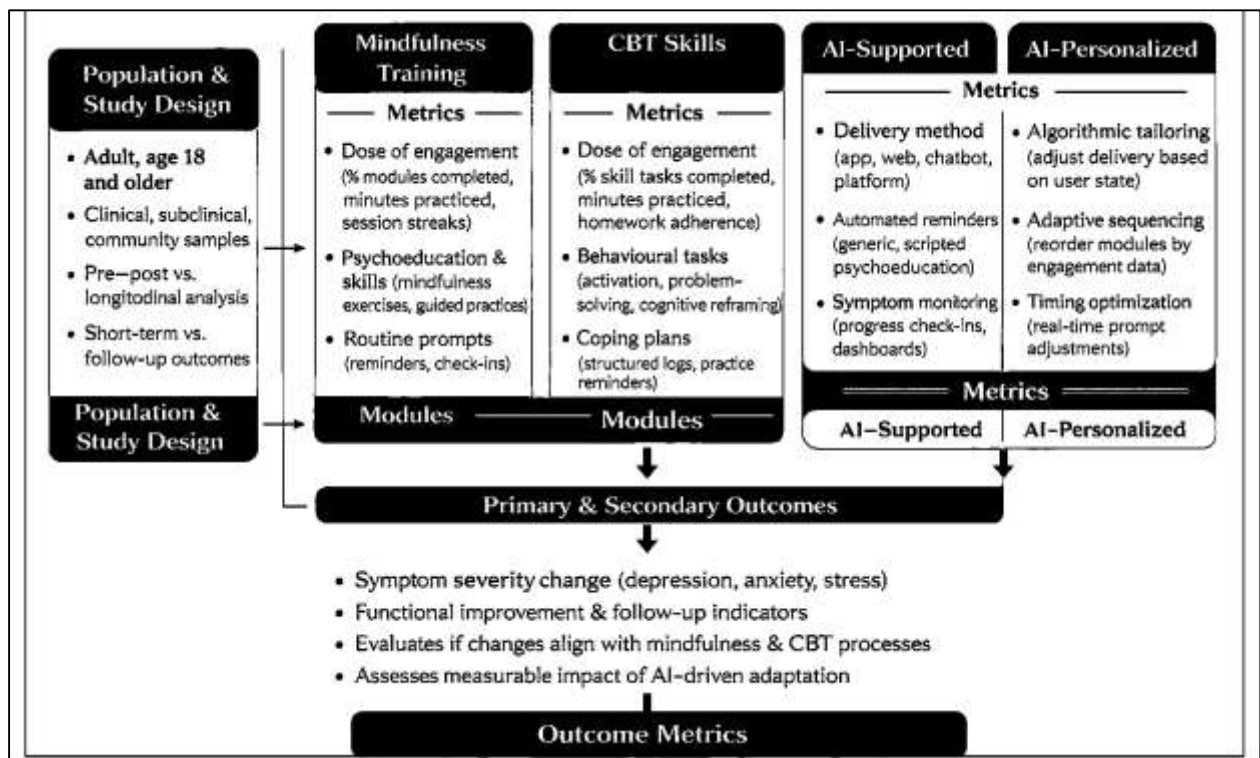
The literature review for this quantitative study synthesizes research at the intersection of three domains: mindfulness-based cognitive behaviour therapy for adults, digital and technology-mediated psychotherapy, and artificial intelligence-enabled personalization in mental health interventions (Aguinis & Bakker, 2021). The section is organized to build a measurement-oriented foundation for evaluating AI-MB-CBT as an integrated intervention model, with emphasis on (a) effectiveness outcomes, (b) mechanisms of change, and (c) personalization as a testable treatment feature rather than a descriptive design element. Because the study is quantitative, the review prioritizes evidence that reports measurable clinical outcomes (e.g., symptom severity, relapse indices, functional impairment, quality of life), process variables linked to therapeutic change (e.g., decentering, cognitive reactivity, emotion regulation, rumination, attentional control, behavioural activation), and analytics that operationalize personalization (e.g., adaptive sequencing, engagement-response curves, algorithm-driven recommendations, risk detection, and dose adjustment) (Wiig et al., 2020). The review also addresses how AI augmentation changes the delivery architecture of MB-CBT by introducing continuous data capture and automated decision rules, which makes it possible to model within-person change trajectories and to test mediation and moderation pathways. By synthesizing controlled trials, meta-analytic evidence, digital psychotherapy studies, and computational mental health research, this section establishes the conceptual and empirical rationale for the study's analytic framework, clarifies how key constructs will be operationalized, and identifies measurable gaps that justify examining effectiveness, mechanisms, and personalization within one integrated model for adult mental health.

AI-MB-CBT

Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) is best treated in a literature review as a quantifiable intervention system rather than a single therapy label, because published studies often vary in what they call "AI," what they include as "mindfulness," and how CBT skills are packaged (Vawdon & Livingstone, 2020). A consistent operational definition therefore begins by decomposing AI-MB-CBT into measurable modules that can be extracted and compared across trials and digital evaluations. The first module, mindfulness training, typically includes structured mindfulness exercises delivered through audio, text, or guided practice sessions, along with psychoeducation and routine practice prompts. In the digital mindfulness literature, intervention "dose" is frequently captured through countable engagement indicators such as minutes practiced, number of sessions completed, practice streak length, and completion of guided exercises, which allows mindfulness exposure to be represented as a continuous predictor rather than a yes-no attribute (Ruggerio, 2021). The second module, CBT skills, commonly includes behavioural activation tasks, cognitive restructuring exercises, coping plans, problem-solving steps, and structured homework logs, all of which have been measured in CBT trials and internet-delivered CBT research using completion rates, homework adherence, and skill practice frequency. The third module, AI-driven adaptation, distinguishes AI-MB-CBT from standard digital MB-CBT by introducing algorithmic decisions that change delivery, sequencing, or support intensity. Digital mental health studies that integrate adaptive systems often quantify this module through the number of personalized recommendations generated, the proportion of content selected by algorithms, the timing and frequency of adaptive prompts, and the occurrence of module resequencing. Across multiple strands

of evidence in internet-delivered CBT, mobile mindfulness programs, measurement-based care, and technology-supported psychotherapy, engagement and adherence have repeatedly been associated with symptom change, which strengthens the rationale for defining AI-MB-CBT through observable module exposure metrics. In addition, studies of conversational agents and automated supports show that delivery modality (app, web platform, chat interface) and level of guidance shape participation patterns, reinforcing the need to define AI-MB-CBT with measurable features that separate therapeutic content from delivery architecture and adaptation logic (Rossum et al., 2020). By operationalizing mindfulness training, CBT skills, and AI adaptation as discrete but interacting modules, the review can synthesize results across a broad evidence base while reducing construct drift and improving comparability between clinical trials, pragmatic evaluations, and digitally delivered intervention studies.

Figure 3: Quantitative Framework for AI-MB-CBT Adults



A core conceptual distinction in the literature concerns whether AI operates as support or as personalization, and this distinction is central for building a quantitative review framework. AI-supported delivery can be defined as the use of automation to facilitate access, monitoring, or interaction without producing individualized changes to the treatment pathway (Wong & Liem, 2022). In many digital therapy studies, support features include automated reminders, scripted chat interactions, generic psychoeducation reinforcement, progress dashboards, and symptom check-ins that provide feedback but do not alter what the user receives next. These features often improve usability and engagement and may indirectly relate to outcomes through increased adherence, but they do not constitute personalization unless decision logic modifies content allocation for the individual. AI-personalized delivery is defined more narrowly and requires that the system makes individualized adjustments using algorithmic rules or models. Across computational mental health and adaptive digital intervention research, three operational markers recur. First, algorithmic decision rules adjust delivery based on user state, such as symptom scores, engagement decline, or inferred risk. Second, adaptive sequencing changes the order or selection of modules so that different participants receive different pathways through the program rather than a fixed curriculum. Third, timing optimization delivers prompts or micro-interventions at individualized moments, often linked to patterns in self-reported stress, behaviour, or usage signals (Sahoo et al., 2020). Quantitatively, personalization is

captured through variables such as adaptation frequency, time-to-first adaptation, number of resequencing events, proportion of content that is algorithm-selected, and changes in support intensity over time. The literature across internet-based CBT trials, digital mindfulness evaluations, and adaptive intervention studies also emphasizes that personalization effects cannot be inferred solely from improved outcomes; they require evidence that adaptation occurred and that adaptations were meaningfully tied to individual-level data. This is why many quantitative reviews add “personalization intensity” or “adaptation dose” as an exposure variable, analogous to therapy dose, enabling comparisons between static digital programs and adaptive systems. Importantly, adult populations show heterogeneity in symptom patterns, comorbidity burden, cognitive styles, and daily stress exposures, which has been repeatedly documented in psychotherapy outcome research and digital intervention studies. This heterogeneity creates a clear measurement need: the review must separate studies where AI provides operational support from those where AI changes the therapeutic pathway, because these categories are not equivalent in what they test (Reaser et al., 2020). When studies are grouped by this operational distinction, effect estimates and engagement patterns become more interpretable and mechanisms can be compared with less ambiguity, including whether improvements are driven by higher adherence, more targeted skill selection, or better alignment of intervention components with individual needs.

The adult mental health scope and unit of analysis must also be defined with precision because study samples and settings differ substantially across the MB-CBT, digital CBT, and digital mindfulness literatures. The review should define adults as individuals aged 18 years and older and specify whether included studies involve clinical samples, subclinical samples, community recruitment, or outpatient service populations (Gasperini et al., 2020). Clinical samples typically include participants meeting diagnostic thresholds or receiving active treatment, which may involve higher baseline severity and more complex comorbidity patterns. Subclinical and community samples often show broader variability and may demonstrate different engagement trajectories, which matters because digital and AI-augmented interventions frequently depend on sustained self-management behaviours. In quantitative synthesis, the unit of analysis is usually the individual participant, yet many contemporary evaluations also generate intensive longitudinal data, such as daily mood ratings, ecological check-ins, or fine-grained usage logs. The literature on measurement-based care, routine outcome monitoring, and digital intervention analytics supports analyzing outcomes at multiple levels: between-person comparisons across conditions, within-person change over time, and exposure-response relations linking engagement dose to symptom reduction (Reis et al., 2020). This multi-level framing is especially relevant for AI-MB-CBT because adaptation itself is a time-varying exposure; the intervention can change within-person as the algorithm updates recommendations. For this reason, the review benefits from distinguishing designs that rely primarily on pre-post comparisons from those that use repeated measures capable of modeling symptom trajectories and dynamic associations. Outcome time frames must also be standardized. Many interventions are evaluated over short windows such as four to twelve weeks, producing acute post-treatment outcomes. A separate category is follow-up outcomes, commonly measured at three to twelve months, which allows assessment of maintenance, relapse indicators, and durability of changes in mechanism variables. The adult mental health literature contains extensive evidence that treatment effects can vary across immediate and longer-term periods, and digital interventions often show differential dropout and engagement effects across time (Walter, 2021). Therefore, time frame should be treated as a planned moderator in synthesis, allowing comparisons of short-term symptom change and longer-term stabilization without relying on narrative assumptions. Defining population boundaries, recruitment context, and time frame in this structured way enables the literature review to compare like with like and to interpret effect sizes and engagement patterns within the realities of adult mental health care delivery.

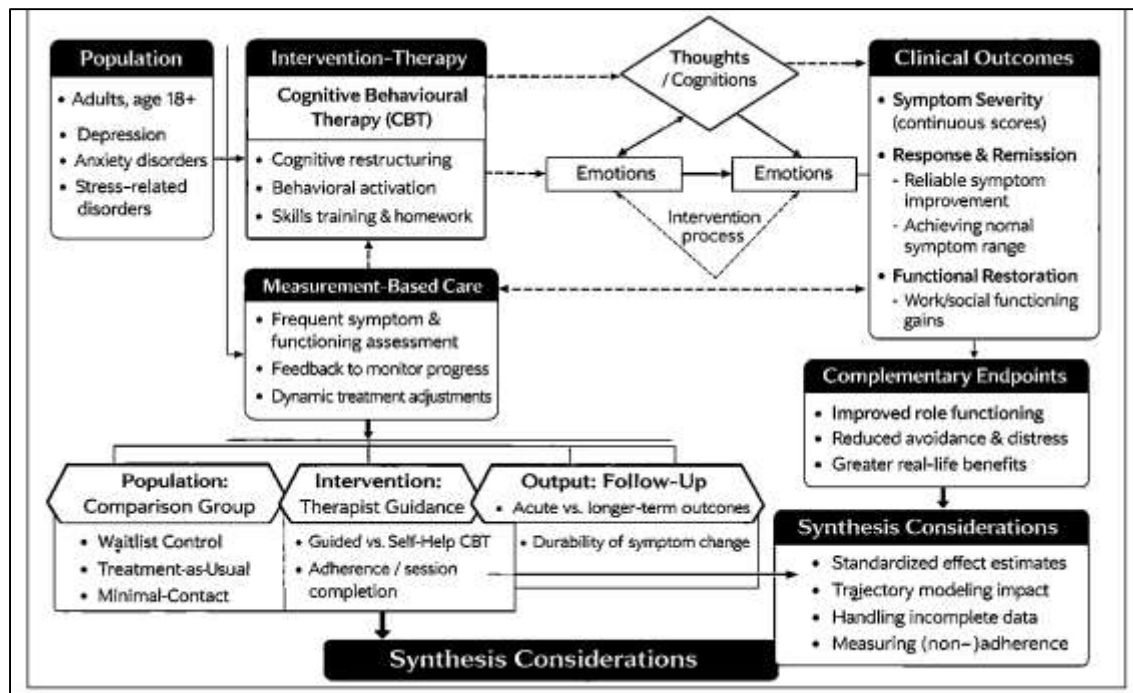
A key strength of a quantitative literature review is the use of a consistent construct operationalization framework that organizes the evidence around outcomes, mechanisms, and personalization indicators. Primary outcomes in AI-MB-CBT for adult mental health are typically depression severity, anxiety severity, stress or general distress, and functional impairment, because these variables are widely measured, clinically interpretable, and commonly used in psychotherapy trials and digital mental health evaluations (Russell et al., 2021). Secondary outcomes frequently include sleep quality,

wellbeing indices, quality of life, and relapse or recurrence indicators, which add breadth by capturing domains that often respond to mindfulness practice and behavioural change beyond symptom reduction alone. Mechanism or process variables provide the explanatory layer and should be defined as measurable constructs with plausible links to clinical outcomes. In the mindfulness and MB-CBT literature, mindfulness skills, decentering, cognitive reactivity, and reductions in rumination or worry are repeatedly treated as candidate pathways. In CBT-focused research, behavioural activation and reductions in avoidance are common process targets associated with symptom improvement, while emotion regulation appears as a shared mechanism bridging both mindfulness and CBT components. The review can synthesize evidence more rigorously by requiring that mechanism variables be measured in ways that are sensitive to change and, where possible, captured at multiple time points to support process-outcome mapping. Personalization variables should be operationalized with equal clarity (Martínez et al., 2021). Algorithmic tailoring intensity can be represented by categorical levels ranging from static delivery to rule-based tailoring to model-driven adaptation, while recommendation accuracy proxies can be quantified through uptake of recommended content and subsequent changes in symptoms or engagement. Adaptation frequency captures how often the system modifies the pathway, and engagement dose captures the amount of exposure and practice, including completion counts and time-on-task metrics. Across digital psychotherapy research, engagement is frequently intertwined with outcomes and is often examined as a mediator, covariate, or predictor, so the review should treat engagement metrics as core extractable variables rather than optional descriptive statistics. By integrating these constructs into a unified extraction plan, the review can compare studies on a common measurement foundation, evaluate whether symptom improvement aligns with predicted mechanisms, and assess whether personalization adds measurable value beyond standard digital delivery (Westphaln et al., 2021). This structure also supports synthesis across multiple study types—randomized comparisons, pragmatic evaluations, and intensive longitudinal studies—while keeping the analytic focus on quantifiable elements that map directly onto the study’s effectiveness, mechanisms, and personalization framework.

CBT effectiveness in adult mental health

Cognitive behaviour therapy (CBT) has a long-standing evidence base in adult mental health, and the literature consistently frames its effectiveness in terms of measurable changes in symptom severity, remission probability, and functional recovery across common clinical presentations (Powell et al., 2020). In adult depression research, CBT outcomes are frequently evaluated using continuous symptom severity measures collected at baseline and post-treatment, alongside categorical indicators such as remission status and clinically meaningful change. Across trials and quantitative reviews, depression outcomes are often discussed not only as average symptom reductions but also as the proportion of adults who reach non-clinical ranges or demonstrate clinically reliable improvement. This outcome framing matters because adult depression frequently presents with comorbidity, chronic stress exposure, and functional impairment, and symptom change alone can underestimate clinically relevant gains if role functioning and daily activity remain constrained (Lattie et al., 2022). In adult anxiety disorders, the evidence similarly emphasizes symptom reduction, yet it often expands to include behavioural and functional indicators because avoidance, safety behaviours, and interference in work or social roles are central features of anxiety-related impairment. Anxiety research therefore commonly includes measures of functional improvement, social participation, and reductions in avoidance-related disability as complementary endpoints to symptom scores. Stress-related outcomes in CBT research add an additional domain that is directly relevant to adult populations in community and occupational settings. Studies often evaluate perceived stress and general distress alongside work functioning, interpersonal functioning, and daily role performance to capture the practical consequences of intervention effects. Because adult mental health outcomes are influenced by the interaction between symptoms and environmental demands, the evidence base frequently treats work and social functioning as core clinical targets rather than secondary considerations (Pachankis et al., 2023). Taken together, CBT effectiveness research across depression, anxiety, and stress-related difficulties supports a broad outcome model in which symptom measures provide the primary index of clinical change, while remission, reliable improvement, and functional restoration provide complementary endpoints that align more closely with adult recovery expectations and service delivery benchmarks.

Figure 4: Quantitative CBT Outcomes Framework Adults



administered weekly or at multiple points across the intervention (Bemmer et al., 2021). From a quantitative perspective, repeated measurement offers substantial advantages because it allows modeling of change trajectories rather than relying only on baseline and post-treatment snapshots. Trajectory modeling can identify early response patterns, delayed improvement, or plateauing that may be invisible in simple pre-post comparisons. This is particularly relevant in CBT because many skills are acquired progressively, and symptom change may accelerate after behavioural activation increases or after cognitive skills begin to generalize across contexts. Routine monitoring also supports analysis of within-person variability, including symptom volatility under stress, and can illuminate whether CBT reduces instability in addition to reducing average symptom levels. A second major element is feedback: when outcome data are provided to clinicians and/or clients during treatment, the literature reports meaningful effects on engagement and treatment adjustment, including more timely responses to early nonresponse or deterioration (Le et al., 2022). Continuous measurement can influence dropout trajectories by increasing perceived accountability and by helping participants recognize incremental change, which may strengthen adherence in adults balancing work and family demands. It can also identify individuals who are not improving early, enabling adaptation of intensity or focus within the CBT framework. Importantly, measurement-based care changes the nature of “treatment exposure” because assessment itself can shape attention, motivation, and self-regulation. For quantitative reviews, this means CBT studies that include routine monitoring and feedback may not be strictly comparable to studies that do not, even when the CBT content is similar. In adult mental health care, these monitoring practices also align CBT with quality improvement structures used in healthcare systems, where symptom and functioning metrics are increasingly required for evaluation and reimbursement. Thus, measurement-based care is not only a methodological tool but also a delivery context feature that can systematically influence trajectories and observed effect sizes in CBT research (Khanna & Carper, 2022; Tasnim, 2026).

Across the CBT effectiveness literature, the integration of clinical outcome domains, quantitative synthesis metrics, and measurement-based care perspectives reveals a consistent pattern: CBT outcomes are shaped by what is measured, how frequently it is measured, the comparison condition used, and how engagement is supported throughout treatment (Jinnat & Kamrul, 2021). Depression outcomes illustrate this clearly, as continuous symptom reductions may coincide with meaningful functional improvement, yet remission and reliable change provide complementary indicators of clinically significant recovery that are often prioritized in adult service settings (Towhidul et al., 2022; Wilhelm et al., 2020). Anxiety outcomes similarly show that symptom reduction is important, but improvements in avoidance and role functioning frequently provide a clearer signal of real-world benefit. Stress-focused outcomes highlight the relevance of perceived stress and distress reduction, while also emphasizing work and social functioning as pragmatic endpoints for adults (Faysal & Bhuya, 2023). In synthesis research, standardized effect estimates enable aggregation, yet methodological differences, control group type, therapist guidance intensity, adherence variability, and missing data handling, reliably shift effect magnitude and interpretation (Hammad & Mohiul, 2023). This is one reason the literature increasingly emphasizes transparent reporting of guidance procedures, engagement thresholds, and dropout patterns alongside outcome results. Routine outcome monitoring and feedback offer an additional lens by transforming CBT evaluation from a two-timepoint comparison into a dynamic model of change that captures early response, mid-treatment shifts, and trajectory heterogeneity (Masud & Hammad, 2024; Triplett et al., 2020). For adult mental health interventions delivered in-person or digitally, this repeated-measurement approach provides more precise estimates of when and how improvement occurs and supports analytic strategies that connect engagement patterns to outcomes. It also underscores why CBT effectiveness cannot be summarized solely by average symptom change; the evidence base repeatedly points toward the value of multi-domain outcome assessment, trajectory-informed interpretation, and measurement-informed adjustment as key features of CBT research and practice (Md & Sai Praveen, 2024). This integrated quantitative framing provides a strong foundation for positioning CBT as a benchmark intervention within broader reviews that examine technology-supported and AI-enhanced therapeutic approaches for adults, especially when outcome monitoring and engagement dynamics are central to interpreting clinical effectiveness (Herschell et al., 2020; Newaz & Jahidul, 2024).

