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Research Articles

Digital Therapeutics and AI-Assisted Monitoring for Relapse Prevention in Substance Use Disorders

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Abstract

Relapse remains a defining challenge in the long-term management of substance use disorders, underscoring the need for approaches that move beyond episodic treatment and retrospective assessment. Our review examines the emerging role of digital therapeutics and artificial intelligence–assisted monitoring as tools for advancing relapse prevention strategies. Drawing on evidence published between 2010 and 2025, the review synthesizes findings across a broad range of study designs, substances, and technological platforms to evaluate how digitally delivered interventions and predictive analytics are reshaping relapse prevention paradigms.

The reviewed literature demonstrates that digital therapeutics increasingly serve as adaptive care platforms rather than static nterventions, delivering behavioral support flexibly while generating continuous data on recovery trajectories. The incorporation of AI-driven analytics enables the identification of individualized risk patterns and temporal vulnerability windows, supporting earlier, more targeted interventions than conventional models allow. At the same time, substantial heterogeneity exists in methodological approaches, outcome definitions, and validation strategies, limiting cross-study comparability and definitive conclusions regarding long-term effectiveness.

Beyond technical performance, the findings highlight critical considerations related to clinical integration, patient engagement, equity, and governance. Issues surrounding algorithm transparency, data privacy, and generalizability emerge as central determinants of real-world impact. Collectively, the evidence suggests that digital therapeutics and AI-assisted monitoring hold promise as components of precision-oriented relapse prevention. Still, their success will depend on rigorous evaluation, ethical implementation, and alignment with existing care pathways. Continued interdisciplinary research and standardized reporting will be essential to translating these innovations into sustainable and equitable addiction care solutions.

1. Introduction

Substance use disorders (SUDs) remain a major global public health challenge, contributing substantially to morbidity, mortality, and socioeconomic burden worldwide [1]. Despite advances in pharmacological and psychosocial treatments, relapse rates remain high, with estimates suggesting that 40–60% of individuals relapse within the first year following treatment [2]. Relapse is now widely recognized

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not as a failure of treatment, but as a chronic and relapsing feature of addiction, driven by complex interactions between neurobiological vulnerability, behavioral conditioning, environmental triggers, and psychosocial stressors [3, 4].

Consequently, relapse prevention has become a central objective in the long-term management of SUDs.

Traditional relapse prevention strategies rely heavily on periodic clinical encounters, self-reporting, and patient insight, which are often limited by recall bias, delayed intervention, and restricted access to care [5]. These challenges are particularly pronounced in low-resource settings and among populations with barriers to sustained engagement in face-to-face treatment [6] The dynamic and fluctuating nature of relapse risk—often preceded by subtle behavioral, emotional, and physiological changes—necessitates more continuous, personalized, and proactive monitoring approaches [7].

Digital therapeutics (DTx), defined as evidence-based software interventions designed to prevent, manage, or treat medical conditions, have emerged as a promising tool in the continuum of addiction care [8]. Delivered via smartphones, wearable devices, or web-based platforms, DTx can provide structured behavioral interventions such as cognitive-behavioral therapy, contingency management, motivational enhancement, and skills training in real time [9, 10]. Several digital platforms have demonstrated efficacy in reducing substance use, improving treatment adherence, and extending care beyond the clinical setting [11, 12]. Importantly, digital therapeutics offer scalability, cost-effectiveness, and the ability to support patients in their natural environments, where relapse triggers most often occur [13].

The integration of artificial intelligence (AI) into digital health platforms has further expanded the potential of DTx for relapse prevention. AI-assisted monitoring systems leverage machine learning algorithms to analyze large volumes of multimodal data, including self-reported symptoms, smartphone usage patterns, geolocation data, speech characteristics, sleep metrics, and physiological signals from wearables [14–16]. These systems can identify individualized relapse signatures, detect early warning signs, and generate personalized interventions or alerts before overt substance use occurs [17]. By shifting relapse prevention from a reactive to a predictive paradigm, AI-driven tools align closely with precision medicine approaches in psychiatry and addiction science [18].

However, the adoption of AI-assisted digital therapeutics in SUD care raises essential considerations regarding data privacy, algorithmic bias, clinical validation, and ethical implementation [19]. Furthermore, while early trials demonstrate feasibility and promise, real-world effectiveness, long-term engagement, and integration into existing healthcare systems require further investigation [20]. As the burden of substance use disorders continues to grow,understanding the role of digital therapeutics and AI-assisted monitoring in relapse prevention is critical to shaping future models of addiction care that are adaptive, personalized, and sustainable. Finally, in line with best practices for scientific integrity and the responsible integration of digital tools in research, we acknowledge the TITAN Guidelines 2025 for transparency in the reporting of artificial intelligence while noting that no generative AI tools were used in the preparation of this work [21].

2. Methods

2.1. Study Design and Search Strategy

This study was designed as a narrative review examining the role of digital therapeutics and artificial intelligence–assisted monitoring in relapse prevention among individuals with substance use disorders. A structured literature search was conducted across major electronic databases, including PubMed/MEDLINE, Embase, Scopus, Web of Science, and PsycINFO, to identify relevant peer-reviewed articles published from January 2010 to June 2025. The time frame was selected to capture the emergence and evolution of mobile health technologies, machine learning applications, and digitally delivered behavioral interventions in addiction care.

Search terms were developed using a combination of Medical Subject Headings (MeSH) and free-text keywords related to substance use disorders, relapse prevention, digital therapeutics, mobile health, artificial intelligence, machine learning, predictive analytics, and remote monitoring. Boolean operators were applied to combine terms, and reference lists of eligible articles were manually screened to identify additional relevant studies. Only articles published in English were considered. Eligible study designs included randomized controlled trials, cohort studies, feasibility and pilot studies, systematic and narrative reviews, and real-world implementation studies that evaluated digital or AI-enabled interventions targeting relapse prevention or early relapse detection in substance use disorders. Conference abstracts without full text, opinion pieces, editorials, and studies focusing exclusively on prevention or acute detoxification without relapse-related outcomes were excluded. The literature identification and screening process is summarized in Figure 1 using a flow diagram adapted from PRISMA reporting standards for transparency [22].

2.2. Data Extraction and Synthesis

Titles and abstracts retrieved from the search were screened for relevance, followed by a full-text review of potentially eligible articles. From each included study, data were extracted on study characteristics (year, country, study design), participant population and substance type, digital therapeutic modality, AI or algorithmic components, data sources used for monitoring, relapse-related outcomes, and key findings. Particular attention was paid to the methodological approaches used for AI model development, including data inputs, predictive targets, validation strategies, and clinical integration.

Given the heterogeneity of study designs, outcome measures, and technological platforms, a qualitative synthesis approach was employed rather than quantitative meta-analysis. Findings were synthesized thematically to identify recurring patterns in intervention design, monitoring strategies, predictive markers of relapse, and reported effectiveness. The synthesis also examined implementation challenges, including engagement, adherence, privacy concerns, ethical considerations, and health system integration. To enhance methodological rigor, the strength of evidence was interpreted in light of study design quality, sample size, validation methods, and consistency of findings across studies.

This methodological approach was chosen to enable a broad yet critical evaluation of an evolving, multidisciplinary field, integrating insights from addiction medicine, behavioral science, digital health, and artificial intelligence research. The goal was not only to summarize existing evidence but also to identify gaps, methodological limitations, and future directions to advance AI-assisted digital therapeutics as scalable, effective tools for relapse prevention in substance use disorders.