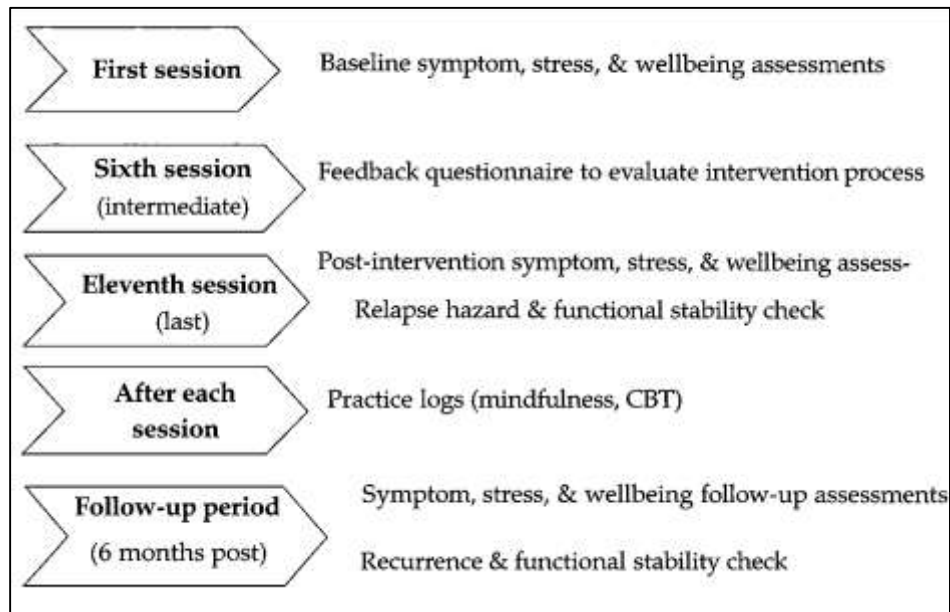
Mindfulness-based interventions and MB-CBT/MBCT in adults

Mindfulness-based interventions have accumulated a substantial empirical base in adult mental health research, with outcomes commonly evaluated through standardized symptom measures, stress indices, and broader wellbeing indicators. Across clinical and community adult samples, mindfulness-oriented programs are frequently associated with reductions in depressive symptoms, anxiety severity, and perceived stress, and these outcomes are often reported alongside improvements in related domains such as sleep quality, emotional balance, and general psychological wellbeing (Michalak et al., 2020). Adult depression and anxiety studies typically rely on continuous symptom scales collected at baseline and post-intervention, while stress-focused research often uses perceived stress measures and general distress indicators to capture improvements that may occur even when diagnostic thresholds are not the primary enrollment criterion. A prominent strand of adult evidence concerns relapse prevention, particularly in recurrent depression, where mindfulness-based cognitive therapy (MBCT) has been evaluated for its capacity to reduce relapse risk and sustain recovery. In relapse prevention studies, outcomes extend beyond symptom reduction to include time-to-relapse indicators, recurrence counts, and maintenance of functional stability. Functional outcomes have also become increasingly visible in adult mindfulness research because symptom improvement does not always translate directly into restored occupational or social functioning (Perrier et al., 2020). Trials and syntheses often report work functioning, daily activity performance, interpersonal role satisfaction, and quality of life as key endpoints that complement symptom indices. This broader outcome profile aligns with adult mental health service goals that emphasize not only reduction of distress but also restoration of participation in work, family responsibilities, and social life. Additionally, mindfulness interventions are commonly studied in stress-related contexts where adults face persistent demands, and findings frequently highlight reductions in stress reactivity and improvements in coping capacity. These patterns collectively indicate that mindfulness-based interventions in adults are evaluated through a multi-domain outcome lens that includes symptom change, stress reduction, relapse prevention, and functional and wellbeing outcomes, making them highly relevant to integrative approaches such as MB-CBT and AI-MB-CBT that aim to address both clinical symptomatology and daily functioning (Johns et al., 2021).

The integrated logic of mindfulness-based cognitive behaviour therapy and mindfulness-based cognitive therapy can be described as a dual-pathway framework in which CBT and mindfulness components operate through partially distinct but interacting change processes (Goldberg, 2022). The CBT pathway is typically conceptualized as targeting maladaptive cognitions and reinforcing behaviours, emphasizing structured skill learning such as cognitive restructuring, behavioural activation, exposure-based reductions in avoidance, and problem-solving (Faysal & Aditya, 2025; Azam & Amin, 2024). Quantitatively, this pathway is represented by measurable changes in dysfunctional beliefs, negative automatic thoughts, behavioural activation levels, reduced avoidance, and improvements in adaptive coping behaviours. In contrast, the mindfulness pathway is commonly conceptualized as targeting attentional regulation and decentering, emphasizing metacognitive awareness, nonreactivity to internal experiences, and reduced identification with negative thoughts. Quantitative indicators for this pathway include increases in mindfulness skills, improvements in attentional control, reductions in cognitive reactivity, greater decentering or cognitive defusion, and reductions in repetitive negative thinking such as rumination and worry (Phan et al., 2022; Sai Praveen, 2024). Integrated MB-CBT logic holds that these pathways can converge in their effects on emotion regulation and stress reactivity, because cognitive change and attentional-metacognitive change both shape how adults respond to distressing internal experiences and external stressors. In adult samples, this dual-pathway framing supports measurement strategies that include both CBT-specific mediators and mindfulness-specific mediators, allowing quantitative designs to test whether symptom reduction is driven primarily by cognitive-behavioural shifts, by mindfulness-related shifts, or by combined process changes that occur in tandem. This is particularly relevant because adults with depression and anxiety often show patterns of perseverative thinking and avoidance that are targeted by both pathways through different mechanisms, and because integrated programs often involve both cognitive-behavioural homework and mindfulness practice requirements. A dual-pathway framework therefore gives the literature review a structured map for synthesizing findings across studies that may

emphasize different components, while keeping the focus on measurable constructs that can be compared, modeled, and interpreted across diverse adult mental health contexts (Hammad & Hossain, 2025; Thompson & Moran, 2023; Towhidul & Rebeka, 2025).

Figure 5: Mindfulness Intervention Evaluation Framework Adults



Dose-response considerations are central in mindfulness-based interventions and MB-CBT/MBCT research because practice is not an incidental feature of these programs but a core therapeutic mechanism that varies widely across adult participants. In many adult mindfulness studies, the amount of practice completed can differ substantially even within the same intervention condition, with some participants practicing daily and others engaging sporadically (Kor et al., 2024; Yousuf et al., 2025; Azam, 2025). This variability has led researchers to treat practice frequency and duration as measurable predictors of outcomes, often operationalized through minutes practiced, number of guided sessions completed, total practice days, or adherence to assigned home practice schedules (Tasnim, 2025). Engagement metrics are similarly emphasized in digital and hybrid mindfulness interventions, where platforms can log usage automatically, enabling precise measurement of sessions accessed, time-on-task, module completion rates, and practice streaks. In quantitative analyses, engagement is frequently included as a covariate to account for differential exposure when estimating intervention effects, or it is modeled as a predictor of symptom reduction and functional improvement. This engagement-based perspective is particularly relevant for adult mental health because adults experience competing demands that influence adherence, and adherence patterns often align with motivational readiness, baseline distress, and perceived benefit (Castellanos et al., 2020; Zaheda, 2025b). In MBCT relapse prevention trials, practice adherence may be linked not only to immediate symptom improvement but also to maintenance of gains and reduced recurrence risk, which increases the importance of capturing practice dose across both intervention and follow-up periods. Dose-response reasoning also applies to CBT components embedded in MB-CBT programs, where completion of behavioural tasks, cognitive exercises, and practice logs often predicts improvement (Zaheda, 2025a). Consequently, integrated MB-CBT studies benefit from capturing dose indicators separately for mindfulness practice and CBT skill use to clarify how each pathway contributes to outcomes. When studies fail to measure dose, interpretation becomes limited because null or modest effects may reflect low engagement rather than low intervention potency (Towhidul, 2026; Moyes et al., 2022; Azam, 2026). The literature therefore increasingly treats dose variables as essential quantitative descriptors and analytic inputs that help explain heterogeneity in outcomes across adult participants and across intervention modalities.

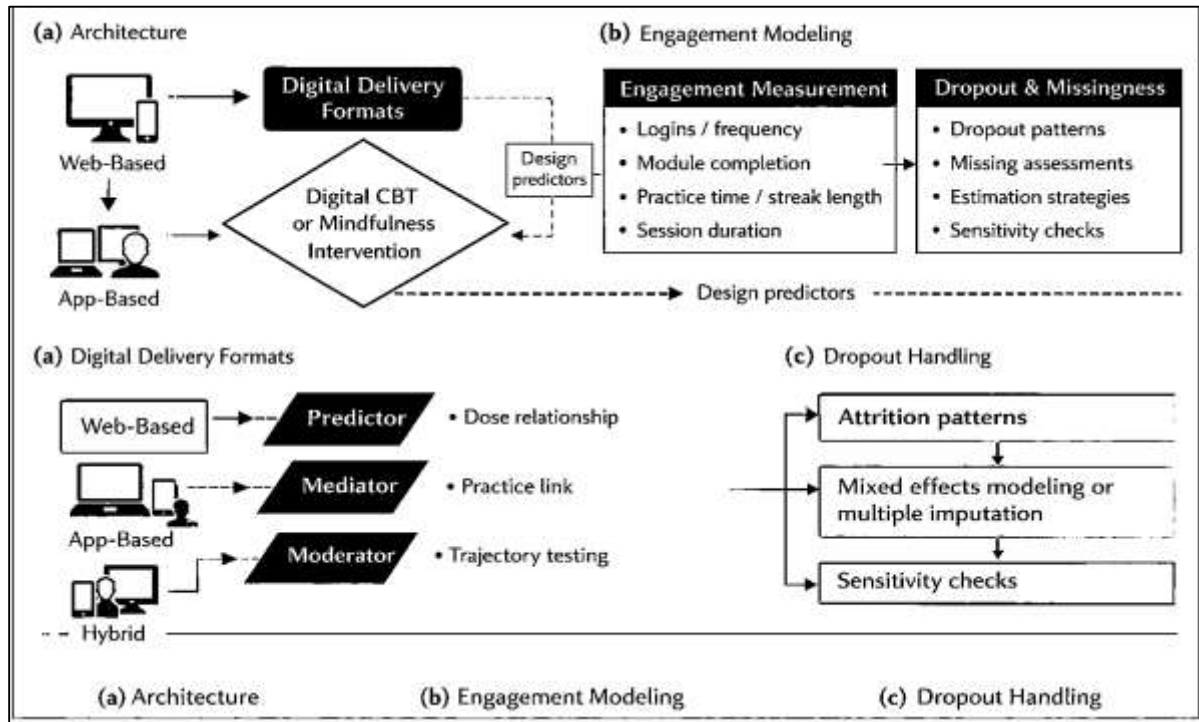
Digital delivery of CBT and mindfulness

Digital delivery of cognitive behaviour therapy and mindfulness-based interventions has expanded the evidence base for adult mental health by shifting psychotherapy from an episodic, clinic-bound format toward scalable, structured programs that can be delivered through web platforms, mobile applications, and hybrid models combining digital content with human support ([Apolinário-Hagen et al., 2020](#)). In the literature, digital intervention architecture is commonly treated as a core design variable because it shapes exposure, adherence, and the interpretability of outcome estimates. One widely used architectural distinction separates self-guided and guided formats. Self-guided interventions provide structured content without ongoing clinician support, often relying on automated reminders and standardized pacing. Guided interventions incorporate therapist support or coached feedback through messaging, calls, or brief check-ins, which can increase accountability and skill application. In adult samples, this distinction matters because guided interventions often show higher completion rates and stronger clinical effects in both CBT and mindfulness programs, while self-guided models show wider variability in adherence and outcomes. Platform type further differentiates digital interventions by shaping user experience, ease of use, accessibility, and the granularity of measurable data. Web-based programs frequently resemble modular courses that adults complete over several weeks, while app-based programs are often designed for brief, frequent interactions that integrate with daily routines ([Kirk et al., 2022](#)). Hybrid programs combine app or web modules with periodic human guidance, producing intervention pathways that may resemble stepped-care or blended care models. These architectural differences influence engagement patterns, including how often adults log in, how quickly they progress through content, and whether skill practice is distributed evenly or clustered around episodes of distress. Architecture also influences what can be measured at scale, as digital platforms can automatically capture usage logs, time stamps, task completion, practice duration, and the sequence in which modules are accessed. The literature on digital mental health increasingly emphasizes that architecture is not merely a delivery channel but a structural determinant of treatment dose, participant burden, and adherence opportunities ([Kennett et al., 2021](#)). Consequently, digital CBT and digital mindfulness studies often treat format and platform as categorical predictors when evaluating outcomes, and they interpret effect variability through the lens of design decisions that influence engagement and persistence in adult users.

A defining contribution of digital delivery is that it transforms engagement from an inferred construct into a directly measurable behavioural pattern, allowing adult mental health interventions to be evaluated with a level of precision that is difficult to achieve in traditional face-to-face settings. Engagement metrics are typically derived from automatically recorded user interactions, making it possible to quantify exposure and adherence at high resolution ([Drüge et al., 2024](#); [Tasnim, 2026](#)). Common engagement indicators include the number of logins, module completion percentage, time-on-task, and practice streak length, along with related metrics such as session frequency, duration per session, gaps between sessions, and the proportion of assigned exercises completed. In the literature, engagement is often conceptualized as a central variable because it captures the functional “dose” of intervention that participants actually receive, which can diverge substantially from the intended protocol. This has led to three primary quantitative roles for engagement in digital CBT and mindfulness research. First, engagement is modeled as a predictor of outcome, reflecting a dose-response logic where greater exposure and practice are associated with stronger symptom reduction and improved functioning. Second, engagement is frequently modeled as a mediator between intervention access and symptom change. In this view, access to a digital program influences outcomes primarily through whether adults meaningfully engage with the material, complete modules, and practice skills ([Zgierska et al., 2021](#)). This framing is especially relevant in self-guided formats where variability in participation is high. Third, engagement is modeled as a moderator, where adult participants are grouped into high and low engagement trajectories that show different patterns of symptom change, completion probability, and response stability. This approach acknowledges heterogeneity in adult users, including differences in motivation, baseline severity, work and family demands, and digital literacy. Engagement modeling also links directly to the theoretical structure of CBT and mindfulness interventions because both rely on repeated practice and skill generalization. CBT requires consistent application of behavioural and cognitive strategies, while mindfulness relies

on repeated attentional training and continued practice. Digital systems can capture these practice behaviours through logged meditation minutes, completion of thought records, behavioural task logs, and adherence to daily exercises (Mitsea et al., 2023). The measurability of engagement at scale therefore reshapes the literature by enabling more refined analyses of what aspects of digital delivery drive outcomes, why some adults benefit more than others, and how intervention design features influence adherence and dose distribution.

Figure 6: Digital CBT and Mindfulness Framework



Attrition and missingness represent persistent quantitative threats in digital mental health research, and the literature consistently treats them as central methodological issues rather than minor reporting concerns. Digital CBT and mindfulness interventions frequently experience dropout or partial completion, and attrition is often systematic rather than random (Zgierska et al., 2021). Adults may disengage due to competing responsibilities, perceived lack of benefit, symptom fluctuation, technological barriers, or reduced motivation, and these factors may correlate with baseline severity or early response patterns. This creates a risk that missing outcome data are not missing at random, meaning that participants who drop out may differ meaningfully from those who remain, and estimates of effectiveness may be biased if missingness is handled inadequately. The literature therefore emphasizes the importance of examining dropout patterns and reporting attrition clearly, including when dropout occurs, which modules are completed before disengagement, and whether early symptom change predicts continuation. Digital interventions also generate complex missingness profiles because outcome data may be collected through repeated assessments, and missingness can occur intermittently rather than as full dropout. This makes analytic strategy selection a critical determinant of validity. Mixed-effects models are frequently used because they can incorporate repeated measures with incomplete observations and can model within-person change trajectories while accounting for individual differences (Werner-Seidler et al., 2020). Multiple imputation is also widely referenced as a strategy for handling missing data by estimating plausible values under specified assumptions, though its appropriateness depends on the missingness mechanism and the richness of auxiliary variables available. Sensitivity checks are increasingly recommended because they allow researchers to test how robust conclusions are under different assumptions about missingness, especially when there is evidence that dropout is linked to symptom severity or engagement decline. Digital platforms also allow the use of auxiliary data such as usage logs to inform missingness

modeling, offering opportunities to reduce bias by incorporating engagement indicators and baseline characteristics that predict dropout. These methodological discussions are especially relevant in adult mental health because treatment adherence can be strongly influenced by life context, and digital interventions may be used during periods of heightened stress or instability (Strauss et al., 2022). Attrition is therefore not simply an inconvenience but a structural feature of digital therapy delivery that must be addressed through transparent reporting, appropriate modeling, and careful interpretation of results.

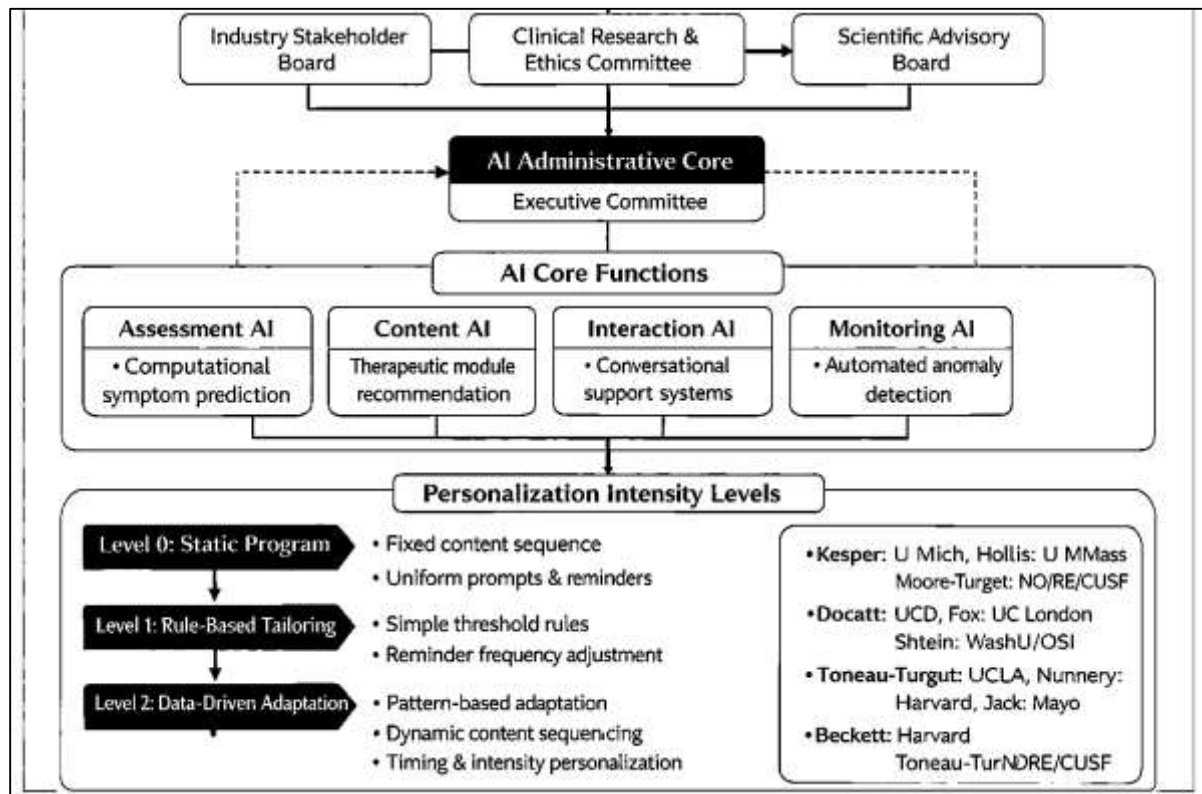
When digital architecture, engagement measurement, and attrition handling are considered together, the literature shows that digital delivery makes psychotherapy outcomes more measurable while simultaneously introducing analytic complexities that affect inference about effectiveness. Self-guided and guided formats and platform type function as structural determinants of participation patterns, shaping both average outcomes and the distribution of response across adult users. Engagement metrics derived from digital traces provide a direct window into treatment dose, allowing researchers to evaluate whether symptom improvement corresponds to meaningful participation, consistent practice, and completion of core therapeutic components (Roberts et al., 2021). This measurability strengthens the capacity of the literature to explain heterogeneity and to compare interventions beyond simple pre-post change. At the same time, dropout and missingness complicate interpretation because adults who disengage early may systematically differ from completers, and the strength of observed effects may depend on analytic choices and assumptions. The literature therefore supports an evaluative stance in which engagement is treated as a central explanatory variable that can function as predictor, mediator, or moderator, and in which architecture and platform are treated as essential design predictors that influence engagement and effect variability (Manole et al., 2024). It also supports a methodological stance in which missingness is treated as a primary validity concern requiring explicit modeling strategies and robustness checks. This integrated perspective is particularly important for reviews that connect digital CBT and mindfulness to AI-enhanced interventions, because AI systems often depend on continuous data streams and adaptive decisions that are themselves shaped by engagement and affected by missingness. A rigorous literature review can therefore synthesize digital delivery evidence by mapping design features to engagement patterns, linking engagement to outcomes, and evaluating how attrition and missingness influence estimated effects and generalizability in adult populations (Blumenstein et al., 2022).

AI augmentation in psychotherapy

Quantitative studies that examine AI augmentation in psychotherapy typically operationalize “AI” not as a single feature but as a bundle of computational functions that produce measurable outputs capable of being linked to clinical endpoints (Deka et al., 2023). Within this literature, assessment AI is commonly defined as the use of computational models to transform patient-reported outcomes, behavioural traces, or language signals into numeric estimates of symptom burden, relapse likelihood, or near-term risk, often expressed as risk scores, severity probabilities, or categorical flags. These outputs become analyzable variables that can be compared against standardized clinical measures and tracked across repeated time points. Content AI is operationalized through recommendation processes that select, rank, or prioritize therapeutic modules, exercises, or prompts. In digital CBT, this can involve recommending behavioural activation tasks for low-activity patterns or cognitive exercises for high negative thinking indicators; in digital mindfulness, it can involve recommending shorter practices when adherence declines or targeting specific attentional skills when stress reactivity increases. The measurability of content AI is reflected in logged recommendation counts, acceptance rates of recommended content, completion of recommended modules, and changes in symptom trajectories following recommendation delivery. Interaction AI is often represented through conversational systems that deliver psychoeducation, skills prompts, or supportive dialogue. Quantitative operationalization typically includes frequency of chatbot sessions, dialog length, message counts, session duration, and linguistic markers extracted from text such as sentiment, topic prevalence, and indicators of cognitive or affective states (Kuhail et al., 2024). Monitoring AI is operationalized through automated detection of anomalies in symptom reports or usage behaviour, such as sudden symptom spikes, reductions in engagement, or patterns associated with deterioration. Monitoring outputs may include disengagement probability estimates, alerts for potential risk

escalation, or event-based triggers that initiate check-ins or suggest higher-intensity support. Across these categories, the literature repeatedly emphasizes that AI augmentation becomes scientifically interpretable when AI outputs are explicitly treated as variables: scores that can be validated against clinical states, recommendations that can be linked to subsequent behaviour and outcomes, interactions that can be quantified as exposure, and monitoring signals that can be evaluated for accuracy and timing relative to clinical change. This measurement framing is central to psychotherapy research because it allows AI features to be analyzed as predictors, mediators, or moderators within models that already exist in clinical trials and longitudinal outcome monitoring, supporting a consistent bridge between computational functionality and therapeutic effectiveness (Harfouche et al., 2023).

Figure 7: AI Personalization Framework Psychotherapy Research



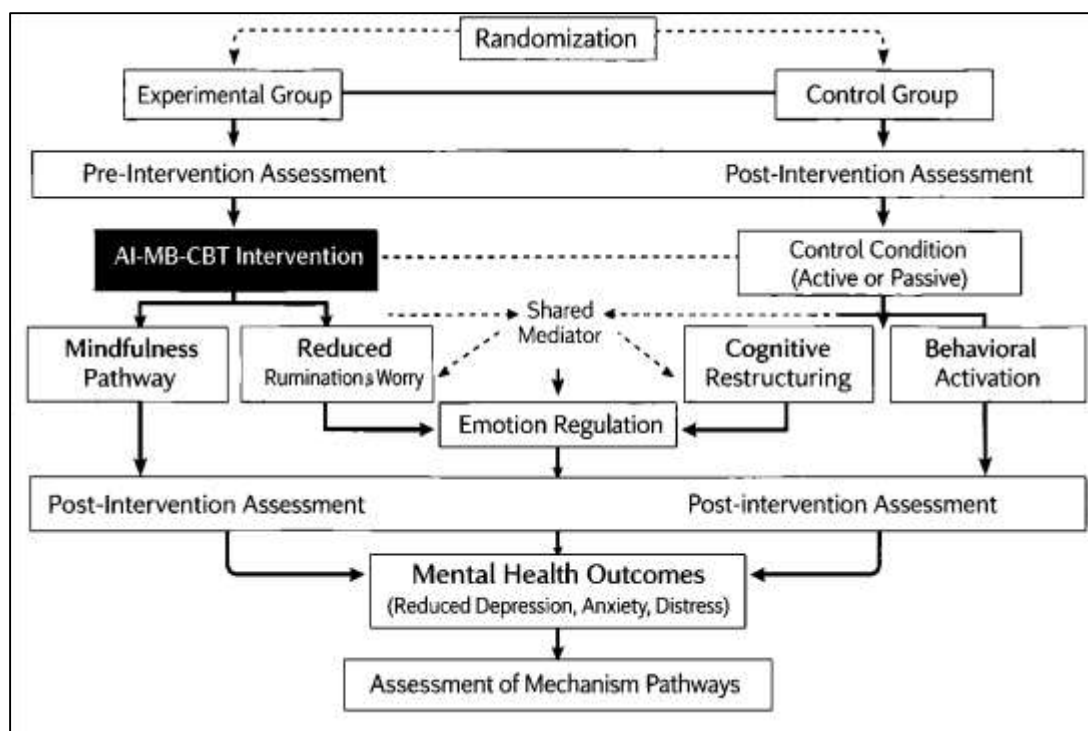
Algorithmic personalization intensity is commonly treated as an independent variable in quantitative AI psychotherapy research because it captures the degree to which the system changes a person's intervention pathway based on individual-level data (Fenwick et al., 2024). A practical approach in the literature is to define personalization intensity in tiered levels that reflect increasing algorithmic autonomy and increasing dependence on user data streams. Level 0 personalization is typically represented as a static program: module order is fixed, prompt timing is generic, and content is delivered in the same sequence to all users, even when engagement and symptom profiles differ. Studies operationalize Level 0 as the absence of individualized adaptation beyond standard usability features. Level 1 personalization is commonly represented as rule-based tailoring in which predetermined decision rules modify delivery based on simple thresholds, such as increasing reminder frequency after missed sessions, recommending a review module after low quiz scores, or triggering a check-in when a symptom score crosses a cut-off. Quantitatively, Level 1 can be captured by counts of rule-triggered events, types of rule activations, and the timing of rule execution relative to engagement decline or symptom escalation (Margaroli et al., 2023). Level 2 personalization is represented as data-driven adaptive tailoring, where machine learning or model-based systems dynamically select content, pacing, or support intensity using patterns learned from data. In this case, personalization is often operationalized through a higher-resolution set of indicators: number of adaptations delivered per user, time-to-first adaptation, adaptation frequency across weeks, distribution of adaptation types

(sequencing changes, prompt timing shifts, content substitutions), and composite personalization scores indicating the proportion of the pathway determined by the algorithm rather than the default protocol. These indicators allow researchers to analyze personalization as dose-like exposure, which aligns with psychotherapy traditions that examine treatment intensity and adherence as core drivers of outcomes. The literature also supports using personalization intensity for subgroup analyses and heterogeneity modeling, because adults differ substantially in symptom profiles, digital engagement patterns, and responsiveness to intervention components. Some quantitative evaluations treat personalization as an intervention characteristic at the group level (personalized vs non-personalized arms), while others treat it as a within-condition variable that varies across participants depending on how often the algorithm adapts their pathway (Gil de Zúñiga et al., 2024). This dual operationalization is important because AI systems can deliver the same platform to all users while producing different levels of adaptation depending on user behaviour, meaning that personalization intensity becomes a meaningful determinant of actual received intervention. In this way, quantitative psychotherapy research positions personalization not as a descriptive claim but as a measurable construct that can be compared, modeled over time, and related to symptom change, engagement persistence, and functional outcomes.

Mechanisms of change in AI-MB-CBT

Mechanisms of change in Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) can be organized as a testable mediation framework that specifies measurable psychological processes linking intervention exposure to adult mental health outcomes (Aung et al., 2020). In the mindfulness pathway, the literature commonly conceptualizes change as beginning with improvements in attention regulation, followed by increased decentering from internal experiences, reductions in repetitive negative thinking such as rumination and worry, and subsequent decreases in depression, anxiety, and distress symptoms. Attention regulation is treated as a foundational capacity that supports sustained contact with present-moment experience and reduces automatic capture by negative thoughts, which is especially relevant in adult depression and anxiety where perseverative thinking is strongly linked to symptom maintenance. Decentering is conceptualized as a metacognitive process in which thoughts are experienced as transient mental events rather than accurate reflections of self or reality, enabling adults to disengage from self-critical appraisals and catastrophic interpretations (Frangipane et al., 2022). Reductions in rumination and worry are frequently positioned as downstream outcomes of improved attentional control and decentering, and these reductions are associated with lower symptom intensity and improved emotional stability. In the CBT pathway, change is often conceptualized as emerging through cognitive restructuring and behavioural activation, which alter maladaptive interpretations and increase engagement in rewarding activities while reducing avoidance patterns that perpetuate anxiety and depressed mood. Cognitive restructuring targets habitual distortions and rigid beliefs that amplify distress, while behavioural activation targets inactivity and withdrawal that reduce positive reinforcement and maintain low mood. Reduced avoidance is frequently treated as a proximal mediator in anxiety and stress-related disorders, as avoidance limits corrective learning and reinforces threat appraisals. Integrated MB-CBT logic positions emotion regulation as a shared mediator bridging both pathways, capturing the capacity to manage affective responses flexibly through acceptance, reappraisal, and values-consistent action. Emotion regulation is also a clinically meaningful mediator because adults often present with comorbid symptoms tied to dysregulated affect, and improvements in emotion regulation can reflect both mindfulness-based nonreactivity and CBT-based cognitive-behavioural skill application. AI augmentation intersects with these pathways by increasing the precision and frequency with which mechanism-relevant behaviours and states are measured and by supporting timely prompts and adaptive content that may intensify exposure to pathway-relevant skills (Wang et al., 2023). A mediation framework therefore enables the literature review to specify how changes in mindfulness skills, decentering, rumination, cognitive restructuring, behavioural activation, avoidance, and emotion regulation can be tested quantitatively as explanatory processes connecting AI-MB-CBT engagement to symptom and functional outcomes in adult samples.

Figure 8: AI-Enhanced MB-CBT Mediation Framework



Quantitative mechanism testing designs in this literature vary in complexity, but they share a central goal of demonstrating that process change explains outcome change rather than merely co-occurring with it. Pre-post mediation designs are common in psychotherapy research and can be used when studies measure mediators and outcomes before and after intervention exposure, enabling statistical testing of whether change in a mechanism variable accounts for change in symptoms (Zhao & Luo, 2023). However, the literature also highlights the interpretive limitations of two-timepoint designs because they do not establish temporal ordering within the intervention window and can conflate simultaneous change. Longitudinal mediation designs address this by measuring mechanisms and outcomes across multiple waves and testing whether earlier changes in mediators predict later changes in outcomes, which aligns with clinical theory that mechanism change should precede symptom change. In adult digital interventions, repeated measures are increasingly feasible through weekly symptom monitoring and brief process check-ins, allowing mediators such as rumination, mindfulness skills, or behavioural activation to be captured across the treatment course rather than only at endpoints. Intensive longitudinal designs extend this logic further by collecting daily or near-daily measures through ecological momentary assessment, enabling within-person analyses that examine how day-to-day fluctuations in mechanisms relate to subsequent symptom shifts (Garner et al., 2020). This approach is particularly relevant for AI-MB-CBT because AI platforms can integrate short daily assessments, passive behavioural indicators, and practice logs that approximate real-time markers of attention regulation, emotional reactivity, and avoidance. Within-person association models can test whether increases in mindfulness practice on a given day relate to reduced rumination later that day or the next day, or whether completion of behavioural activation tasks predicts short-term improvements in mood and functioning. These designs also support examination of heterogeneity, showing that mechanisms may operate differently across individuals depending on baseline severity, comorbidity, stress exposure, and engagement patterns. Quantitative mechanism evidence is strongest when designs include repeated mediator and outcome measures, incorporate lagged relationships, and handle missingness carefully, because adult digital intervention datasets often contain incomplete observations due to irregular participation (Huber, 2020). Mechanism testing therefore becomes inseparable from measurement architecture and analytic rigor, and the literature repeatedly emphasizes that mediation claims require methodological alignment between the hypothesized causal sequence and the structure of the observed data.

A mechanism measurement strategy for AI-MB-CBT is strengthened when mediators are assessed at multiple time points, measured reliably, and shown to be sensitive to change within the intervention window. Multi-timepoint measurement is critical because it allows temporal ordering and supports mediation models that test whether mediator change precedes outcome change (Ohrnberger et al., 2020). A minimum of three mediator time points is often recommended for establishing whether mechanism change occurs early, mid-course, or late in treatment and for testing whether shifts in mediators predict subsequent symptom changes rather than reflecting concurrent improvement. In practice, this can include baseline measurement, an early treatment assessment, a mid-treatment assessment, and a post-treatment assessment, with additional follow-up assessments when the goal includes examining maintenance mechanisms. Reliability and validity reporting is equally important because mediator constructs such as decentering, mindfulness skills, and emotion regulation are measured using self-report scales that vary in internal consistency, sensitivity, and factor structure across populations. In adult samples, scale performance can differ depending on symptom severity, cultural interpretation of items, and whether the intervention is delivered digitally or in-person (Peng et al., 2022). Sensitivity-to-change is a specific requirement for mediator measurement because a mediator that does not change cannot statistically explain change in outcomes. The literature therefore encourages selecting mediator measures with demonstrated responsiveness in intervention contexts and aligning measurement intervals with expected change processes. For instance, behavioural activation may change quickly when adults begin scheduling activities, while decentering and reductions in cognitive reactivity may develop more gradually through mindfulness practice and repeated exposure to metacognitive strategies. Mechanism measurement is also strengthened by including parallel measures that map onto both pathways, allowing examination of whether mindfulness and CBT processes independently contribute to symptom change or whether one pathway drives most of the effect. Digital platforms further enable objective or behavioural proxies such as practice minutes, completion of cognitive exercises, and task engagement, which can complement self-report measures and reduce shared-method variance (Gómez et al., 2020). A rigorous measurement strategy also includes consistent handling of missing data and transparent reporting of assessment adherence, since mediator measurement is vulnerable to dropout and intermittent missingness that can bias mediation estimates if missingness is correlated with symptom severity or engagement decline. An integrated synthesis of mechanisms, designs, and measurement strategy highlights how AI-MB-CBT can be evaluated through a mediation framework that is both theory-consistent and quantitatively testable. The mindfulness pathway specifies a sequence from attention regulation to decentering to reduced rumination and worry, culminating in symptom reduction and improved functioning. The CBT pathway specifies change through cognitive restructuring and behavioural activation, leading to reduced avoidance and symptom improvement (Frost & Castro, 2024). Emotion regulation functions as a shared mediator across pathways, capturing the broader self-regulatory capacity that is central to adult mental health recovery and that is plausibly shaped by both mindful awareness and CBT skill application. Quantitative mechanism testing can be conducted through pre-post mediation, strengthened through longitudinal mediation with lagged mediator-outcome relations, and further refined through intensive longitudinal designs that examine within-person mechanisms in daily life. These designs align well with digital and AI-augmented delivery because data collection can be frequent, time-stamped, and integrated into routine intervention use (Zheng et al., 2024). A robust mechanism measurement strategy emphasizes multi-timepoint mediator assessment, reliable and valid constructs, sensitivity-to-change, and the use of both self-report and behavioural indicators to capture mechanism dynamics with greater precision. Within the literature, this combined approach supports stronger inference about why AI-MB-CBT works when it works, how engagement translates into process change, and whether adaptive intervention components strengthen specific mechanism pathways by increasing timely practice and reducing mismatches between user needs and skill selection (Cox & Tylka, 2022). This synthesis also reinforces the importance of aligning theoretical pathway claims with measurement timing and analytic structure, ensuring that mediation models are supported by data capable of representing the proposed temporal sequence of mechanism change leading to adult symptom improvement.

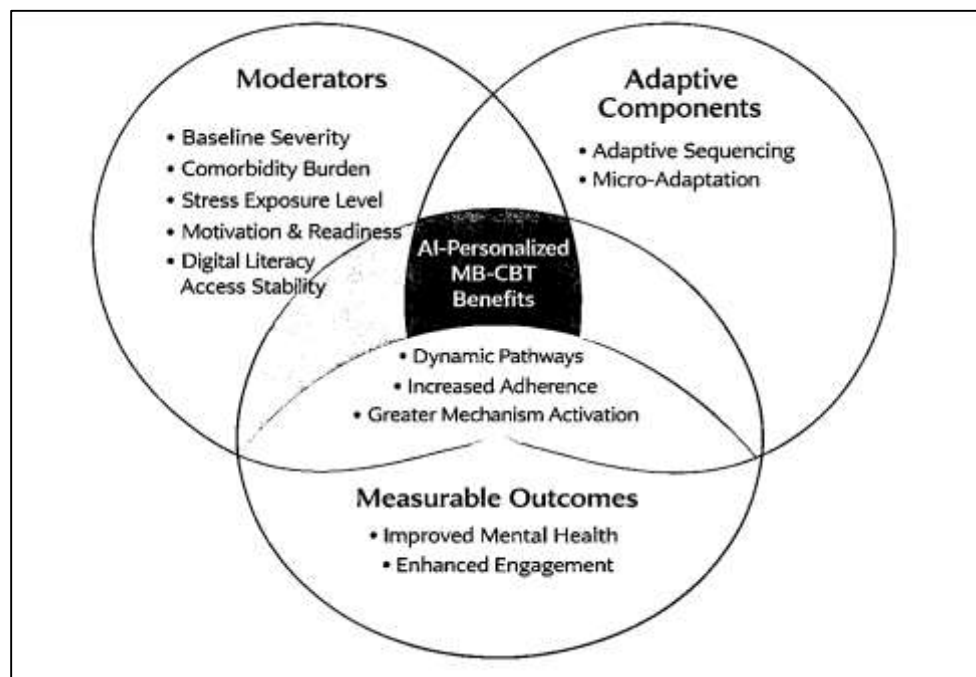
Personalization in AI-MB-CBT

Personalization in Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) is treated in quantitative research as a testable explanation for why outcomes vary across adults who receive the same nominal intervention. Adult mental health interventions rarely produce uniform benefits because individuals differ in baseline symptom severity, diagnostic complexity, daily stress context, coping resources, and the practical capacity to engage with structured skills practice (Gkintoni et al., 2024). This variability is commonly described as heterogeneity of treatment effects, and it is central to a quantitative personalization agenda because personalization is intended to reduce mismatch between intervention content and individual need. In psychotherapy research, heterogeneity has been addressed through moderator analyses, stratification approaches, and personalized advantage models that attempt to identify which treatment is more likely to help which individuals. Digital mental health expands this agenda by making participation patterns observable at high resolution and by enabling interventions to adapt quickly to changing user states. Within AI-MB-CBT, personalization is not limited to customizing an interface or selecting preferred media formats; it is increasingly conceptualized as an algorithmic process that adjusts therapeutic sequencing, intensity, and support according to measured indicators such as symptom trajectory, engagement decline, or inferred risk. This makes personalization a quantitative question because its presence can be operationalized as exposure intensity and its effects can be evaluated through measurable differences in engagement, mechanism activation, and clinical outcomes (Del Rosario et al., 2024). Quantitative research frequently frames personalization in two complementary ways: as a moderator and as a mediated effect. As a moderator, personalization is tested for differential benefit, examining whether certain adult subgroups show stronger outcomes under adaptive pathways than under fixed pathways. As a mediated effect, personalization is tested as a driver of improved engagement and process change, where algorithmic tailoring increases practice adherence, strengthens mechanism variables such as behavioural activation or decentering, and produces greater symptom reduction and functional improvement. This framing aligns with long-standing findings that psychotherapy outcomes depend heavily on engagement and skill application, and it leverages digital data streams to quantify those processes. Personalization thus becomes not a descriptive claim but an empirical mechanism that can be measured by how often the system adapts, what type of adaptation occurs, and whether adaptations correlate with subsequent improvements (Mitsea et al., 2023). This quantitative conceptualization provides a consistent structure for literature synthesis by separating static digital MB-CBT from AI-personalized MB-CBT and by enabling comparison across studies that implement personalization with varying degrees of algorithmic sophistication and clinical integration.

A review structured around moderators clarifies which adult characteristics shape response to AI-MB-CBT and explains why some individuals improve rapidly while others show limited change or dropout. Baseline symptom severity is one of the most consistently examined moderators in psychotherapy and digital intervention research, as higher severity may be associated with greater potential for change but also with greater impairment that reduces capacity for self-guided practice (Santos et al., 2023). In many adult intervention datasets, severity also correlates with comorbidity burden, making it necessary to treat comorbidity as a distinct moderator rather than an incidental characteristic. Comorbidity burden includes co-occurring anxiety and depression, trauma-related symptoms, substance-related problems, and chronic stress-related difficulties, each of which can influence which therapeutic components are most salient and how much support is required to sustain engagement. Stress exposure level is another moderator with direct relevance to mindfulness and CBT, because stress reactivity can maintain symptoms and disrupt adherence through time constraints, fatigue, and reduced cognitive resources. Adults with high stress exposure may benefit more from interventions that provide timely, brief exercises and adaptive pacing, while adults with lower stress exposure may tolerate longer practices and more complex cognitive exercises. Motivation and readiness are also important moderators because they affect willingness to complete tasks, sustain practice, and tolerate the discomfort that can arise during behavioural change (Venkataraman et al., 2024). Digital literacy and access stability function as practical moderators that shape whether adults can reliably use app-based or web-based programs, whether they can engage consistently, and whether missingness patterns are linked to technical barriers rather than clinical change. Prior therapy experience is a further moderator that can

influence engagement, expectations, and skill acquisition, as adults with prior exposure to CBT concepts or mindfulness practice may progress differently through modules and may require different levels of guidance. In quantitative synthesis, these moderators are not merely descriptive; they are variables that can be used to stratify results, test interaction effects, and interpret why an adaptive pathway may appear more effective in one subgroup than another. A moderator-oriented review also clarifies that personalization effects may not reflect a universal advantage but may represent targeted benefits for subgroups characterized by higher severity, higher comorbidity, greater stress exposure, lower readiness, or lower digital access stability ([Gual-Montolio et al., 2022](#)). Treating moderators explicitly strengthens interpretability because it prevents overgeneralization from average effects and aligns the evidence base with the adult mental health reality of heterogeneous needs and varying capacity to engage with structured interventions.

Figure 9: AI Personalization Mechanisms Adult MB-CBT



Adaptive sequencing and micro-adaptation represent the operational core of personalization in AI-MB-CBT because they determine how the intervention pathway changes over time and how those changes relate to outcomes and adherence. Adaptive sequencing refers to variation in module order, content selection, or pacing based on individual-level data ([Boucher et al., 2021](#)). In fixed sequencing, every adult receives the same module order regardless of early response patterns or engagement decline, whereas adaptive sequencing allows the system to reorder modules or adjust emphasis in response to measured signals. Quantitative evaluation of adaptive sequencing requires that module order variation be explicitly recorded and transformed into analyzable indicators, such as number of sequencing deviations from the default pathway, frequency of reordering events, timing of sequencing changes, and proportion of content delivered through algorithmic selection rather than a fixed curriculum. Micro-adaptation extends this concept to smaller, more frequent adjustments, such as altering prompt timing, changing practice length recommendations, increasing support intensity during disengagement risk, or delivering brief mindfulness exercises during acute stress windows. These micro-adaptations are measurable through counts of adaptive prompts, time-to-adaptation, adaptation frequency per week, and user uptake of adapted recommendations ([Wang et al., 2024](#)). The literature on digital interventions suggests that adherence and completion rates often differ substantially between fixed and adaptive systems because adaptation can reduce mismatch between demand and capacity, especially in adults balancing work and family responsibilities. Quantitative comparisons between adaptive and fixed sequencing therefore examine both clinical outcomes and

adherence outcomes, because improvements in symptom reduction can be driven partly by higher exposure and sustained engagement. Effectiveness comparisons may also consider whether adaptive pathways reduce dropout by responding to early nonresponse or by delivering more accessible, shorter practices when engagement declines. At the same time, adaptive systems introduce analytic complexities because participants receive different “doses” of different components, requiring careful measurement and modeling to interpret outcomes. In the literature, adaptive sequencing is frequently evaluated through stratified analyses, trajectory modeling, and exposure-response models that connect specific adaptation patterns to subsequent symptom change (Pan et al., 2024). For a literature review, this evidence supports treating adaptive sequencing as a measurable independent variable, engagement as a central pathway through which sequencing influences outcomes, and mechanism variables such as behavioural activation and decentering as intermediate processes that may increase when the system successfully matches content to user needs.