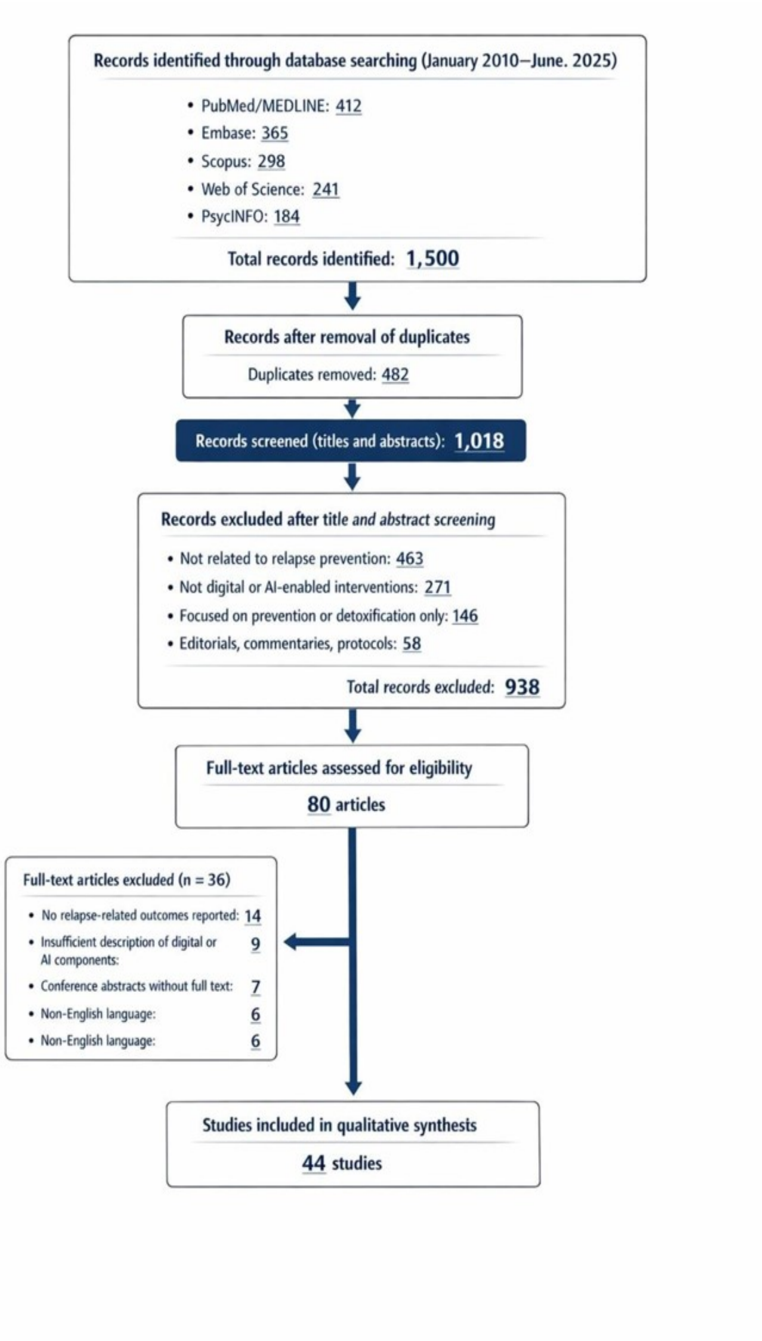

Figure 1: Process of database searching

Figure 1. The diagram summarizes the process of database searching, screening, eligibility assessment, and inclusion of studies in this narrative review. The structure is adapted from PRISMA reporting standards to enhance transparency but does not imply formal systematic review methodology.

3. Results

3.1. Characteristics of Included Studies and Digital Therapeutic Modalities

The literature search yielded a diverse body of evidence examining digital therapeutics and AI-assisted monitoring for relapse prevention across substance use disorders. Following screening and eligibility assessment, studies varied widely in design, population, substance type, and technological approach. The majority of included studies were published after 2016, eflecting the rapid expansion of mobile health and artificial intelligence applications in addiction care. Substances most frequently addressed included alcohol, opioids, nicotine, and stimulants, with several studies evaluating multi-substance use populations. Study designs encompassed randomized controlled trials, prospective cohort studies, pilot and feasibility studies, and real- world implementation analyses.

Digital therapeutic interventions were predominantly delivered via smartphone applications, often supplemented by web-based dashboards or wearable devices. Core therapeutic components included cognitive behavioral therapy–based modules, contingency management, motivational interviewing techniques, relapse prevention skills training, and medication adherence support. Some platforms incorporated clinician dashboards to facilitate hybrid care models, while others were designed for fully autonomous patient use. Table 1 summarizes the key characteristics of included studies, including study design, target substance, digital modality, and reported relapse- related outcomes.