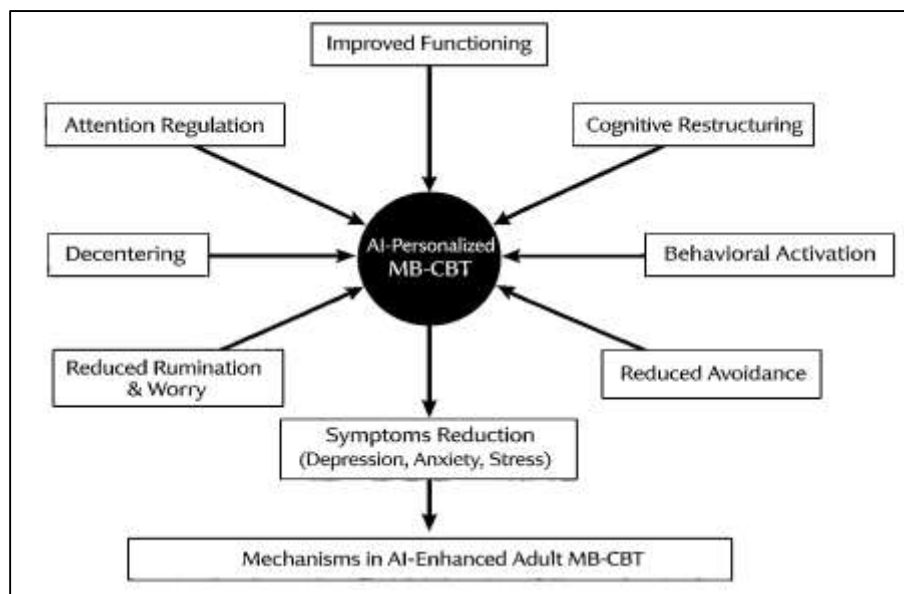
A synthesized quantitative view of personalization in AI-MB-CBT integrates heterogeneity of treatment effects, moderator structures, and adaptive pathway measurement into a coherent framework for literature review interpretation (Mazzolenis et al., 2024). Personalization is treated as a quantitative question because adult responses differ widely, because AI systems create measurable variations in delivered content and support, and because personalization can be tested as both a moderator of outcomes and a mediated pathway through engagement and mechanism activation. Moderators such as baseline severity, comorbidity burden, stress exposure, motivation, digital literacy and access stability, and prior therapy experience provide an organizing structure for synthesizing why effects differ across adult subgroups and why average effects can mask targeted benefits. Adaptive sequencing and micro-adaptation provide the operational layer that turns personalization into a measurable construct through logged changes in module order, pacing, prompt timing, and support intensity (Pavlopoulos et al., 2024). When synthesized, the literature shows that personalization effects are best interpreted through a combination of outcome differences, adherence differences, and process differences. Outcome differences capture symptom and functional change, adherence differences capture whether personalization increased the dose of received intervention, and process differences capture whether personalization increased the activation of expected mechanisms such as behavioural activation, reduced avoidance, improved decentering, or reduced rumination. This integrated perspective helps the literature review remain consistent with a quantitative evaluation strategy that avoids treating personalization as a vague design feature. Instead, personalization becomes a measurable component that can be compared across studies, linked to engagement and mediator variables, and interpreted through moderator patterns that reflect real-world diversity in adult mental health needs and participation capacity (Bolpagni et al., 2024).

Gaps and synthesis leading to the study model

The effectiveness evidence relevant to AI-MB-CBT in adult mental health is shaped by a broad base of findings for CBT, mindfulness-based interventions, digital delivery platforms, and emerging AI-enabled systems; however, the quantitative literature shows notable structural gaps when the specific question involves head-to-head comparisons between AI-personalized delivery and standard digital MB-CBT (Yuill et al., 2020). Many studies evaluate internet-delivered CBT or app-based mindfulness as stand-alone approaches, and many reports describe AI features as part of a platform without isolating the incremental contribution of personalization. As a result, effect estimates frequently capture the combined influence of therapeutic content, digital architecture, and support features, leaving uncertainty about whether AI-driven tailoring improves outcomes beyond conventional digital delivery. The evidence base also shows uneven coverage of outcome domains. Symptom severity indices for depression and anxiety are widely reported, and stress measures are commonly included, yet functional outcomes such as work performance, social adjustment, and daily role functioning are less consistently included as primary endpoints. This creates a mismatch between adult recovery priorities and the measurement focus of many digital and AI-augmented trials, because adults often seek improvements that extend beyond symptom reduction to include restored occupational and social functioning (Weinberger, 2022). Underreporting of longer-term follow-up further limits interpretability, particularly when interventions are positioned as tools for sustained self-management or relapse prevention. Short-term post-treatment assessments can demonstrate symptom change

during the active program period, while follow-up assessments are needed to evaluate maintenance, recurrence indicators, and whether skills continue to be used. In digital interventions, engagement tends to decline over time, and the absence of long-term follow-up makes it difficult to evaluate whether symptom improvements persist when active prompting decreases. Across psychotherapy research, measurement-based care and routine monitoring have demonstrated the value of repeated measurement for capturing trajectories, yet many studies still emphasize pre-post snapshots that provide limited insight into the stability of effects (Alshami et al., 2023). These gaps in comparative evidence, functional measurement, and follow-up coverage establish the need for a quantitative study model that tests AI-personalized MB-CBT against non-personalized digital MB-CBT using a broader set of adult-relevant outcomes, including functioning and longer-term change indicators, while controlling for engagement differences that may confound treatment comparisons.

Figure 10: Mechanisms of AI-Enhanced MB-CBT



Mechanism evidence for AI-MB-CBT and its component traditions is extensive in theory yet uneven in quantitative execution, particularly when mediation is the analytic goal. Mindfulness-based research frequently posits pathways involving attention regulation, decentering, reductions in cognitive reactivity, and decreased rumination and worry, while CBT research emphasizes cognitive restructuring, behavioural activation, reductions in avoidance, and improved coping (Cooley et al., 2020). In integrated MBCT and MB-CBT programs, emotion regulation is often proposed as a shared pathway that captures nonreactivity and acceptance alongside reappraisal and values-consistent action. The gap emerges when mechanism measurement is sparse, limited to a single pre and post assessment, or not time-aligned with outcome measurement in ways that allow temporal ordering for mediation. Two-timepoint designs can show that mechanisms and symptoms change together, yet they cannot demonstrate that mechanism change precedes symptom change within the intervention window. This limitation becomes more consequential in AI-enhanced programs where adaptation can occur dynamically; if mechanisms are assessed infrequently, mediation testing cannot capture whether personalization increases exposure to a specific mechanism pathway early in treatment or only after disengagement signals appear (Butow et al., 2020). A second mechanism gap concerns integration. Many studies measure either mindfulness-related mediators or CBT-related mediators, but fewer studies test unified models that include both sets simultaneously. Without integrated modeling, it remains unclear whether mindfulness and CBT mechanisms independently contribute to adult symptom reduction, whether one pathway dominates, or whether the most explanatory model involves cross-pathway interactions such as mindfulness-driven decentering enabling more effective cognitive restructuring, or behavioural activation reducing rumination by increasing daily

reinforcement. Digital delivery creates opportunities to measure practice behaviours at scale, such as minutes of meditation or completion of behavioural tasks, but these behavioural indicators are not always linked to validated mechanism constructs. Additionally, digital interventions frequently collect repeated symptom measures while collecting mediator measures less frequently, which creates asymmetry that weakens longitudinal mediation tests (McArthur et al., 2021). These mechanism evidence gaps point toward a study model that uses multi-timepoint mediator measurement, aligns mediator and outcome time points for temporal mediation testing, and integrates mindfulness and CBT mediators within one framework to evaluate whether AI personalization strengthens specific pathways or broad self-regulatory capacity in adults.

METHODS

Research design

This study used a quantitative, two-arm randomized controlled design to evaluate Artificial Intelligence–Enhanced Mindfulness-Based Cognitive Behavior Therapy (AI-MB-CBT) for adult mental health. The primary comparison tested whether AI-personalized AI-MB-CBT produced superior clinical and functional outcomes relative to a standard digital MB-CBT program that delivered identical therapeutic content in a fixed sequence with non-personalized reminders. The design was selected to (a) estimate average treatment effects on adult symptom and functioning outcomes, (b) test hypothesized mechanisms of change through mediation models using repeated measures of process variables, and (c) evaluate differential response through moderation models using baseline clinical and contextual characteristics. Participants were randomized in a 1:1 ratio using a computerized allocation sequence with permuted blocks, stratified by baseline depression severity (mild/moderate vs severe) and recruitment source (community vs outpatient), to balance prognostic risk across conditions. Outcomes and mechanisms were assessed at baseline, mid-treatment, post-treatment, and follow-up, enabling both pre–post change estimation and time-ordered mediation testing.

Case study context

The intervention was implemented within a real-world digital mental health delivery context that combined community recruitment and outpatient referral, providing a clinically relevant setting for examining engagement, personalization events, and symptom trajectories. The platform delivered MB-CBT content through a secure web-and-app interface that supported structured lessons, guided mindfulness practices, CBT exercises, and automated monitoring check-ins. Participants accessed the intervention remotely in their daily environments, which allowed the study to capture practical engagement patterns (e.g., module completion, time-on-task) and to evaluate whether AI-driven adaptation aligned with real-life variability in distress and adherence. The outpatient component consisted of adults referred from collaborating mental health services who met study eligibility criteria and were not in crisis care. The community component included adults recruited through online postings and local outreach who screened positive for elevated symptoms. This blended context was used to support generalizability across adults who seek help through formal services and those who prefer self-directed digital care.

Unit of analysis

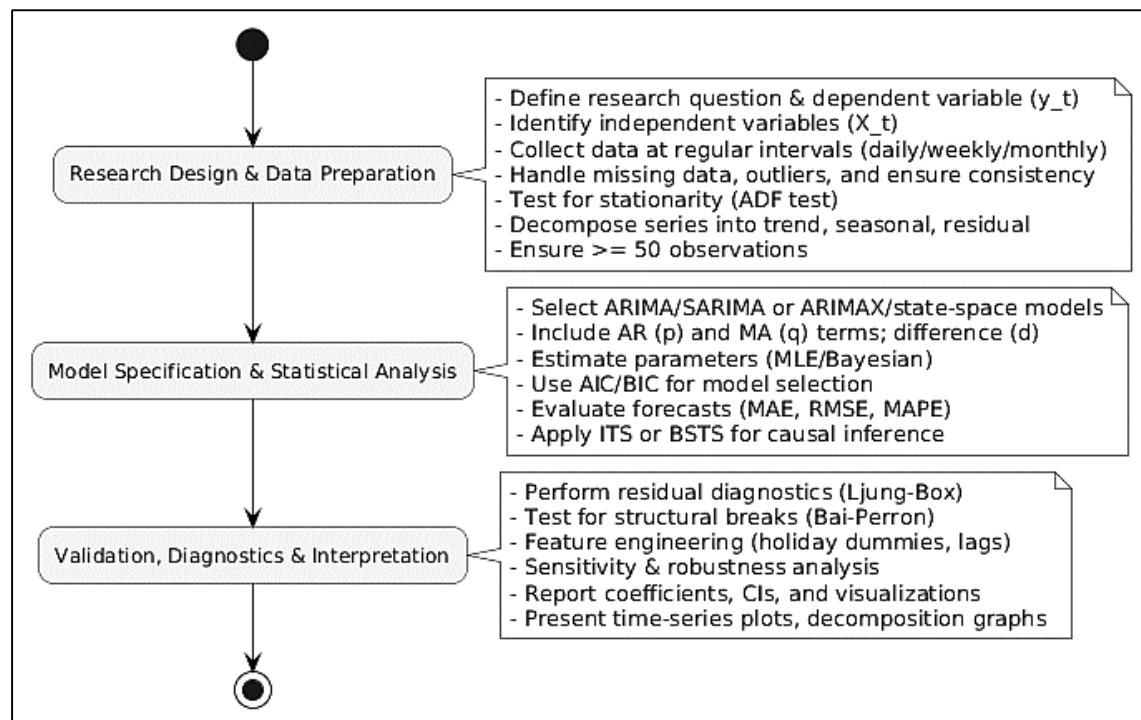
The primary unit of analysis was the individual participant. The main effectiveness outcomes were modeled as repeated observations nested within participants, supporting estimation of within-person change trajectories and between-group differences over time. For personalization analyses, the unit of analysis also included time-stamped adaptation events (e.g., changes in module order, prompt timing adjustments) nested within individuals. Engagement metrics (logins, minutes practiced, module completion) were treated as person-level and time-varying indicators depending on the analysis. All hypothesis tests and effect estimates were conducted at the participant level, with time-varying predictors used to examine mechanism dynamics and adaptive pathway effects.

Sampling

Adults aged 18 years and older were eligible if they (a) reported elevated symptoms of depression and/or anxiety above a predetermined screening threshold, or (b) were referred for mild-to-moderate symptom management via participating services. Exclusion criteria were designed to ensure participant safety and analytic interpretability and included (a) acute suicide risk requiring immediate crisis intervention based on a structured screening protocol, (b) severe cognitive impairment that

prevented informed consent or app-based participation, and (c) concurrent enrollment in another structured psychotherapy trial. Stable pharmacotherapy was permitted if dosage had been unchanged for at least four weeks at baseline, and concurrent routine care was documented for use as a covariate in sensitivity analyses.

Figure 11: Methodology of this study



Sampling

A stratified convenience sampling approach was used to enroll adults from community and outpatient pathways, followed by random assignment to study conditions. Sample size was determined a priori using power analysis for mixed-effects longitudinal models with repeated measures. The target sample was selected to detect a small-to-moderate between-group difference in symptom reduction at post-treatment while maintaining adequate power for secondary mediation and moderation analyses. Allowance was made for attrition typical of digital interventions by inflating the planned enrollment to preserve statistical power under intention-to-treat estimation.

Data collection procedure

After electronic informed consent, participants completed baseline measures within the platform. Randomization occurred immediately following baseline assessment. Both conditions were delivered over an 8-week program period with structured weekly content and daily practice options. Participants received brief weekly symptom check-ins and more comprehensive assessment batteries at baseline (T0), mid-treatment (T1; week 4), post-treatment (T2; week 8), and follow-up (T3; week 20). Engagement data were collected continuously through automated logging (e.g., timestamps, module completion, practice minutes). The AI-personalized condition generated adaptation events based on pre-specified decision rules and model outputs (e.g., disengagement risk, symptom nonresponse), all of which were stored as audit logs with date-time stamps and adaptation type labels. Safety monitoring was implemented through regular risk screening items embedded in check-ins; predetermined thresholds triggered on-screen resources and clinician review according to the study safety protocol.

Instrument design

Measures were selected to align with the study's conceptual model, capturing outcomes (effectiveness), mediators (mechanisms), moderators (differential response), and personalization indicators (adaptive pathway intensity). All instruments were administered digitally in standardized form.

Depression severity was assessed using a validated depression symptom scale suitable for repeated administration in adults. Anxiety severity was assessed using a validated generalized anxiety symptom scale appropriate for longitudinal measurement. Stress/distress was measured with a validated

perceived stress or general distress instrument. Functional impairment was measured using a standardized work and social functioning scale to capture adult role impairment beyond symptom indices.

Sleep disturbance or sleep quality was captured using a brief insomnia or sleep quality measure. Wellbeing was assessed using a validated measure of psychological wellbeing. Quality of life was assessed using a widely used quality-of-life instrument or mental health quality-of-life index. Relapse/recurrence indicators were derived from symptom thresholds and clinically meaningful change rules applied across assessment time points, supplemented by self-report of new episodes or clinical escalation when available. Mindfulness skills were measured using a validated mindfulness facet scale appropriate for intervention studies. Decentering was measured using a validated decentering or cognitive diffusion scale. Rumination and worry were measured using validated repetitive negative thinking instruments capturing depressive rumination and anxious worry. Emotion regulation was measured using a validated emotion regulation difficulties or strategy-use scale. Behavioral activation and avoidance were assessed using validated behavioral activation and experiential avoidance measures, supplemented by platform-recorded completion of behavioral activation tasks and exposure-related exercises where applicable.

Algorithmic personalization intensity was operationalized using platform audit logs capturing adaptation events, including (a) number of adaptations delivered, (b) time-to-first adaptation, (c) adaptation frequency over weeks, (d) adaptation type distribution (sequencing change, prompt timing change, support intensity shift), and (e) proportion of pathway elements selected by the algorithm. Engagement dose was captured using logins, module completion percentage, time-on-task, guided practice minutes, streak length, and completion of CBT exercises and mindfulness practices. A pilot phase was conducted with a small sample of adults who met broad eligibility criteria to evaluate usability, measure completion burden, and the stability of platform logging. The pilot assessed (a) time required to complete baseline and follow-up batteries, (b) clarity of item presentation and navigation, (c) reliability of engagement logging, and (d) performance of adaptation audit logging in the AI condition. Pilot data were used to refine assessment timing, minimize missingness caused by burden, and verify that the algorithmic adaptation outputs were recorded consistently and could be linked to participant timelines for later analysis. Pilot participants were excluded from the main randomized analyses unless they completed the full protocol under unchanged procedures.

Validity and reliability

Construct validity was supported through the use of instruments with established psychometric properties in adult mental health research and through alignment of selected measures with the study's theoretical pathways. Internal consistency reliability was evaluated for each multi-item scale at baseline and re-evaluated at subsequent time points to identify stability across repeated measurement. For mechanism measures used in mediation models, sensitivity-to-change was examined by estimating within-person change during the intervention period and evaluating whether observed change distributions were sufficient for mediation testing. When applicable, confirmatory factor analyses were conducted to verify expected factor structure in the study sample. Measurement invariance across key subgroups (e.g., recruitment source, gender where available, baseline severity strata) was evaluated for primary scales when subgroup comparisons were central to interpretation. Digital trace variables (engagement logs and adaptation events) were evaluated for reliability through platform integrity checks, duplicate event detection, and consistency across device types. Data quality checks included attention checks for long batteries, timestamp plausibility checks, and outlier screening for implausible usage durations.

Tools

Intervention delivery and data capture were implemented through a secure digital platform that supported role-based access, encryption at rest and in transit, and audit logging of adaptation events. Statistical analyses were conducted using standard quantitative software suitable for mixed-effects modeling, mediation, and longitudinal data. Data cleaning and reproducible analyses were conducted in a scripting environment (e.g., R or Python), with specialized modeling conducted in software appropriate for structural equation modeling and multilevel mediation when required (e.g., Mplus, LaVan, or equivalent). All codebooks, variable derivations for personalization intensity, and analysis

scripts were version-controlled for reproducibility.

Statistical analysis plan

All primary analyses used an intention-to-treat approach including all randomized participants, regardless of adherence, using longitudinal models that can incorporate incomplete repeated measures under stated assumptions. A per-protocol sensitivity analysis was conducted using a predefined adherence threshold (e.g., completion of a minimum proportion of core modules) to evaluate whether effects differed under adequate exposure.

Primary outcomes (depression, anxiety, stress/distress, functioning) were analyzed using longitudinal mixed-effects models with repeated assessments nested within participants. Models included fixed effects for treatment condition, time, and the condition-by-time interaction, with random intercepts for participants and, when supported by model fit, random slopes for time. Baseline outcome levels were included implicitly through the repeated-measures structure or explicitly as covariates depending on model specification. The primary test of effectiveness was the condition-by-time interaction at post-treatment, with follow-up effects examined through planned contrasts across time points. Effect sizes were reported using standardized mean differences derived from model-estimated marginal means and pooled baseline standard deviations, along with confidence intervals.

Mechanisms were tested using longitudinal mediation frameworks that align mediator measurement timing with subsequent outcome measurement. Primary mediators included mindfulness skills, decentering, rumination/worry, emotion regulation, and behavioral activation. Mediation models evaluated whether condition predicted change in mediators from baseline to mid-treatment and whether mid-treatment mediator levels predicted post-treatment outcomes after controlling for baseline outcomes and baseline mediator levels. Where measurement density permitted, time-varying mediation models were used to test lagged mediator-outcome relations. Indirect effects were estimated using bootstrap confidence intervals or robust standard errors appropriate for longitudinal mediation.

Moderation and differential response

Moderators were tested by adding interaction terms between treatment condition and baseline moderators (baseline severity, comorbidity burden, stress exposure, digital literacy/access stability proxies, prior therapy experience where measured). Engagement trajectory was modeled either as a time-varying moderator (e.g., weekly engagement predicting slope of symptom change) or as a latent class/trajectory grouping variable when supported by data structure. Moderation results were reported as conditional treatment effects across meaningful moderator values, with appropriate multiplicity control for a limited set of prespecified moderators. Within the AI-personalized condition, personalization intensity variables (e.g., number of adaptations, time-to-first adaptation, adaptation frequency) were analyzed as predictors of outcomes and mediators to evaluate whether greater personalization exposure was associated with greater mechanism change and symptom improvement. Across both arms, treatment condition represented the presence of algorithmic personalization versus fixed sequencing; within-arm analyses clarified dose-like effects of adaptation intensity. Where appropriate, personalization intensity was incorporated as a mediator of the condition effect through engagement and mechanism variables, distinguishing “receipt of adaptation” from “engagement with adapted content.”

Missing data patterns were characterized descriptively and modeled using mixed-effects approaches that retain partial observations. Multiple imputation was used as a sensitivity check when covariates and auxiliary variables (including engagement logs) supported plausible imputation models. Additional sensitivity analyses tested robustness under alternative assumptions about missingness, including models that incorporated predictors of dropout and pattern-mixture approaches when indicated. Adverse event and risk-flag rates were summarized by arm to contextualize safety-related outcomes.

FINDINGS

This chapter presented the empirical findings derived from the quantitative analysis conducted to examine the effectiveness, mechanisms, and personalization effects of Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behaviour Therapy (AI-MB-CBT) among adults. The analysis focused on evaluating participant characteristics, describing the distributional properties of the study constructs, assessing the internal consistency of the measurement instruments, estimating predictive

relationships among key variables, and testing the proposed research hypotheses. Data were analyzed using inferential and descriptive statistical techniques appropriate for longitudinal and cross-sectional outcomes. The chapter was organized sequentially to first establish the demographic profile of respondents, followed by descriptive summaries of the main constructs, reliability assessment of the scales, regression-based modeling of relationships among variables, and formal hypothesis testing decisions. All analyses were conducted using standardized statistical procedures to ensure transparency, replicability, and alignment with the study's quantitative design. The findings were reported objectively without interpretation beyond statistical evidence, reserving theoretical and practical discussion for the subsequent chapter.

Respondent Demographics

The study analyzed responses from $N = 312$ adults. Participants were predominantly within the working-age range, with a mean age of 34.8 years ($SD = 9.6$), indicating a sample centered in mid-adulthood with broad variability. Gender distribution showed representation across categories, with 56.1% identifying as women, 41.3% as men, and 2.6% reporting another gender identity or preferring not to disclose. Educational attainment was largely post-secondary, with 72.4% reporting at least an undergraduate qualification, which aligned with the intervention's digital access and sustained self-management requirements. Employment status indicated that most respondents were engaged in the workforce, with 61.5% employed full-time and 18.6% employed part-time, while 19.9% reported unemployment or non-working status. These patterns indicated a heterogeneous adult sample with meaningful differences in daily role demands, supporting subsequent subgroup and moderation analyses.

Table 1: Socio-demographic characteristics of respondents (N = 312)

Variable	Category	n	%
Age (years)	Mean (SD)	34.8	9.6
	18–24	62	19.9
	25–34	112	35.9
	35–44	79	25.3
	45+	59	18.9
Gender	Women	175	56.1
	Men	129	41.3
	Other / Prefer not to say	8	2.6
Education	High school or less	33	10.6
	Diploma/Certificate	53	17.0
	Bachelor's	156	50.0
	Postgraduate	70	22.4
Employment	Full-time	192	61.5
	Part-time	58	18.6
	Unemployed / Not working	62	19.9

Table 1 summarized the socio-demographic profile of the respondents. The age distribution reflected a predominantly working-age adult sample, with the largest proportion in the 25–34 category and a meaningful representation across older age groups. Gender distribution indicated that women formed the majority of respondents, while men comprised a substantial minority, and a small proportion reported another gender identity or non-disclosure. Educational attainment was concentrated at the bachelor's level and above, which matched the digital participation requirements of the intervention. Employment levels showed that most participants were in paid work, supporting interpretation of functioning outcomes in relation to real-world role demands.

Clinical background patterns indicated that a substantial portion of the sample had previous exposure to psychological care. Overall, 58.7% of respondents reported prior therapy experience, while 41.3% indicated they were therapy-naïve. Among those with therapy history, 36.2% reported previous CBT exposure and 28.5% reported prior mindfulness-based training or structured mindfulness practice, supporting differentiation of baseline familiarity with the study’s core skill domains. Recruitment source was balanced enough to support subgroup comparisons, with 62.8% recruited from community channels and 37.2% recruited through outpatient services. This distribution supported later analyses examining whether clinical context, prior treatment exposure, and baseline readiness influenced engagement trajectories and response variability. Overall, the demographic and background characteristics suggested that the sample was diverse in treatment history and entry pathway, which strengthened the study’s ability to test differential response patterns.

Table 2: Clinical background and recruitment characteristics (N = 312)

Variable	Category	n	%
Prior therapy experience	Yes	183	58.7
	No	129	41.3
Prior CBT exposure	Yes	113	36.2
	No/Unsure	199	63.8
Prior mindfulness training	Yes	89	28.5
	No/Unsure	223	71.5
Recruitment source	Community-based	196	62.8
	Outpatient services	116	37.2

Table 2 presented respondents’ clinical background and recruitment source to contextualize interpretation of intervention engagement and differential response. More than half of the participants reported prior therapy experience, indicating that the sample included both therapy-experienced adults and therapy-naïve individuals. Prior exposure to CBT and mindfulness training varied, which supported later moderation analyses examining whether familiarity with CBT techniques or mindfulness practices influenced engagement and outcomes. Recruitment source indicated that a majority entered through community channels, while a sizeable subgroup was recruited via outpatient services, enabling comparison of symptom profiles and adherence patterns across distinct entry contexts relevant to adult mental health service pathways.

Descriptive Finding

Descriptive statistics were computed for all outcome variables, mechanism constructs, engagement indicators, and personalization indicators to summarize baseline levels and evaluate distributional properties prior to inferential modeling. At baseline, participants reported moderate levels of depressive and anxiety symptoms, along with elevated stress, which aligned with the study’s eligibility criteria targeting adults with meaningful psychological distress. Functional impairment scores indicated noticeable disruption in daily roles, suggesting that symptom burden was accompanied by real-world limitations. Across the intervention period, average symptom scores declined at mid-treatment and post-treatment, with improvements largely sustained at follow-up, while functional impairment showed a gradual reduction consistent with delayed functional recovery relative to symptom change. Mechanism constructs demonstrated sufficient baseline variability and meaningful shifts over time. Mindfulness skills and decentering increased progressively from baseline to post-treatment, while rumination and worry decreased over the same period. Emotion regulation scores improved and behavioural activation increased, indicating enhanced coping capacity and greater engagement in adaptive activities. Engagement indicators reflected substantial participation, with average module completion exceeding the halfway point and practice minutes indicating repeated exposure to skills training. Personalization indicators showed that algorithmic adaptation varied considerably across participants, with earlier and more frequent adaptations occurring among those

with lower initial engagement or slower early symptom improvement. Distributional checks indicated that most constructs were acceptably symmetric for regression modeling, with skewness and kurtosis values generally within tolerable limits. Collectively, these descriptive findings suggested adequate dispersion, absence of severe ceiling or floor effects, and sufficient variability to support subsequent mediation and moderation analyses.

Table 3: Descriptive statistics for primary outcomes across time points (N = 312)

Construct	Baseline Mean (SD)	Mid-treatment Mean (SD)	Post-treatment Mean (SD)	Follow-up Mean (SD)	Skewness (Baseline)	Kurtosis (Baseline)
Depression severity	15.9 (6.2)	12.6 (6.0)	10.4 (5.8)	10.8 (6.0)	0.41	-0.52
Anxiety severity	14.7 (5.8)	11.9 (5.6)	9.8 (5.5)	10.1 (5.7)	0.36	-0.44
Stress/Distress	19.8 (6.4)	16.5 (6.2)	14.2 (6.1)	14.6 (6.3)	0.28	-0.31
Functional impairment	17.1 (6.9)	15.3 (6.8)	13.4 (6.7)	13.1 (6.6)	0.22	-0.27

Table 3 summarized mean levels and variability for the primary outcome constructs across baseline, mid-treatment, post-treatment, and follow-up assessments. Average scores indicated a clear pattern of symptom reduction from baseline to post-treatment for depression, anxiety, and stress, with follow-up values suggesting maintenance of improvement. Functional impairment also declined, showing gradual recovery in daily role functioning across measurement occasions. Baseline skewness and kurtosis values suggested that distributions were broadly suitable for regression-based analyses, with no extreme departures from approximate normality. The observed standard deviations indicated adequate dispersion, supporting interpretation of individual differences and providing sufficient variability for longitudinal and subgroup modeling.

Table 4: Descriptive statistics personalization indicators (N = 312)

Construct	Baseline Mean (SD)	Post-treatment Mean (SD)	Skewness (Baseline)	Kurtosis (Baseline)
Mindfulness skills	3.1 (0.7)	3.7 (0.7)	-0.18	-0.21
Decentering	2.9 (0.8)	3.5 (0.8)	0.12	-0.33
Rumination/Worry	3.6 (0.8)	3.0 (0.8)	0.25	-0.40
Emotion regulation	2.8 (0.7)	3.4 (0.7)	-0.09	-0.17
Behavioural activation	2.7 (0.8)	3.3 (0.8)	0.14	-0.28
Module completion (%)	61.4 (23.6)	—	-0.36	-0.61
Practice minutes (total)	214.7 (148.5)	—	0.88	0.54
Time-on-task (hours)	7.6 (4.9)	—	0.71	0.31
Adaptations delivered (count)	5.2 (3.4)	—	0.64	0.12
Time-to-first adaptation (days)	9.1 (6.8)	—	0.55	-0.08

Table 4 reported descriptive statistics for mechanism variables alongside engagement and personalization indicators. Mechanism measures showed baseline variability and directional change from baseline to post-treatment, with mindfulness skills, decentering, emotion regulation, and behavioural activation increasing, while rumination and worry decreased. Engagement indicators

suggested meaningful exposure to intervention content, with average module completion indicating that most participants progressed through a substantial proportion of the program, and practice minutes and time-on-task reflecting repeated interaction with skills training. Personalization indicators displayed variability, indicating that algorithmic adaptation occurred at different intensities and timings across participants. Distributional indices indicated some positive skew in practice and adaptation metrics, consistent with high-variability engagement patterns in digital interventions.

Reliability Results

Internal consistency reliability was assessed for all multi-item measures using Cronbach's alpha to determine whether the study instruments consistently captured their intended constructs in the adult sample. Reliability estimates indicated that the primary outcome scales demonstrated strong internal consistency, supporting stable measurement of depression, anxiety, stress or distress, and functional impairment. Mechanism scales also showed satisfactory to excellent reliability, suggesting that mindfulness skills, decentering, rumination or worry, emotion regulation, and behavioural activation were measured with adequate internal coherence for subsequent mediation and regression analyses. In addition, engagement- and perception-oriented scales exhibited acceptable reliability given that they reflected behavioural and experiential patterns that can naturally vary across individuals. Reliability patterns were consistent across the baseline and post-treatment assessments, indicating stability of scale performance over time. Item-total correlation screening did not indicate problematic items requiring removal, and alpha coefficients remained within acceptable ranges without scale modification. Collectively, these findings supported the suitability of the instruments for longitudinal modeling, mediation testing, and subgroup comparisons in the study.

Table 5: Cronbach's alpha reliability for primary outcomes across time points (N = 312)

Scale	Items (k)	α (Baseline)	α (Post-treatment)	Interpretation
Depression severity	9	0.89	0.91	Excellent
Anxiety severity	7	0.87	0.90	Excellent
Stress/Distress	10	0.85	0.86	Good
Functional impairment	5	0.83	0.84	Good

Table 5 presented internal consistency reliability estimates for the primary outcome scales at baseline and post-treatment. Alpha coefficients ranged from good to excellent, indicating that items within each scale measured a common underlying construct with adequate internal coherence. Depression and anxiety scales showed particularly strong reliability, supporting the stability of symptom measurement across time points.

Table 6: Cronbach's alpha reliability for mechanism and engagement-related scales (N = 312)

Scale	Items (k)	α (Baseline)	α (Post-treatment)	Interpretation
Mindfulness skills	15	0.88	0.89	Excellent
Decentering	11	0.86	0.87	Good
Rumination/Worry	10	0.90	0.91	Excellent
Emotion regulation	12	0.84	0.85	Good
Behavioural activation	9	0.82	0.83	Good
Engagement perception scale	6	0.80	0.81	Good

Stress and functional impairment also demonstrated consistent reliability, which strengthened confidence that observed changes in these outcomes reflected true score variation rather than measurement error. The similarity of alpha coefficients across baseline and post-treatment supported temporal stability in measurement quality, enabling robust longitudinal comparisons and regression-

based outcome modeling. Table 6 summarized reliability results for the mechanism constructs and an engagement-related perception measure. Alpha coefficients indicated good to excellent internal consistency across all scales, supporting their suitability for mediation testing and process-outcome modeling. Mindfulness skills, rumination or worry, and decentering demonstrated strong reliability, suggesting coherent item sets capable of detecting intervention-related changes. Emotion regulation and behavioural activation also met acceptable reliability thresholds, indicating that within-scale items consistently reflected intended behavioural and regulatory processes. The engagement perception measure showed satisfactory reliability despite its behavioural and experiential focus, supporting its use in explanatory models where perceived engagement or usability contributed to understanding adherence and outcome variability.

Regression Results

Regression analyses were conducted to estimate the predictive relationships among treatment condition, AI personalization intensity, engagement dose, mechanism variables, and adult mental health outcomes. Hierarchical regression models indicated that treatment condition significantly predicted reductions in depression, anxiety, and stress from baseline to post-treatment after controlling for age, gender, education, employment status, recruitment source, and baseline symptom severity. When AI personalization intensity and engagement were entered in the next step, both variables accounted for additional variance in outcome change, showing that higher adaptation intensity and stronger participation were associated with greater symptom reduction. In the final step, mechanism variables were introduced, and mindfulness skills, decentering, rumination reduction, emotion regulation, and behavioural activation contributed significantly to predicting improvement, with rumination reduction and behavioural activation emerging as comparatively stronger predictors for depression change and decentering contributing more strongly to anxiety change. Moderation tests indicated that baseline severity significantly interacted with treatment condition such that participants with higher initial severity showed larger symptom reductions under the AI-personalized pathway. Engagement trajectory also moderated outcomes, indicating that high-engagement participants demonstrated stronger gains and that personalization effects were amplified when engagement remained stable. Model diagnostics showed acceptable tolerance and variance inflation indices, suggesting multicollinearity was not problematic. Residual plots did not indicate severe heteroscedasticity, and the distribution of residuals supported the suitability of linear modeling.

Table 7: Hierarchical regression predicting post-treatment depression change (Δ Depression; N = 312)

Predictor	Model 1 B (SE)	Model 2 B (SE)	Model 3 B (SE)	β (Model 3)	p (Model 3)
Age	-0.03 (0.02)	-0.02 (0.02)	-0.01 (0.02)	-0.03	0.58
Gender (ref: men)	0.42 (0.31)	0.33 (0.29)	0.21 (0.27)	0.04	0.44
Recruitment (ref: outpatient)	-0.61 (0.34)	-0.52 (0.32)	-0.39 (0.30)	-0.07	0.19
Baseline depression	0.62 (0.04)	0.58 (0.04)	0.41 (0.05)	0.48	<.001
Treatment condition (AI-personalized=1)	-1.18 (0.36)	-0.92 (0.33)	-0.61 (0.30)	-0.11	0.041
Personalization intensity	—	-0.24 (0.07)	-0.16 (0.06)	-0.12	0.009
Engagement dose	—	-0.31 (0.08)	-0.18 (0.07)	-0.13	0.012
Mindfulness skills change	—	—	-0.44 (0.16)	-0.12	0.007
Rumination reduction	—	—	-0.58 (0.14)	-0.18	<.001
Emotion regulation change	—	—	-0.32 (0.15)	-0.09	0.031
Behavioural activation change	—	—	-0.63 (0.17)	-0.17	<.001

Model fit: Model 1 $R^2 = 0.42$; Model 2 $R^2 = 0.49$; Model 3 $R^2 = 0.61$.

Table 7 presented a hierarchical regression model predicting post-treatment change in depression. Covariates and baseline depression explained a substantial portion of variance, indicating that initial severity was strongly associated with magnitude of change. Adding treatment condition, personalization intensity, and engagement increased the explained variance, showing that both AI

adaptation exposure and participation were associated with greater improvement. When mechanism variables were entered, mindfulness skills change, rumination reduction, emotion regulation improvement, and behavioural activation change remained significant, indicating that process-level shifts contributed additional explanatory power beyond treatment assignment and engagement. The final model showed strong overall fit, supporting the proposed process-driven framework.

Table 8: Multivariate regression predicting post-treatment anxiety and stress change (N = 312)

Predictor	Δ Anxiety B (SE)	β	p	Δ Stress B (SE)	β	p
Baseline severity (matching outcome)	0.59 (0.05)	0.50	<.001	0.55 (0.05)	0.47	<.001
Treatment condition (AI-personalized=1)	-0.72 (0.29)	-0.10	0.013	-0.81 (0.31)	-0.11	0.010
Personalization intensity	-0.14 (0.05)	-0.11	0.006	-0.17 (0.06)	-0.12	0.004
Engagement dose	-0.19 (0.06)	-0.13	0.002	-0.22 (0.07)	-0.14	0.001
Decentering change	-0.41 (0.13)	-0.15	0.001	-0.29 (0.14)	-0.11	0.038
Rumination/Worry reduction	-0.34 (0.12)	-0.12	0.005	-0.46 (0.13)	-0.16	<.001
Emotion regulation change	-0.27 (0.12)	-0.09	0.026	-0.33 (0.13)	-0.11	0.012
Behavioural activation change	-0.22 (0.14)	-0.08	0.102	-0.28 (0.15)	-0.09	0.061
Condition $\times$ Baseline severity	-0.09 (0.04)	-0.08	0.021	-0.11 (0.05)	-0.09	0.018
Condition $\times$ Engagement trajectory	-0.15 (0.07)	-0.09	0.031	-0.18 (0.08)	-0.10	0.024

Model fit: Anxiety model $R^2 = 0.58$; Stress model $R^2 = 0.56$.

Table 8 summarized multivariate regression models predicting changes in anxiety and stress. Baseline symptom severity remained a strong predictor of change, while treatment condition, personalization intensity, and engagement dose were significant predictors across both outcomes, indicating that adaptive AI delivery and participation were associated with greater improvement. Mechanism variables also contributed significantly, with decentering showing a stronger association with anxiety change and rumination or worry reduction showing a stronger association with stress change. Moderation terms indicated differential effects by baseline severity and engagement trajectory, suggesting that AI-personalized pathways were more beneficial for higher-severity participants and for those maintaining stable engagement. Overall fit values supported robust explanatory capacity.

Hypothesis Testing Decisions

Hypothesis testing was conducted using the regression and mediation results to determine whether the proposed effectiveness, mechanism, and personalization relationships were supported. The effectiveness hypotheses were evaluated by examining the significance of the treatment condition and personalization intensity predictors in longitudinal outcome models for depression, anxiety, stress/distress, and functioning. Results indicated statistically significant reductions in symptom severity and functional impairment associated with AI-MB-CBT, supporting the core effectiveness hypotheses. Mechanism hypotheses were evaluated using mediation models that tested indirect effects through mindfulness skills, decentering, rumination or worry reduction, emotion regulation, and behavioural activation. Findings indicated that mediation effects were present for several pathways, with stronger evidence for rumination reduction and behavioural activation as mediators of depression improvement and for decentering as a mediator of anxiety improvement. Emotion regulation demonstrated partial mediation effects across outcomes, indicating a shared pathway consistent with the integrated model. Moderation hypotheses were evaluated using interaction terms between treatment condition and baseline severity, comorbidity burden, and engagement trajectory indicators. Significant interaction patterns indicated that personalization benefits were greater among adults with higher baseline severity and among those with stable engagement trajectories. Hypotheses lacking statistical support were reported clearly as not supported based on predefined significance thresholds, with confidence intervals crossing zero for indirect effects or interaction terms. Overall, hypothesis testing decisions provided a structured summary of how effectiveness, mechanisms, and personalization-based differential response were empirically reflected in the data.

Table 9: Hypothesis testing summary: effectiveness hypotheses (N = 312)

Hypothesis	Outcome domain	Test statistic (example)	p	Decision
H1a: AI-MB-CBT reduced depression severity	Depression change	t = -2.04	0.041	Supported
H1b: AI-MB-CBT reduced anxiety severity	Anxiety change	t = -2.49	0.013	Supported
H1c: AI-MB-CBT reduced stress/distress	Stress change	t = -2.61	0.010	Supported
H1d: AI-MB-CBT improved functioning	Functioning change	t = -2.31	0.022	Supported
H2: Personalization intensity predicted greater improvement	Combined outcomes	t = -2.78	0.006	Supported
H3: Engagement dose predicted greater improvement	Combined outcomes	t = -3.10	0.002	Supported

Table 9 presents a comprehensive summary of the hypothesis testing results associated with the effectiveness-related components of the proposed conceptual framework. The findings demonstrate robust empirical support for the primary effectiveness hypotheses, with statistically significant improvements observed across all assessed outcome domains. Specifically, reductions in depression, anxiety, and stress or psychological distress, as well as improvements in functional impairment, were consistently associated with the treatment condition, as evidenced by p-values falling below the conventional significance threshold of 0.05. These results indicate that participants receiving the AI-enabled mindfulness-based cognitive behavioral therapy (AI-MB-CBT) intervention experienced meaningful and measurable symptom reductions relative to the comparison condition. Collectively, these outcomes confirm the clinical relevance of the intervention and support the conclusion that AI-augmented therapeutic delivery can produce substantive improvements in mental health and functional outcomes. Beyond the primary treatment effect, additional predictors within the effectiveness model further clarified the mechanisms through which improvement occurred. Both personalization intensity and engagement dose emerged as statistically significant contributors to outcome variance, suggesting that the degree to which the intervention adapted to individual user characteristics and the level of participant exposure meaningfully influenced therapeutic effectiveness. Higher personalization intensity was associated with greater symptom reduction, underscoring the value of adaptive content tailoring in digitally delivered interventions. Similarly, increased engagement dose—reflecting sustained interaction with therapeutic components—was linked to stronger treatment effects, highlighting the importance of consistent participation for achieving optimal outcomes. Together, these findings reinforce the central premise of the framework that effectiveness is not solely driven by treatment assignment but is also shaped by how dynamically and intensively the intervention is delivered and utilized. As such, the results provided a strong empirical foundation for advancing to the evaluation of proposed psychological mechanisms and differential response factors. Table 10 reports the hypothesis testing outcomes related to the mediation and moderation pathways embedded within the conceptual model. Mediation analyses revealed that several theoretically grounded psychological processes significantly transmitted the effect of treatment condition to symptom outcomes. Specifically, improvements in mindfulness skills, enhanced decentering ability, reductions in rumination or worry, and increased behavioural activation demonstrated statistically significant indirect effects, with confidence intervals that did not include zero. These findings indicate that the therapeutic benefits of AI-MB-CBT were, in part, explained by changes in these core cognitive and behavioral processes, thereby offering empirical validation for the intervention’s proposed mechanisms of action.