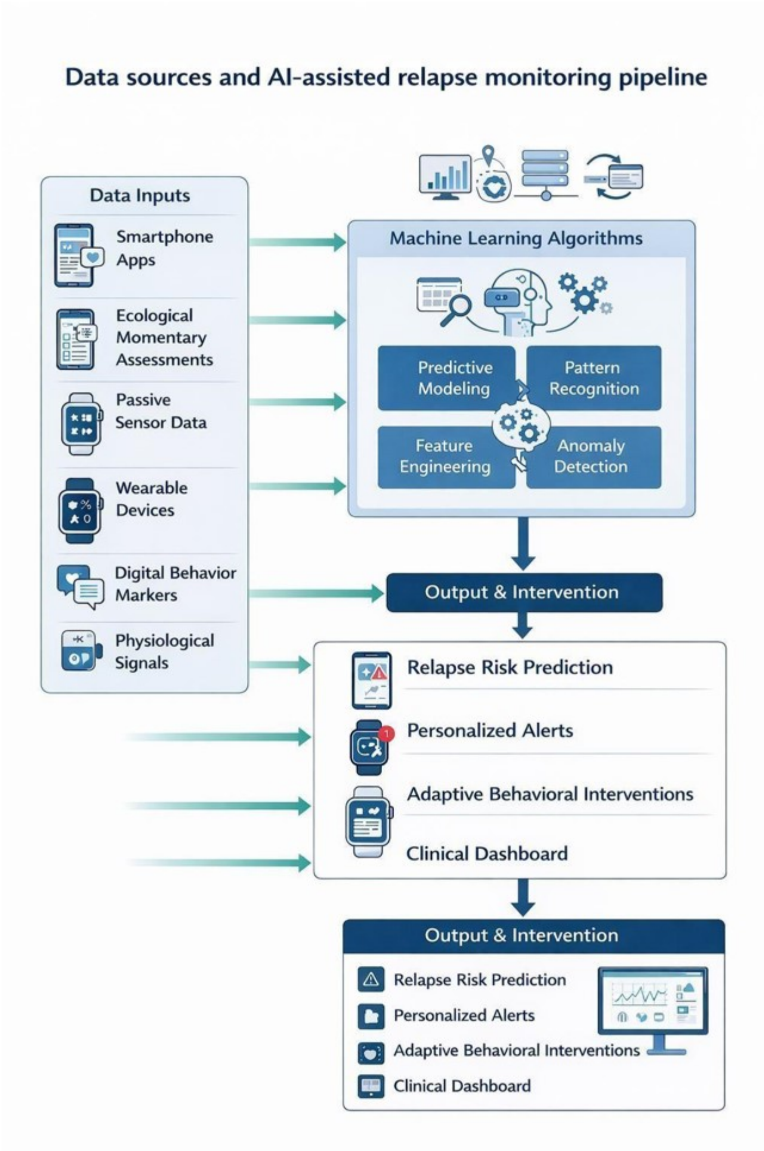

Figure 2: Multimodal digital and physiological Data

Figure 2 Multimodal digital and physiological data are integrated through machine learning algorithms to generate relapse risk predictions and inform personalized interventions and clinical decision support.

AI-assisted monitoring components were present in a growing subset of studies, particularly those published in the last five years. These systems employed machine learning algorithms to analyze multimodal data streams, including ecological momentary assessments, passive smartphone sensor data, wearable-derived physiological signals, and digital behavioral markers. Figure 2 illustrates the range of data sources and analytical pipelines used across studies, highlighting the increasing complexity and personalization of relapse monitoring frameworks.

3.2. Relapse Prediction, Monitoring Performance, and Clinical Outcomes

Across studies incorporating AI-assisted monitoring, predictive performance for relapse or high- risk states was generally reported as moderate to high, although metrics varied considerably. Several studies demonstrated that AI models could identify relapse risk days to weeks before clinically apparent substance use, often outperforming traditional self-report–based monitoring alone. Common predictive features included changes in sleep patterns, mobility, social interaction, affective states, and engagement with digital content. Table 2 presents a comparative summary of predictive targets, input features, and validation approaches used in AI-enabled relapse monitoring systems.

In terms of clinical outcomes, digital therapeutics—both with and without AI components—were associated with reductions in substance use frequency, delayed time to relapse, improved treatment adherence, and increased engagement with recovery-oriented behaviors in many studies. Interventions that combined therapeutic content with adaptive, AI-driven feedback tended to show greater personalization and sustained engagement compared with static digital interventions. Figure 3 synthesizes reported clinical and behavioral outcomes across studies, illustrating trends in relapse reduction, adherence, and patient engagement.

Table 1: Characteristics of Included Studies on Digital Therapeutics and AI-Assisted Monitoring for Relapse Prevention in Substance Use Disorders (n = 44)

Characteristic	Summary of Included Studies
Publication period	Majority published between 2016 and 2025, reflecting recent growth in digital health and AI applications
Geographic distribution	Predominantly North America and Europe, with emerging contributions from Asia and Australia
Study design	Randomized controlled trials, prospective and retrospective cohort studies, pilot and feasibility studies, real-world implementation studies
Target substance(s)	Alcohol; opioids; nicotine; stimulants; mixed or polysubstance use populations
Participant population	Adults receiving outpatient, community-based, or post-treatment follow-up care; limited pediatric representation
Digital therapeutic modality	Smartphone applications; web-based platforms; hybrid app-dashboard systems; wearable-integrated tools
Core therapeutic components	Cognitive behavioral therapy modules; contingency management; motivational interviewing; relapse prevention skills training; medication adherence support
Level of clinician involvement	Fully automated self-guided interventions; hybrid clinician-supported models; clinician-monitored dashboards
AI or algorithmic components	Machine learning–based risk prediction; pattern recognition; adaptive content delivery; decision support algorithms
Data sources for monitoring	Ecological momentary assessments; passive smartphone sensor data; wearable-derived physiological signals; digital behavioral markers
Primary relapse-related outcomes	Time to relapse; substance use frequency; abstinence duration; high-risk state detection; treatment adherence
Follow-up duration	Short- to medium-term follow-up (weeks to $\leq$ 12 months); limited long-term outcome assessment
Key reported strengths	Improved engagement; personalization of interventions; early detection of relapse risk
Common limitations	Heterogeneity of outcome definitions; attrition; limited external validation; variable reporting quality