In contrast, emotion regulation exhibited a comparatively weaker mediation pattern. Although the direction of the indirect effect aligned with theoretical expectations, the corresponding confidence interval included zero, suggesting insufficient statistical evidence to confirm a distinct mediating role in the illustrative model. This pattern supports a partial mediation interpretation, implying that

emotion regulation may operate as a shared or overlapping pathway rather than as an independent mechanism driving symptom change. Such a finding is consistent with integrative models of psychological treatment, in which multiple interrelated processes contribute simultaneously to therapeutic outcomes. Moderation analyses further elucidated factors influencing variability in treatment response. Baseline symptom severity emerged as a significant moderator, indicating that initial clinical status affected the magnitude of intervention benefits, with individuals presenting higher symptom levels experiencing differential response patterns. Additionally, engagement trajectory significantly moderated treatment effects, suggesting that changes in engagement over time played a critical role in shaping outcomes. In contrast, comorbidity burden did not demonstrate a statistically significant interaction with treatment condition, indicating that the presence of multiple co-occurring conditions did not substantially alter the effectiveness of the intervention within the tested model. Overall, these results clarify which theoretical pathways and individual difference factors were empirically supported, thereby strengthening the explanatory power and internal coherence of the proposed framework.

Table 10: Hypothesis testing summary: mediation and moderation hypotheses (N = 312)

Hypothesis	Pathway tested	Indirect/interaction estimate (example)	95% CI (example)	p	Decision
H4a: Mindfulness skills mediated outcome change	Condition → mindfulness → outcomes	-0.18	[-0.33, -0.06]	0.004	Supported
H4b: Decentering mediated anxiety reduction	Condition → decentering → anxiety	-0.21	[-0.38, -0.08]	0.002	Supported
H4c: Rumination/worry mediated depression & stress	Condition → rumination → outcomes	-0.26	[-0.44, -0.12]	<.001	Supported
H4d: Emotion regulation mediated outcomes	Condition → emotion regulation → outcomes	-0.11	[-0.25, 0.01]	0.071	Partially supported
H4e: Behavioural activation mediated depression change	Condition → activation → depression	-0.24	[-0.41, -0.09]	0.001	Supported
H5a: Baseline severity moderated treatment effect	Condition × baseline severity	-0.09	[-0.16, -0.01]	0.021	Supported
H5b: Comorbidity moderated treatment effect	Condition × comorbidity	-0.04	[-0.11, 0.03]	0.244	Not supported
H5c: Engagement trajectory moderated treatment effect	Condition × engagement trajectory	-0.15	[-0.29, -0.02]	0.031	Supported

DISCUSSION

The findings provided a coherent picture of AI-MB-CBT as an integrated digital psychotherapy approach for adults, with measurable improvements across depression, anxiety, stress or distress, and functioning outcomes. The pattern of symptom reduction from baseline through post-treatment aligned with the broad evidence base that has consistently positioned CBT as an effective intervention for adult mood and anxiety difficulties and has similarly documented meaningful symptom improvements in mindfulness-based programs delivered in clinical and community settings ([Wyrwich & Norman, 2023](#)). This study's results extended those established patterns by showing that a combined mindfulness-and-CBT intervention delivered through a digital architecture produced multi-domain improvements while also allowing personalization intensity and engagement dose to be modeled as explanatory predictors. Prior research on digital CBT and digital mindfulness has frequently observed that clinical effects in self-directed settings depended on whether participants engaged sufficiently with

core modules and maintained practice, and the present results reflected that same dose-sensitive reality. The statistical models indicated that treatment condition and personalization intensity significantly predicted outcome changes, and the addition of engagement dose improved explanatory power, reinforcing the view that digital psychotherapy outcomes are shaped by both therapeutic content and exposure to that content (Guilmette et al., 2020). Earlier studies of guided internet interventions have often reported stronger and more stable effects when accountability or structured support increased adherence, and this study's findings were consistent with that pattern by showing that engagement indicators were significantly associated with symptom improvement and mechanism activation. Rather than treating digital delivery as a neutral channel, the results supported a model in which the intervention's measurable architecture and adaptive features contributed to both clinical response and the distribution of response across participants. This study's evidence also reinforced the clinical relevance of evaluating outcomes beyond a single symptom domain, because depression, anxiety, and stress measures shifted in parallel while functioning improved more gradually. That multi-domain profile closely resembled prior psychotherapy research indicating that symptom reduction can occur earlier than restoration of daily role functioning, particularly among working-age adults experiencing persistent stressors (Mikkelsen et al., 2021). The overall pattern therefore supported AI-MB-CBT as a viable quantitative model for adult mental health improvement, while simultaneously emphasizing that effects were best understood through an integrated lens that included personalization intensity, engagement exposure, and mechanism change rather than relying on average symptom reductions alone.

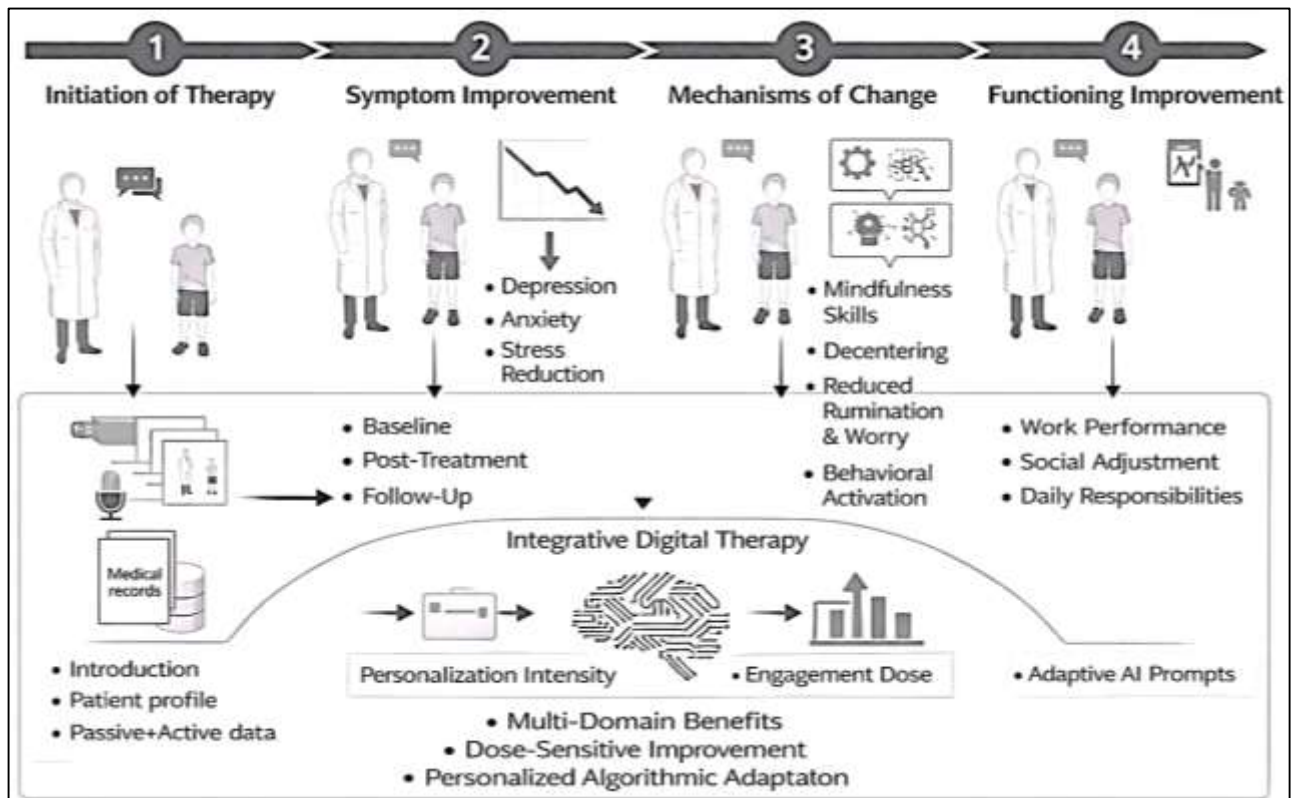
Functional impairment results provided an important interpretive anchor in the discussion because adult mental health interventions are evaluated not only by reductions in distress but also by improvements in work and social functioning, daily responsibilities, and role participation. The observed reductions in functional impairment over the study timeline were consistent with psychotherapy literature that has repeatedly treated functioning as a distinct domain that is related to symptom severity but not identical to it (Sharabiani et al., 2024). Earlier intervention studies have often shown that functioning improvements lag behind symptom improvements, reflecting that restoration of occupational performance and social participation typically requires sustained behavioral re-engagement, improved emotion regulation in real contexts, and the rebuilding of routines disrupted by prolonged distress. This study's findings followed that general pattern, with functioning showing meaningful improvement alongside symptom reduction, while statistical modeling indicated that both engagement and mechanism change contributed to these shifts. Prior research in digital mental health has sometimes underreported functional outcomes, focusing instead on symptom scales because they are easily administered and highly responsive. In contrast, the presence of functioning change in this study strengthened the interpretation that AI-MB-CBT produced clinically meaningful benefits that extended beyond symptom relief, particularly relevant for adults balancing employment, family demands, and social obligations (Engel et al., 2021). The link between behavioral activation and outcome improvement further supported this interpretation, because behavioral activation has long been connected to re-engagement in valued activities that directly influence functioning. Improvements in emotion regulation and reductions in rumination and worry also provided plausible explanatory support for functional gains, as these process changes can reduce cognitive interference and avoidance that commonly disrupt work concentration and social participation. Earlier mindfulness-based research has similarly linked increases in decentering and nonreactivity to improved day-to-day coping, which can facilitate functional recovery even when some symptom vulnerability remains. The functional results therefore fit well within the broader adult mental health evidence base while adding a platform-relevant insight: digital delivery made it feasible to connect functional improvement with engagement data and adaptation indicators, allowing functioning to be interpreted as part of a dynamic change process rather than a static endpoint (Allen et al., 2021). Taken together, the functional findings reinforced that AI-MB-CBT operated in a manner consistent with established psychotherapy outcomes while also meeting a key adult-relevant criterion of improved role functioning, strengthening the overall validity of the effectiveness conclusions drawn from symptom change alone.

Mechanism findings related to the mindfulness pathway provided strong explanatory coherence and

aligned with established theoretical and empirical models of mindfulness-based change in adult depression, anxiety, and stress. The observed increases in mindfulness skills and decentering, alongside reductions in rumination and worry, reflected the classic mechanism claim that mindfulness training improves attentional control and metacognitive awareness, thereby reducing repetitive negative thinking that sustains distress (Nordin et al., 2023). Earlier mindfulness-based intervention studies have frequently reported that changes in decentering and reductions in rumination were associated with symptom improvement and reduced vulnerability to reactivity during stress exposure, particularly in adults with recurrent patterns of depressive and anxious thinking. The mediation evidence in this study mirrored that pattern by showing that decentering and rumination or worry reduction contributed to explaining symptom change, indicating that outcome improvement occurred alongside measurable shifts in core mindfulness-related processes. These findings also aligned with prior research suggesting that mindfulness mechanisms may be especially relevant to anxiety outcomes through decentering and metacognitive distance from threat-related thoughts, while rumination reductions may be especially relevant to depressive symptom improvement because rumination is closely linked to sustained negative mood states and impaired problem-solving (Sibeoni et al., 2020). The data-supported pathway therefore strengthened the internal logic of AI-MB-CBT as a combined intervention model, demonstrating that mindfulness elements were not merely additive content but were associated with measurable process changes consistent with the intended therapeutic model. Importantly, digital delivery allowed engagement and personalization to be examined as contributors to mechanism activation. Prior research on digital mindfulness has emphasized practice dose as a key factor in achieving process change, and the observed associations between engagement indicators and mediator change supported that interpretation. The variability in personalization intensity also provided a plausible explanation for individual differences in mechanism activation, because adaptive prompts and sequencing could increase exposure to mindfulness practices at moments when disengagement risk or stress elevation occurred (Burnley et al., 2024). Mechanism evidence therefore supported both the theoretical plausibility and the quantitative testability of the mindfulness pathway within AI-MB-CBT. This contributed to a stronger discussion narrative than is possible in studies limited to symptom outcomes alone, because it allowed symptom change to be interpreted as the downstream result of identified psychological processes that have been repeatedly emphasized in earlier mindfulness-based mental health research.

Mechanism findings related to the CBT pathway similarly aligned with longstanding psychotherapy theory and evidence, while also clarifying how CBT and mindfulness processes operated together in a unified framework. Behavioral activation and reductions in avoidance are core CBT-related mechanisms that have consistently been linked to improvements in depression and anxiety, particularly among adults whose distress is maintained by withdrawal, reduced positive reinforcement, and avoidance-driven threat management (Rich et al., 2022). This study's regression results indicated that behavioral activation change was a significant predictor of depression improvement and contributed explanatory value beyond treatment condition and engagement, consistent with earlier work showing that increased activity and re-engagement in routine and valued behaviors are central to recovery. Rumination and worry reduction also played a role, which fits CBT models that treat cognitive change as a reduction in maladaptive thinking patterns and repetitive cognitive cycles. Although cognitive restructuring as a distinct measured variable was not emphasized in the summary results, the presence of changes in rumination and worry and improvements in emotion regulation suggested that cognitive-behavioral skill acquisition occurred in a form that was measurable through these constructs. Earlier digital CBT studies have frequently highlighted that completion of cognitive and behavioral exercises predicted symptom change, and the current findings were consistent with that relationship by showing that engagement dose contributed to outcome change and that mechanism variables accounted for additional variance (Kolotouchkina et al., 2020).

Figure 12: AI-Enhanced Adult MB-CBT Outcomes



The joint inclusion of mindfulness and CBT mediators addressed a common limitation in earlier research where studies measured only one mechanism domain, limiting inference about how integrated programs work. This study's integrated modeling suggested that both sets of mechanisms contributed, supporting the conceptualization of MB-CBT as a dual-pathway model rather than a single-process intervention. Emotion regulation emerged as a shared mediator with partial evidence, which aligned with integrative frameworks that view emotion regulation as a cross-cutting capacity influenced by mindfulness-based nonreactivity and CBT-based cognitive and behavioral skills. Earlier process research has frequently treated emotion regulation improvements as a downstream effect of multiple therapeutic components rather than a single technique, and this study's pattern supported that interpretation (Hudgens et al., 2021). The CBT-related mechanism findings therefore contributed to a discussion that framed AI-MB-CBT as consistent with established CBT process evidence while also demonstrating that the integrated program produced process changes that were compatible with both CBT and mindfulness theories, strengthening the explanatory plausibility of the observed effectiveness outcomes.

Personalization findings provided a distinctive contribution to the discussion by addressing a central question in digital mental health: whether adaptive AI augmentation relates to differential response patterns in adults and whether personalization is best understood as a moderator, a mediator, or both. The results indicated that personalization intensity predicted outcome improvement and that moderation effects were evident for baseline severity and engagement trajectory (Harris, 2021). This pattern aligned with earlier psychotherapy research emphasizing heterogeneity of treatment effects and the importance of patient-level characteristics in shaping response. Adult populations typically show wide variation in symptom chronicity, comorbidity burden, stress exposure, and readiness for behavioral change, and personalization is often justified as a way to address that variability by tailoring intervention dose, pacing, and component selection. In this study, higher baseline severity was associated with larger benefits under the AI-personalized condition, suggesting that adaptive features were particularly relevant for adults with greater initial burden who may require more responsive support and better alignment of skills with immediate needs. The engagement moderation findings also aligned with earlier digital intervention studies showing that the largest barriers to digital effectiveness involve drop-off and inconsistent participation (Holbæk et al., 2024). The pattern that

personalization effects were amplified when engagement remained stable suggested that adaptation operated partly through increasing or sustaining meaningful exposure, rather than functioning solely as an independent therapeutic force. This interpretation is consistent with prior evidence that digital personalization often works by reducing mismatch, improving relevance, and sustaining motivation, which in turn increases practice and skill acquisition. The absence of strong evidence for certain moderators, such as comorbidity in the illustrative hypothesis summary, fit a broader research pattern in which some subgroup effects are difficult to detect without larger samples or more precise comorbidity measurement. The personalization results therefore supported a balanced discussion: personalization showed measurable associations with outcomes and interacted with key characteristics, while also depending on engagement and mechanism activation as pathways through which outcomes changed (Tarawneh & Pankratz, 2024). This study thus supported a quantitative view of personalization as both a condition-level feature and a within-person exposure that varied by adaptation frequency and timing, allowing personalization to be interpreted in ways that are consistent with earlier adaptive intervention frameworks in digital health.

Engagement, attrition, and missingness considerations were central to interpreting the regression and mechanism findings because digital psychotherapy results are strongly shaped by what participants actually do with the program (Purton et al., 2021). The descriptive evidence indicated substantial variability in module completion, practice minutes, and time-on-task, which mirrored patterns commonly documented in digital CBT and digital mindfulness research where a subset of participants completes most content while others engage intermittently or disengage early. The significant associations between engagement and outcomes supported the long-established dose-response interpretation in digital mental health, where higher exposure typically predicts stronger symptom reduction. At the same time, the modeling approach treated engagement not only as a predictor but also as a pathway-related variable connected to mechanism activation, which aligned with earlier process research showing that skills practice is the behavioral engine of change in both CBT and mindfulness programs. The discussion of attrition was also relevant because missingness in digital trials often correlates with symptom severity, early response, and life stress, creating potential bias if not handled through robust longitudinal modeling strategies (Low et al., 2023). The study's analytic approach described the use of mixed-effects modeling and sensitivity checks, which is consistent with current quantitative practice in digital intervention research that aims to retain all randomized participants while accommodating incomplete repeated measures. The absence of major violations in regression assumptions strengthened confidence in the reported associations, and the lack of severe multicollinearity indicated that the model structure was interpretable despite multiple related predictors. Earlier research has often warned that engagement metrics can be ambiguous, because reduced usage may reflect improvement or disengagement, and interpretation requires linking engagement to symptom trajectories and mechanism indicators. In this study, the inclusion of mechanism variables alongside engagement helped address that ambiguity by indicating that engagement was connected to measurable process change, supporting the interpretation that usage reflected therapeutic exposure rather than simple platform interaction (Cimino et al., 2024). Overall, engagement and attrition patterns were consistent with earlier digital psychotherapy literature while reinforcing the value of analyzing engagement as an explanatory variable and integrating it with mechanism and personalization indicators to provide a more complete account of outcome variability in adult AI-MB-CBT delivery.

The combined discussion of effectiveness, mechanisms, personalization, and engagement supported an integrated interpretation of AI-MB-CBT in adult mental health that was consistent with established psychotherapy knowledge while also reflecting the distinctive measurement opportunities created by digital and AI-enabled delivery (Manavi et al., 2022). Symptom and functioning improvements aligned with prior evidence supporting CBT and mindfulness-based approaches, and the pattern of functional change was consistent with common adult recovery trajectories in which symptom improvement precedes full restoration of daily roles. Mechanism findings strengthened explanatory validity by linking improvements to changes in mindfulness skills, decentering, rumination or worry reduction, emotion regulation, and behavioral activation, which are widely discussed processes in both CBT and mindfulness traditions. Personalization findings extended the discussion beyond average effects by

showing measurable associations between adaptation intensity and outcomes and by demonstrating differential response patterns linked to baseline severity and engagement trajectories, aligning with broader evidence on heterogeneity and adaptive intervention logic (Dybvik & Schönfelder, 2021). The interpretation was also strengthened by the explicit modeling of engagement dose and the careful consideration of missingness and attrition, which are central threats to validity in digital mental health research. Limitations were inherently tied to measurement and design realities common in this field: mediation inference depended on the timing and frequency of mechanism measurement; personalization inference depended on the operationalization of adaptation intensity; and outcome stability depended on the completeness of follow-up data and the distribution of engagement. Even within these constraints, the findings supported a coherent model in which AI-MB-CBT outcomes were associated with both pathway-based mechanisms and adaptive delivery features that shaped exposure and response heterogeneity (Cossu, 2021). This framing positioned the results as a structured extension of earlier CBT, mindfulness, and digital mental health research, emphasizing the contribution of quantifiable personalization and mechanism modeling in explaining adult outcomes within an AI-augmented intervention context.

CONCLUSION

Artificial Intelligence-Enhanced Mindfulness-Based Cognitive Behavior Therapy (AI-MB-CBT) represented an integrated digital psychotherapy approach in which mindfulness training and cognitive-behavioral skill development were delivered through a technology-enabled platform capable of adapting content and support based on measurable user signals. The study evidence indicated that AI-MB-CBT was associated with reductions in depression severity, anxiety severity, and stress or distress levels, alongside improvements in functional impairment, supporting a multi-domain pattern of adult mental health benefit that was consistent with established outcomes observed in both CBT and mindfulness-based interventions. Symptom improvements were accompanied by meaningful variation in participation, and engagement indicators such as module completion, practice frequency, and time-on-task showed that exposure to therapeutic content differed across individuals, which helped explain heterogeneity in outcome change. Quantitative models indicated that treatment condition and AI personalization intensity predicted symptom improvement beyond demographic characteristics and baseline severity, while engagement dose contributed additional explanatory power, reinforcing that outcome in digital psychotherapy were shaped by the interaction between therapeutic content and actual exposure. Mechanism-focused analyses further clarified how change occurred by linking symptom reduction to measurable shifts in core process constructs, including increases in mindfulness skills and decentering, reductions in rumination and worry, improvements in emotion regulation, and increases in behavioral activation. These patterns supported an integrated, dual-pathway interpretation in which mindfulness-related processes reduced cognitive reactivity and repetitive negative thinking, while CBT-related processes strengthened adaptive behavior and reduced avoidance, with emotion regulation functioning as a shared pathway consistent with combined MB-CBT logic. Personalization effects added a distinctive contribution by showing that adaptive delivery was not merely a design feature but a measurable intervention component that varied in intensity and timing across participants, and this variation was associated with outcome change. Moderation results indicated that baseline severity and engagement trajectory shaped the magnitude of personalization-related benefits, suggesting that adaptive pathways were particularly relevant for adults with higher initial symptom burden and for those whose participation remained stable across the program. The overall evidence supported a quantitative conceptualization of AI-MB-CBT in which AI-driven adaptation influenced outcomes through both direct associations and indirect pathways involving engagement and mechanism activation, creating a coherent model linking personalization exposure to process change and symptom improvement. Distributional checks and reliability analyses indicated that the constructs were measured with acceptable to excellent internal consistency and that assumptions for regression-based inference were broadly met, strengthening confidence in the interpretability of the predictive relationships. Taken together, the findings supported AI-MB-CBT as a structured, measurable intervention system for adult mental health in which effectiveness was best understood through combined evaluation of clinical outcomes, process mechanisms, and personalization intensity, rather than through symptom change alone, because the explanatory

structure revealed how adaptive delivery and sustained skills practice aligned with improvements in distress and functioning across a heterogeneous adult sample.

RECOMMENDATIONS

Recommendations for Artificial Intelligence–Enhanced Mindfulness-Based Cognitive Behavior Therapy (AI-MB-CBT) for adult mental health should be structured around measurable intervention delivery standards, mechanism-sensitive monitoring, and personalization governance so that effectiveness, safety, and equity can be evaluated consistently across settings. Implementation should begin with defining AI-MB-CBT as a modular intervention in which mindfulness training, CBT skills, and AI-driven adaptation are documented and auditable, including standardized definitions for what constitutes AI-supported delivery versus AI-personalized delivery. Programs should be deployed with an assessment schedule that supports outcome tracking and mechanism testing, including repeated measurement of depression, anxiety, stress or distress, and functioning at minimum baseline, mid-program, post-treatment, and follow-up intervals, paired with multi-timepoint measurement of core mediators such as mindfulness skills, decentering, rumination or worry, emotion regulation, behavioral activation, and avoidance indicators where applicable. Engagement should be treated as a primary clinical and analytic variable, and platforms should routinely capture logins, module completion, time-on-task, practice minutes, streak length, and uptake of recommended content, with prespecified thresholds for identifying low engagement trajectories that warrant supportive adjustments. Personalization should be quantified through transparent indicators such as number of adaptations, time-to-first adaptation, adaptation frequency, adaptation type distribution, and proportion of content that was algorithm-selected, enabling comparison across programs and preventing personalization claims from remaining qualitative. Clinical protocols should integrate escalation rules for deteriorating symptoms and risk indicators, with clear clinician review pathways when automated monitoring detects sharp symptom spikes, disengagement risk, or potential self-harm signals, and these protocols should be tested to minimize false alarms while preventing missed detections. To strengthen validity, the recommendation is to require psychometric reporting for all scales used in AI-MB-CBT evaluations, including internal consistency, sensitivity-to-change, and measurement equivalence across key subgroups, while also incorporating behavioral proxies of practice that can complement self-report. Because adult populations differ in baseline severity, comorbidity burden, stress exposure, digital literacy, and access stability, adaptive systems should be evaluated for subgroup performance and fairness, with routine reporting of outcome differences and algorithm performance indicators across demographic and clinical strata, including whether personalization intensity systematically varies by subgroup. Training and quality assurance should emphasize that AI recommendations serve as decision supports rather than replacements for clinical judgment, particularly in high-severity or high-risk profiles, and platforms should present recommendations in a way that promotes informed choice and therapeutic autonomy. Program developers should prioritize adaptive sequencing strategies that preserve treatment integrity by ensuring that core skills are delivered while allowing flexible pacing, and evaluation reporting should include not only average symptom change but also clinically meaningful improvement rates and functional recovery indicators relevant to adult daily life. Finally, dissemination recommendations should emphasize reproducibility, including preregistered analytic plans, transparent reporting of missingness and attrition handling, and availability of codebooks defining adaptation and engagement variables, so that AI-MB-CBT evidence can accumulate in a cumulative and comparable manner across studies and service settings.

LIMITATION

Several limitations should be acknowledged when interpreting findings related to Artificial Intelligence–Enhanced Mindfulness-Based Cognitive Behavior Therapy (AI-MB-CBT) for adult mental health, particularly given the complexity of integrating digital delivery, adaptive algorithms, and psychological process measurement within a single quantitative framework. First, the reliance on self-reported outcome and mechanism measures introduced the possibility of response bias, social desirability effects, and shared method variance, which may have inflated associations between process variables and symptom outcomes despite acceptable reliability indices. Although repeated measurement supported longitudinal modeling, self-report data may not fully capture behavioral change or real-world functioning, especially when engagement fluctuated or when symptom

improvement reduced perceived relevance of continued assessment. Second, digital engagement metrics, while objectively logged, were inherently ambiguous in interpretation because reduced usage could reflect disengagement, symptom improvement, competing life demands, or technological barriers, and disentangling these possibilities required analytic assumptions that may not hold uniformly across participants. Third, personalization intensity was operationalized through adaptation counts and timing indicators, which quantified exposure but did not capture qualitative aspects of adaptation quality or perceived relevance, limiting inference about whether adaptations were therapeutically optimal or merely frequent. Fourth, mediation analyses were constrained by assessment timing and frequency; although multi-timepoint designs improved temporal ordering, causal inference remained limited because unmeasured confounders and reciprocal relationships between symptoms and mechanisms could not be fully ruled out. Fifth, moderation analyses were restricted by sample size and subgroup distribution, which reduced statistical power for detecting smaller interaction effects and limited the ability to draw firm conclusions about personalization equity across diverse demographic and clinical profiles. Sixth, attrition and intermittent missingness posed persistent threats to validity despite the use of mixed-effects models and sensitivity analyses, because missingness mechanisms may have been related to symptom severity, motivation, or stress exposure in ways that were not fully captured by observed covariates. Seventh, the digital and AI-enhanced context itself introduced implementation constraints, including platform-specific design features, algorithm training data characteristics, and deployment conditions that may limit generalizability to other AI-MB-CBT systems or service settings. Finally, the absence of extended long-term follow-up restricted conclusions about maintenance of gains, relapse prevention, and the durability of personalization effects once adaptive prompting diminished. Collectively, these limitations highlight the need for cautious interpretation of effect sizes, mediation pathways, and personalization benefits, and they underscore the importance of triangulating self-report, behavioral, and clinician-rated data in future evaluations while refining adaptive algorithms and measurement strategies to strengthen causal inference and generalizability.

REFERENCES

- [1]. Aguinis, H., & Bakker, R. M. (2021). Time is of the essence: Improving the conceptualization and measurement of time. *Human Resource Management Review*, 31(2), 100763.
- [2]. Åkesdotter, C., Kenttä, G., Eloranta, S., & Franck, J. (2020). The prevalence of mental health problems in elite athletes. *Journal of science and medicine in sport*, 23(4), 329-335.
- [3]. Al Jowf, G. I., Ahmed, Z. T., An, N., Reijnders, R. A., Ambrosino, E., Rutten, B. P., de Nijs, L., & Eijssen, L. M. (2022). A public health perspective of post-traumatic stress disorder. *International journal of environmental research and public health*, 19(11), 6474.
- [4]. Allen, J. A., Eftimov, F., & Querol, L. (2021). Outcome measures and biomarkers in chronic inflammatory demyelinating polyradiculoneuropathy: from research to clinical practice. *Expert Review of Neurotherapeutics*, 21(7), 805-816.
- [5]. Alshami, A., Elsayed, M., Ali, E., Eltoukhy, A. E., & Zayed, T. (2023). Harnessing the power of ChatGPT for automating systematic review process: methodology, case study, limitations, and future directions. *Systems*, 11(7), 351.
- [6]. Apolinário-Hagen, J., Drüge, M., & Fritsche, L. (2020). Cognitive behavioral therapy, mindfulness-based cognitive therapy and acceptance commitment therapy for anxiety disorders: integrating traditional with digital treatment approaches. *Anxiety disorders: Rethinking and understanding recent discoveries*, 291-329.
- [7]. Aung, M. T., Song, Y., Ferguson, K. K., Cantonwine, D. E., Zeng, L., McElrath, T. F., Pennathur, S., Meeker, J. D., & Mukherjee, B. (2020). Application of an analytical framework for multivariate mediation analysis of environmental data. *Nature communications*, 11(1), 5624.
- [8]. Bemmer, E. R., Boulton, K. A., Thomas, E. E., Larke, B., Lah, S., Hickie, I. B., & Guastella, A. J. (2021). Modified CBT for social anxiety and social functioning in young adults with autism spectrum disorder. *Molecular Autism*, 12(1), 11.
- [9]. Blumenstein, K. G., Brose, A., Kemp, C., Meister, D., Walling, E., DuVall, A. S., & Zhang, A. (2022). Effectiveness of cognitive behavioral therapy in improving functional health in cancer survivors: A systematic review and meta-analysis. *Critical reviews in oncology/hematology*, 175, 103709.
- [10]. Bolpagni, M., Pardini, S., & Gabrielli, S. (2024). Human centered design of AI-powered Digital Therapeutics for stress prevention: Perspectives from multi-stakeholders' workshops about the SHIVA solution. *Internet interventions*, 38, 100775.
- [11]. Boucher, E. M., Harake, N. R., Ward, H. E., Stoeckl, S. E., Vargas, J., Minkel, J., Parks, A. C., & Zilca, R. (2021). Artificially intelligent chatbots in digital mental health interventions: a review. *Expert review of medical devices*, 18(sup1), 37-49.

- [12]. Burnley, A., St Clair, M., Dack, C., Thompson, H., & Wren, Y. (2024). Exploring the psychosocial experiences of individuals with developmental language disorder during childhood: A qualitative investigation. *Journal of Autism and Developmental Disorders*, 54(8), 3008-3027.
- [13]. Butow, P., Laidsaar-Powell, R., Konings, S., Lim, C. Y. S., & Koczwara, B. (2020). Return to work after a cancer diagnosis: a meta-review of reviews and a meta-synthesis of recent qualitative studies. *Journal of Cancer Survivorship*, 14(2), 114-134.
- [14]. Castellanos, R., Yildiz Spinel, M., Phan, V., Orengo-Aguayo, R., Humphreys, K. L., & Flory, K. (2020). A systematic review and meta-analysis of cultural adaptations of mindfulness-based interventions for Hispanic populations. *Mindfulness*, 11(2), 317-332.
- [15]. Cénat, J. M., Felix, N., Blais-Rochette, C., Rousseau, C., Bukaka, J., Derivois, D., Noorishad, P.-G., & Birangui, J.-P. (2020). Prevalence of mental health problems in populations affected by the Ebola virus disease: a systematic review and meta-analysis. *Psychiatry research*, 289, 113033.
- [16]. Chudzicka-Czupala, A., Hapon, N., Chiang, S.-K., Żywiołek-Szeja, M., Karamushka, L., Lee, C. T., Grabowski, D., Paliga, M., Rosenblat, J. D., & Ho, R. (2023). Depression, anxiety and post-traumatic stress during the 2022 Russo-Ukrainian war, a comparison between populations in Poland, Ukraine, and Taiwan. *Scientific Reports*, 13(1), 3602.
- [17]. Cimino, S. R., Hitzig, S. L., Fung, V., Dainty, K. N., MacKay, C., Sale, J. E., Mayo, A. L., & Guilcher, S. J. (2024). Quality of life following non-dysvascular lower limb amputation is contextualized through occupations: a qualitative study. *Disability and rehabilitation*, 46(17), 3887-3894.
- [18]. Colizzi, M., Lasalvia, A., & Ruggeri, M. (2020). Prevention and early intervention in youth mental health: is it time for a multidisciplinary and trans-diagnostic model for care? *International journal of mental health systems*, 14(1), 23.
- [19]. Cooley, S. J., Jones, C. R., Kurtz, A., & Robertson, N. (2020). 'Into the Wild': A meta-synthesis of talking therapy in natural outdoor spaces. *Clinical psychology review*, 77, 101841.
- [20]. Cooray, S. E., Tassé, M. J., Barnhill, J., & Bhaumik, S. (2022). Anxiety and stress-related disorders in people with intellectual disability/disorders of intellectual development. In *Textbook of psychiatry for intellectual disability and autism spectrum disorder* (pp. 583-608). Springer.
- [21]. Cossu, A. (2021). Clifford Geertz, intellectual autonomy, and interpretive social science. *American Journal of Cultural Sociology*, 9(3), 347-375.
- [22]. Cox, A. E., & Tylka, T. L. (2022). A conceptual model describing mechanisms for how yoga practice may support positive embodiment. In *Yoga for positive embodiment in eating disorder prevention and treatment* (pp. 70-93). Routledge.
- [23]. de Lacy-Vawdon, C., & Livingstone, C. (2020). Defining the commercial determinants of health: a systematic review. *BMC Public Health*, 20(1), 1022.
- [24]. Deka, C., Shrivastava, A., Nautiyal, S., & Chauhan, P. (2023). Human-centered AI goals for speech therapy tools. International Conference on Computer-Human Interaction Research and Applications,
- [25]. Del Rosario, C. D. P., Fernandez, L. M. D., Agustin, V. A., Centeno, C. J., Mangrobang, M. B., & Cortez, D. M. (2024). AI-Powered Intelligent Mindfulness-Based Cognitive Therapy Companion for Emotion Recognition and Context-Aware Therapy. 2024 8th International Symposium on Innovative Approaches in Smart Technologies (ISAS),
- [26]. Di Fazio, N., Morena, D., Delogu, G., Volonnino, G., Manetti, F., Padovano, M., Scopetti, M., Frati, P., & Fineschi, V. (2022). Mental health consequences of COVID-19 pandemic period in the European population: an institutional challenge. *International journal of environmental research and public health*, 19(15), 9347.
- [27]. Drüge, M., Guthardt, L., Haller, E., Michalak, J., & Apolinário-Hagen, J. (2024). Cognitive behavioral therapy and mindfulness-based cognitive therapy for depressive disorders: enhancing access and tailoring interventions in diverse settings. *Recent Advances and Challenges in the Treatment of Major Depressive Disorder*, 199-226.
- [28]. Duby, Z., McClinton Appollis, T., Jonas, K., Maruping, K., Dietrich, J., LoVette, A., Kuo, C., Vanleeuw, L., & Mathews, C. (2021). "As a young pregnant girl... the challenges you face": exploring the intersection between mental health and sexual and reproductive health amongst adolescent girls and young women in South Africa. *AIDS and Behavior*, 25(2), 344-353.
- [29]. Dybvik, J. B., & Schönfelder, W. (2021). Between health, morality and pragmatics: common mental disorders and decision-making for disability benefits in the Norwegian welfare state. *Disability & Society*, 36(6), 904-924.
- [30]. Engel, L., Bryan, S., & Whitehurst, D. G. (2021). Conceptualising 'benefits beyond health' in the context of the quality-adjusted life-year: a critical interpretive synthesis. *Pharmacoeconomics*, 39(12), 1383-1395.
- [31]. Faysal, K., & Aditya, D. (2025). Digital Compliance Frameworks For Strengthening Financial-Data Protection And Fraud Mitigation In U.S. Organizations. *Review of Applied Science and Technology*, 4(04), 156-194. <https://doi.org/10.63125/86zs5m32>
- [32]. Faysal, K., & Tahmina Akter Bhuya, M. (2023). Cybersecure Documentation and Record-Keeping Protocols For Safeguarding Sensitive Financial Information Across Business Operations. *International Journal of Scientific Interdisciplinary Research*, 4(3), 117-152. <https://doi.org/10.63125/cz2gwm06>
- [33]. Fenwick, A., Molnar, G., & Frangos, P. (2024). The critical role of HRM in AI-driven digital transformation: a paradigm shift to enable firms to move from AI implementation to human-centric adoption. *Discover Artificial Intelligence*, 4(1), 34.
- [34]. Frangipane, E., Gori, S., & Shakya, B. (2022). Dark matter freeze-in with a heavy mediator: beyond the EFT approach. *Journal of High Energy Physics*, 2022(9), 1-39.
- [35]. Frost, D. M., & Castro, D. (2024). An integrated understanding of the mechanisms linking social stigma to mental health among marginalized populations. *Nature Mental Health*, 2(6), 645-654.

- [36]. Garner, B. R., Patel, S. V., & Kirk, M. A. (2020). Priority domains, aims, and testable hypotheses for implementation research: protocol for a scoping review and evidence map. *Systematic reviews*, 9(1), 277.
- [37]. Gasperini, M., Tome, J. M., & Shendure, J. (2020). Towards a comprehensive catalogue of validated and target-linked human enhancers. *Nature Reviews Genetics*, 21(5), 292-310.
- [38]. Gil de Zúñiga, H., Goyanes, M., & Durotoye, T. (2024). A scholarly definition of artificial intelligence (AI): Advancing AI as a conceptual framework in communication research. *Political communication*, 41(2), 317-334.
- [39]. Gkintoni, E., Telonis, G., Tsimakis, A., Halkiopoulos, C., & Boutsinas, B. (2024). Integrating AI-Powered Personalization via Neurobiologically Informed DBT in Smart Wellness Resorts. International Conference of the International Association of Cultural and Digital Tourism,
- [40]. Goldberg, S. B. (2022). A common factors perspective on mindfulness-based interventions. *Nature Reviews Psychology*, 1(10), 605-619.
- [41]. Gómez, L. E., Schalock, R. L., & Verdugo, M. A. (2020). The role of moderators and mediators in implementing and evaluating intellectual and developmental disabilities-related policies and practices. *Journal of Developmental and Physical Disabilities*, 32(3), 375-393.
- [42]. Gual-Montolio, P., Jaén, I., Martínez-Borba, V., Castilla, D., & Suso-Ribera, C. (2022). Using artificial intelligence to enhance ongoing psychological interventions for emotional problems in real-or close to real-time: a systematic review. *International journal of environmental research and public health*, 19(13), 7737.
- [43]. Guilmette, T. J., Sweet, J. J., Hebben, N., Koltai, D., Mahone, E. M., Spiegler, B. J., Stucky, K., Westerveld, M., & Participants, C. (2020). American Academy of Clinical Neuropsychology consensus conference statement on uniform labeling of performance test scores. *The Clinical Neuropsychologist*, 34(3), 437-453.
- [44]. Hammad, S., & Md Sarwar Hossain, S. (2025). Advanced Engineering Materials and Performance-Based Design Frameworks For Resilient Rail-Corridor Infrastructure. *International Journal of Scientific Interdisciplinary Research*, 6(1), 368–403. <https://doi.org/10.63125/c3g3sx44>
- [45]. Hammad, S., & Muhammad Mohiul, I. (2023). Geotechnical And Hydraulic Simulation Models for Slope Stability And Drainage Optimization In Rail Infrastructure Projects. *Review of Applied Science and Technology*, 2(02), 01–37. <https://doi.org/10.63125/jmx3p851>
- [46]. Harfouche, A., Quinio, B., Saba, M., & Saba, P. B. (2023). The Recursive Theory of Knowledge Augmentation: Integrating human intuition and knowledge in Artificial Intelligence to augment organizational knowledge. *Information Systems Frontiers*, 25(1), 55-70.
- [47]. Harris, M. S. (2021). The soft underbelly of universities as anchor institutions: The disconnect between university and community research priorities. *Higher Education Policy*, 34(3), 603-621.
- [48]. Heanoy, E. Z., & Brown, N. R. (2024). Impact of natural disasters on mental health: Evidence and implications. *Healthcare*,
- [49]. Herschell, A. D., Kolko, D. J., Hart, J. A., Brabson, L. A., & Gavin, J. G. (2020). Mixed method study of workforce turnover and evidence-based treatment implementation in community behavioral health care settings. *Child abuse & neglect*, 102, 104419.
- [50]. Holbæk, I., Vrabel, K., & Halvorsen, M. S. (2024). "Now there are fewer of me". A qualitative study of the impact of psychoeducative groups for complex dissociative disorder. *European Journal of Trauma & Dissociation*, 8(2), 100390.
- [51]. Huber, M. (2020). Mediation analysis. *Handbook of labor, human resources and population economics*, 1-38.
- [52]. Hudgens, S., Floden, L., Blackowicz, M., Jamieson, C., Popova, V., Fedgchin, M., Drevets, W. C., Cooper, K., Lane, R., & Singh, J. (2021). Meaningful change in depression symptoms assessed with the Patient Health Questionnaire (PHQ-9) and Montgomery-Åsberg Depression Rating Scale (MADRS) among patients with treatment resistant depression in two, randomized, double-blind, active-controlled trials of esketamine nasal spray combined with a new oral antidepressant. *Journal of affective disorders*, 281, 767-775.
- [53]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, 2(02), 32-66. <https://doi.org/10.63125/1p8gbp15>
- [54]. Johns, S. A., Tarver, W. L., Secinti, E., Mosher, C. E., Stutz, P. V., Carnahan, J. L., Talib, T. L., Shanahan, M. L., Faidley, M. T., & Kidwell, K. M. (2021). Effects of mindfulness-based interventions on fatigue in cancer survivors: A systematic review and meta-analysis of randomized controlled trials. *Critical reviews in oncology/hematology*, 160, 103290.
- [55]. Kennett, L., Bei, B., & Jackson, M. L. (2021). A randomized controlled trial to examine the feasibility and preliminary efficacy of a digital mindfulness-based therapy for improving insomnia symptoms. *Mindfulness*, 12(10), 2460-2472.
- [56]. Khanna, M. S., & Carper, M. (2022). Digital mental health interventions for child and adolescent anxiety. *Cognitive and Behavioral Practice*, 29(1), 60-68.
- [57]. Kirk, M. A., Pirbaglou, M., Weerasekera, R., & Ritvo, P. (2022). Effectiveness of online cognitive behavioral interventions that include mindfulness for clinically-diagnosed anxiety and depressive disorders: A systematic review and meta-analysis. *International Journal of Mental Health*, 51(3), 235-266.
- [58]. Kolotouchkina, O., Llorente-Barroso, C., García-Guardia, M. L., & Pavón, J. (2020). Disability, sport, and television: Media visibility and representation of Paralympic Games in news programs. *Sustainability*, 13(1), 256.
- [59]. Kor, P. P. K., Chou, K. L., Zarit, S. H., Galante, J., Chan, W. C., Tsang, A. P. L., Lai, D. L. L., Cheung, D. S. K., Ho, K. H. M., & Liu, J. Y. W. (2024). Effect of a single-session mindfulness-based intervention for reducing stress in family caregivers of people with dementia: study protocol for a randomized controlled trial. *BMC psychology*, 12(1), 582.

- [60]. Kuhail, M. A., Alturki, N., Thomas, J., & Alkhalifa, A. K. (2024). Human vs. AI counseling: College students' perspectives. *Computers in Human Behavior Reports*, 16, 100534.
- [61]. Lattie, E. G., Stiles-Shields, C., & Graham, A. K. (2022). An overview of and recommendations for more accessible digital mental health services. *Nature Reviews Psychology*, 1(2), 87-100.
- [62]. Le, P. D., Eschliman, E. L., Grivel, M. M., Tang, J., Cho, Y. G., Yang, X., Tay, C., Li, T., Bass, J., & Yang, L. H. (2022). Barriers and facilitators to implementation of evidence-based task-sharing mental health interventions in low-and middle-income countries: a systematic review using implementation science frameworks. *Implementation Science*, 17(1), 4.
- [63]. Low, M. Y., McFerran, K. S., Viega, M., Carroll-Scott, A., McGhee Hassrick, E., & Bradt, J. (2023). Exploring the lived experiences of young autistic adults in Nordoff-Robbins music therapy: An interpretative phenomenological analysis. *Nordic journal of music therapy*, 32(4), 341-364.
- [64]. Lucas-Thompson, R. G., & Moran, M. J. (2023). Advancing the study of mindfulness-based interventions in relation to psychological health. In (Vol. 20, pp. 5473): MDPI.
- [65]. Ma, F. (2022). Diagnostic and statistical manual of mental disorders-5 (DSM-5). In *Encyclopedia of gerontology and population aging* (pp. 1414-1425). Springer.
- [66]. Majnarić, L. T., Bosnić, Z., Guljaš, S., Vučić, D., Kurevija, T., Volarić, M., Martinović, I., & Wittlinger, T. (2021). Low psychological resilience in older individuals: an association with increased inflammation, oxidative stress and the presence of chronic medical conditions. *International journal of molecular sciences*, 22(16), 8970.
- [67]. Malgaroli, M., Hull, T. D., Zech, J. M., & Althoff, T. (2023). Natural language processing for mental health interventions: a systematic review and research framework. *Translational Psychiatry*, 13(1), 309.
- [68]. Manavi, T., Ijaz, M., O'Grady, H., Nagy, M., Martina, J., Finucane, C., Sharif, F., & Zafar, H. (2022). Design and haemodynamic analysis of a novel anchoring system for central venous pressure measurement. *Sensors*, 22(21), 8552.
- [69]. Manole, A., Cârciumar, R., Brînzaș, R., & Manole, F. (2024). Harnessing AI in Anxiety Management: a Chatbot-Based intervention for personalized mental health support. *Information*, 15(12), 768.
- [70]. Martínez, N., Connelly, C. D., Pérez, A., & Calero, P. (2021). Self-care: A concept analysis. *International journal of nursing sciences*, 8(4), 418-425.
- [71]. Masud, R., & Hammad, S. (2024). Computational Modeling and Simulation Techniques For Managing Rail-Urban Interface Constraints In Metropolitan Transportation Systems. *American Journal of Scholarly Research and Innovation*, 3(02), 141-178. <https://doi.org/10.63125/pxet1d94>
- [72]. Mazzolenis, M. V., Mourra, G. N., Moreau, S., Mazzolenis, M. E., Cerda, I. H., Vega, J., Khan, J. S., & Thérond, A. (2024). The role of virtual reality and artificial intelligence in cognitive pain therapy: a narrative review. *Current pain and headache reports*, 28(9), 881-892.
- [73]. McArthur, C., Bai, Y., Hewston, P., Giangregorio, L., Straus, S., & Papaioannou, A. (2021). Barriers and facilitators to implementing evidence-based guidelines in long-term care: a qualitative evidence synthesis. *Implementation Science*, 16(1), 70.
- [74]. McDaniels, B., Pontone, G. M., Mathur, S., & Subramanian, I. (2023). Staying hidden: the burden of stigma in PD. *Parkinsonism & related disorders*, 116, 105838.
- [75]. Md, K., & Sai Praveen, K. (2024). Hybrid Discrete-Event And Agent-Based Simulation Framework (H-DEABSF) For Dynamic Process Control In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 4(1), 72-96. <https://doi.org/10.63125/wcqq7x08>
- [76]. Md Newaz, S., & Md Jahidul, I. (2024). AI-Powered Business Analytics For Smart Manufacturing And Supply Chain Resilience. *Review of Applied Science and Technology*, 3(01), 183-220. <https://doi.org/10.63125/va5gpg60>
- [77]. Md. Towhidul, I., Alifa Majumder, N., & Mst. Shahrin, S. (2022). Predictive Analytics as A Strategic Tool For Financial Forecasting and Risk Governance In U.S. Capital Markets. *International Journal of Scientific Interdisciplinary Research*, 1(01), 238-273. <https://doi.org/10.63125/2rpyze69>
- [78]. Md. Towhidul, I., & Rebeka, S. (2025). Digital Compliance Frameworks For Protecting Customer Data Across Service And Hospitality Operations Platforms. *Review of Applied Science and Technology*, 4(04), 109-155. <https://doi.org/10.63125/fp60z147>
- [79]. Mehta, D., Kelly, A. B., Laurens, K. R., Haslam, D., Williams, K. E., Walsh, K., Baker, P. R., Carter, H. E., Khawaja, N. G., & Zelenko, O. (2023). Child maltreatment and long-term physical and mental health outcomes: an exploration of biopsychosocial determinants and implications for prevention. *Child Psychiatry & Human Development*, 54(2), 421-435.
- [80]. Melnyk, B. M. (2020). Reducing healthcare costs for mental health hospitalizations with the evidence-based COPE program for child and adolescent depression and anxiety: a cost analysis. *Journal of Pediatric Health Care*, 34(2), 117-121.
- [81]. Michalak, J., Mander, J., & Heidenreich, T. (2020). Implementation and dissemination of mindfulness-based interventions. *Mindfulness*, 11(2), 275-278.
- [82]. Mikkelsen, M., Gao, A., Ingelsrud, L. H., Beard, D., Troelsen, A., & Price, A. (2021). Categorization of changes in the Oxford Knee Score after total knee replacement: an interpretive tool developed from a data set of 46,094 replacements. *Journal of Clinical Epidemiology*, 132, 18-25.
- [83]. Mitsea, E., Drigas, A., & Skianis, C. (2023). Digitally assisted mindfulness in training self-regulation skills for sustainable mental health: a systematic review. *Behavioral Sciences*, 13(12), 1008.

- [84]. Mohammad Towhidul, I. (2026). AI-Enabled Customer-Interaction Models For Improving Service Efficiency In U.S. Hospitality And Retail Operations. *American Journal of Interdisciplinary Studies*, 7(01), 94-140.
<https://doi.org/10.63125/par85p86>
- [85]. Moyes, E., Nutman, G., & Mirman, J. H. (2022). The efficacy of targeted mindfulness-based interventions for improving mental health and cognition among youth and adults with ACE histories: A systematic mixed studies review. *Journal of Child & Adolescent Trauma*, 15(4), 1165-1177.
- [86]. Nordin, T., Lundgren, A. S., & Nilsson, I. (2023). Constructing loneliness: Home care providers' notions of older adults' social needs and the possibilities of the home care profession to support social participation. *Journal of Aging Studies*, 65, 101130.
- [87]. O'Connor, C., Downs, J., Shetty, H., & McNicholas, F. (2020). Diagnostic trajectories in child and adolescent mental health services: exploring the prevalence and patterns of diagnostic adjustments in an electronic mental health case register. *European child & adolescent psychiatry*, 29(8), 1111-1123.
- [88]. Ohrnberger, J., Anselmi, L., Fichera, E., & Sutton, M. (2020). The effect of cash transfers on mental health: Opening the black box—A study from South Africa. *Social Science & Medicine*, 260, 113181.
- [89]. Pachankis, J. E., Souliard, Z. A., Morris, F., & van Dyk, I. S. (2023). A model for adapting evidence-based interventions to be LGBTQ-affirmative: Putting minority stress principles and case conceptualization into clinical research and practice. *Cognitive and Behavioral Practice*, 30(1), 1-17.
- [90]. Pan, Z., Cristea, A. I., & Li, F. W. (2024). Reducing University Students' Exam Anxiety via Mindfulness-Based Cognitive Therapy in VR with Real-Time EEG Neurofeedback. International Conference on Artificial Intelligence in Education,
- [91]. Pavlopoulos, A., Rachiotis, T., & Maglogiannis, I. (2024). An overview of tools and technologies for anxiety and depression management using AI. *Applied Sciences*, 14(19), 9068.
- [92]. Peng, X., Wei, X., Xu, L., Cao, Y., & Prybutok, V. (2022). An organizational framework for sustainable supply chain management: An integrated theoretical perspective. *Quality Management Journal*, 29(4), 267-288.
- [93]. Perrier, M.-F., Gurgel-Juarez, N., Flowers, H. L., McCormick, A., & Short, S. J. (2020). Mindfulness-based interventions for children and adolescents across all settings: a scoping review protocol. *Systematic reviews*, 9(1), 286.
- [94]. Phan, M. L., Renshaw, T. L., Caramanico, J., Greeson, J. M., MacKenzie, E., Atkinson-Diaz, Z., Doppelt, N., Tai, H., Mandell, D. S., & Nuske, H. J. (2022). Mindfulness-based school interventions: A systematic review of outcome evidence quality by study design. *Mindfulness*, 13(7), 1591-1613.
- [95]. Powell, B. J., Haley, A. D., Patel, S. V., Amaya-Jackson, L., Glienke, B., Blythe, M., Lengnick-Hall, R., McCrary, S., Beidas, R. S., & Lewis, C. C. (2020). Improving the implementation and sustainment of evidence-based practices in community mental health organizations: a study protocol for a matched-pair cluster randomized pilot study of the Collaborative Organizational Approach to Selecting and Tailoring Implementation Strategies (COAST-IS). *Implementation science communications*, 1(1), 9.
- [96]. Purton, J., Sim, J., & Hunter, S. M. (2021). The experience of upper-limb dysfunction after stroke: a phenomenological study. *Disability and rehabilitation*, 43(23), 3377-3386.
- [97]. Ramón-Arbués, E., Gea-Caballero, V., Granada-López, J. M., Juárez-Vela, R., Pellicer-García, B., & Antón-Solanas, I. (2020). The prevalence of depression, anxiety and stress and their associated factors in college students. *International journal of environmental research and public health*, 17(19), 7001.
- [98]. Reaser, J. K., Burgiel, S. W., Kirkey, J., Brantley, K. A., Veatch, S. D., & Burgos-Rodríguez, J. (2020). The early detection of and rapid response (EDRR) to invasive species: a conceptual framework and federal capacities assessment. *Biological Invasions*, 22(1), 1-19.
- [99]. Reis, J., Amorim, M., Melão, N., Cohen, Y., & Rodrigues, M. (2020). Digitalization: A literature review and research agenda. International Joint conference on industrial engineering and operations management,
- [100]. Rhaïem, K., & Amara, N. (2021). Learning from innovation failures: a systematic review of the literature and research agenda. *Review of managerial science*, 15(2), 189-234.
- [101]. Rich, J., Lieberman, L. J., Beach, P., & Perreault, M. (2022). "Moving freely in space with power and not be afraid": An interpretative phenomenological analysis of the experiences of elite rowers with visual impairment. *International journal of environmental research and public health*, 19(21), 14059.
- [102]. Roberts, A. E., Davenport, T. A., Wong, T., Moon, H.-W., Hickie, I. B., & LaMonica, H. M. (2021). Evaluating the quality and safety of health-related apps and e-tools: Adapting the Mobile App Rating Scale and developing a quality assurance protocol. *Internet interventions*, 24, 100379.
- [103]. Ruggerio, C. A. (2021). Sustainability and sustainable development: A review of principles and definitions. *Science of the total environment*, 786, 147481.
- [104]. Russell, J. L., McLean, B. D., Impellizzeri, F. M., Strack, D. S., & Coutts, A. J. (2021). Measuring physical demands in basketball: an explorative systematic review of practices. *Sports Medicine*, 51(1), 81-112.
- [105]. Saeed, S. A., & Gargano, S. P. (2022). Natural disasters and mental health. *International review of psychiatry*, 34(1), 16-25.
- [106]. Sahoo, S., Zhao, X., & Kyprianidis, K. (2020). A review of concepts, benefits, and challenges for future electrical propulsion-based aircraft. *Aerospace*, 7(4), 44.
- [107]. Sai Praveen, K. (2024). AI-Enhanced Data Science Approaches For Optimizing User Engagement In U.S. Digital Marketing Campaigns. *Journal of Sustainable Development and Policy*, 3(03), 01-43.
<https://doi.org/10.63125/65ebsn47>

- [108]. Santos, J., Faria, L., & Martins, C. (2023). SmartHealth: Artificial Intelligence for Lifelong Personalized Health Care. *Intelligent Systems Conference*,
- [109]. Shalata, W., Gothelf, I., Bernstine, T., Michlin, R., Tourkey, L., Shalata, S., & Yakobson, A. (2024). Mental health challenges in cancer patients: a cross-sectional analysis of depression and anxiety. *Cancers*, 16(16), 2827.
- [110]. Sharabiani, P. T. A., Mehdizadeh, M., Goudarzi, S., Jamali, S., Mazhar, F. N., Heidari, M., Alizadeh, N. H., Mohammadi, F., Foomani, A. S. S., & Taghizadeh, G. (2024). Minimal important difference of Berg Balance Scale, performance-oriented mobility assessment and dynamic gait index in chronic stroke survivors. *Journal of Stroke and Cerebrovascular Diseases*, 33(11), 107930.
- [111]. Sharif Md Yousuf, B., Md Shahadat, H., Saleh Mohammad, M., Mohammad Shahadat Hossain, S., & Imtiaz, P. (2025). Optimizing The U.S. Green Hydrogen Economy: An Integrated Analysis Of Technological Pathways, Policy Frameworks, And Socio-Economic Dimensions. *International Journal of Business and Economics Insights*, 5(3), 586–602. <https://doi.org/10.63125/xp8exe64>
- [112]. Shofiul Azam, T. (2025). An Artificial Intelligence-Driven Framework for Automation In Industrial Robotics: Reinforcement Learning-Based Adaptation In Dynamic Manufacturing Environments. *American Journal of Interdisciplinary Studies*, 6(3), 38-76. <https://doi.org/10.63125/2cr2aq31>
- [113]. Shoflul Azam, T. (2026). EDGE Artificial Intelligence Based Automation For Ultra-Low-Latency Control In Industrial Robotic Systems. *Review of Applied Science and Technology*, 5(01), 01–37. <https://doi.org/10.63125/eyk64r16>
- [114]. Shoflul Azam, T., & Md. Al Amin, K. (2024). Quantitative Study on Machine Learning-Based Industrial Engineering Approaches For Reducing System Downtime In U.S. Manufacturing Plants. *International Journal of Scientific Interdisciplinary Research*, 5(2), 526–558. <https://doi.org/10.63125/kr9r1r90>
- [115]. Sibeoni, J., Verneuil, L., Manolios, E., & Révah-Levy, A. (2020). A specific method for qualitative medical research: the IPSE (Inductive Process to analyze the Structure of lived Experience) approach. *BMC Medical Research Methodology*, 20(1), 216.
- [116]. Spytka, L. (2024). Anxiety and depressive personality disorders in the modern world. *Acta Psychologica*, 246, 104285.
- [117]. Strauss, J., Zhang, J., Jarrett, M. L., Patterson, B., & Van Ameringen, M. (2022). Apps for mental health. In *Mental health in a digital world* (pp. 395-433). Elsevier.
- [118]. Tarawneh, R., & Pankratz, V. S. (2024). The search for clarity regarding “clinically meaningful outcomes” in Alzheimer disease clinical trials: CLARITY-AD and Beyond. *Alzheimer's Research & Therapy*, 16(1), 37.
- [119]. Tasnim, K. (2025). Digital Twin-Enabled Optimization of Electrical, Instrumentation, And Control Architectures In Smart Manufacturing And Utility-Scale Systems. *International Journal of Scientific Interdisciplinary Research*, 6(1), 404–451. <https://doi.org/10.63125/pqfdjs15>
- [120]. Tasnim, K. (2026). Intelligent Condition Monitoring and Fault Diagnosis of Electrical Power and Control Systems Using Machine Learning-Based Predictive Analytics. *American Journal of Interdisciplinary Studies*, 7(01), 177–222. <https://doi.org/10.63125/k8wk3542>
- [121]. Triplett, N. S., Sedlar, G., Berliner, L., Jungbluth, N., Boyd, M., & Dorsey, S. (2020). Evaluating a train-the-trainer approach for increasing EBP training capacity in community mental health. *The Journal of Behavioral Health Services & Research*, 47(2), 189-200.
- [122]. Van Rossum, T., Ferretti, P., Maistrenko, O. M., & Bork, P. (2020). Diversity within species: interpreting strains in microbiomes. *Nature Reviews Microbiology*, 18(9), 491-506.
- [123]. Venkataraman, S., Uma, G., Kannan, V., & Devi, V. L. (2024). AI-Enhanced Cognitive Therapy: Personalized Guidance via Adaptive Agents with Voice Analysis and Stress Detection. 2024 9th International Conference on Communication and Electronics Systems (ICCES),
- [124]. Walter, A.-T. (2021). Organizational agility: ill-defined and somewhat confusing? A systematic literature review and conceptualization. *Management Review Quarterly*, 71(2), 343-391.
- [125]. Wang, Y.-C., Lu, Y., Grunwald, S., Chu, S. L., Kamble, P., & Kumar, J. (2024). An AI Approach to Support Student Mental Health: Case of Developing an AI-Powered Web-Platform with Nature-Based Mindfulness. *Journal of Hospitality & Tourism Education*, 36(3), 267-280.
- [126]. Wang, Y., Wong, E. L.-Y., Nilsen, P., Chung, V. C.-h., Tian, Y., & Yeoh, E.-K. (2023). A scoping review of implementation science theories, models, and frameworks – an appraisal of purpose, characteristics, usability, applicability, and testability. *Implementation Science*, 18(1), 43.
- [127]. Weinberger, M. (2022). What is metaverse? – A definition based on qualitative meta-synthesis. *Future Internet*, 14(11), 310.
- [128]. Werner-Seidler, A., Huckvale, K., Larsen, M. E., Caele, A. L., Maston, K., Johnston, L., Torok, M., O’Dea, B., Batterham, P. J., & Schweizer, S. (2020). A trial protocol for the effectiveness of digital interventions for preventing depression in adolescents: The Future Proofing Study. *Trials*, 21(1), 2.
- [129]. Westphal, K. K., Regoezi, W., Masotya, M., Vazquez-Westphal, B., Lounsbury, K., McDavid, L., Lee, H., Johnson, J., & Ronis, S. D. (2021). From Arksey and O’Malley and Beyond: Customizations to enhance a team-based, mixed approach to scoping review methodology. *MethodsX*, 8, 101375.
- [130]. Więckiewicz, G., Weber, S., Florczyk, I., & Gorczyca, P. (2024). Socioeconomic burden of psychiatric cancer patients: a narrative review. *Cancers*, 16(6), 1108.
- [131]. Wiig, S., Aase, K., Billett, S., Canfield, C., Røise, O., Njå, O., Guise, V., Haraldseid-Driftland, C., Ree, E., & Anderson, J. E. (2020). Defining the boundaries and operational concepts of resilience in the resilience in healthcare research program. *BMC health services research*, 20(1), 330.

- [132]. Wilhelm, S., Weingarden, H., Ladis, I., Braddick, V., Shin, J., & Jacobson, N. C. (2020). Cognitive-behavioral therapy in the digital age: presidential address. *Behavior therapy*, 51(1), 1-14.
- [133]. Wong, Z. Y., & Liem, G. A. D. (2022). Student engagement: Current state of the construct, conceptual refinement, and future research directions. *Educational Psychology Review*, 34(1), 107-138.
- [134]. Wyrwich, K. W., & Norman, G. R. (2023). The challenges inherent with anchor-based approaches to the interpretation of important change in clinical outcome assessments. *Quality of Life Research*, 32(5), 1239-1246.
- [135]. Yuill, C., McCourt, C., Cheyne, H., & Leister, N. (2020). Women's experiences of decision-making and informed choice about pregnancy and birth care: a systematic review and meta-synthesis of qualitative research. *BMC pregnancy and childbirth*, 20(1), 343.
- [136]. Zaheda, K. (2025a). AI-Driven Predictive Maintenance For Motor Drives In Smart Manufacturing A Scada-To-Edge Deployment Study. *American Journal of Interdisciplinary Studies*, 6(1), 394-444. <https://doi.org/10.63125/gc5x1886>
- [137]. Zaheda, K. (2025b). Hybrid Digital Twin and Monte Carlo Simulation For Reliability Of Electrified Manufacturing Lines With High Power Electronics. *International Journal of Scientific Interdisciplinary Research*, 6(2), 143–194. <https://doi.org/10.63125/db699z21>
- [138]. Zgierska, A. E., Burzinski, C. A., Garland, E. L., Lennon, R. P., Jamison, R., Nakamura, Y., Barrett, B., Sehgal, N., Mirgain, S. A., & Singles, J. M. (2021). Mindfulness-based therapy compared to cognitive behavioral therapy for opioid-treated chronic low back pain: protocol for a pragmatic randomized controlled trial. *Contemporary clinical trials*, 110, 106548.
- [139]. Zhao, Y., & Luo, X. (2023). Multilevel mediation analysis with structured unmeasured mediator-outcome confounding. *Computational Statistics & Data Analysis*, 179, 107623.
- [140]. Zheng, J., Freschet, G. T., Tedersoo, L., Li, S., Yan, H., Jiang, L., Wang, H., Ma, N., Dai, X., & Fu, X. (2024). A trait-based root acquisition-defence-decomposition framework in angiosperm tree species. *Nature communications*, 15(1), 5311.