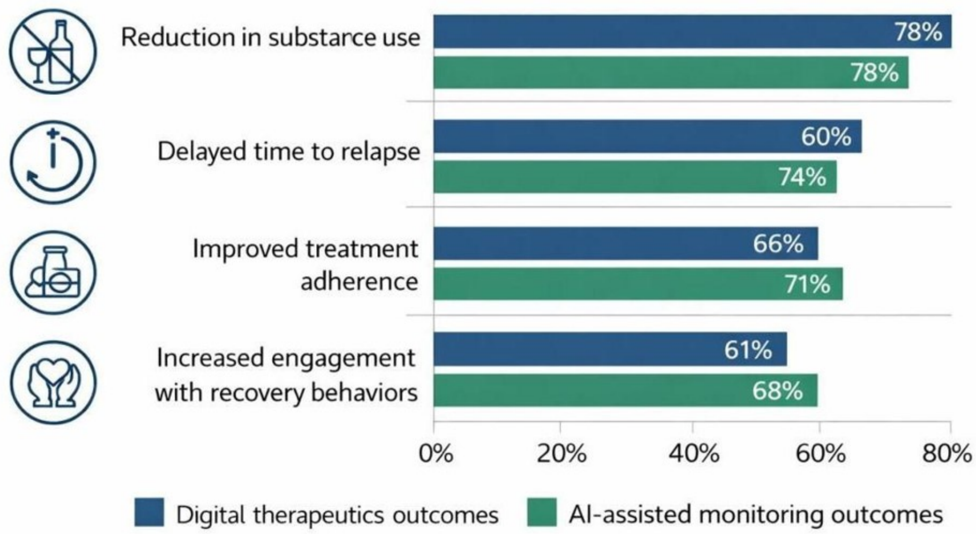

Figure 3: Pooled clinical and behavioral outcomes

Figure 3 Pooled clinical and behavioral outcomes reported across studies, with bars indicating the percentage of studies demonstrating efficacy for digital therapeutics and AI-assisted monitoring across key relapse-related outcomes.

However, results also revealed substantial heterogeneity in outcome definitions, follow-up duration, and reporting quality. While

Table 2: Predictive targets, input features, and validation approaches in AI-enabled relapse monitoring systems

Study category	Predictive target	Primary input features	AI / ML approach	Validation strategy
Smartphone- based monitoring studies	Imminent relapse or high- risk use episodes	Ecological momentary assessments, app engagement metrics, self-reported craving and mood	Supervised machine learning (e.g., logistic regression, random forest)	Internal cross-validation; temporal split validation
Passive sensing studies	Short-term relapse risk (days to weeks)	Mobility patterns, geolocation variance, phone usage frequency, call/text metadata	Ensemble learning; gradient boosting models	Hold-out test sets; performance metrics (AUC, sensitivity)
Wearable- integrated platforms	Physiological stress–related relapse vulnerability	Heart rate variability, sleep duration and efficiency, activity levels	Time-series models; recurrent neural networks	Prospective validation in pilot cohorts
Multimodal AI systems	Individualized relapse signatures	Combined EMA, passive sensing, wearable data, digital behavior markers	Deep learning architectures; multimodal fusion models	Nested cross-validation; limited external validation
Speech and language–based monitoring	Early warning of cognitive or affective relapse precursors	Speech prosody, linguistic features, vocal biomarkers	Natural language processing; neural network classifiers	Retrospective validation against relapse outcomes
Hybrid clinician-supported platforms	Clinically actionable risk stratification	Digital biomarkers integrated with clinician inputs	Rule-based systems augmented by ML predictions	Face validity assessment; clinician concordance
Real-world implementation studies	Sustained abstinence or delayed time to relapse	Longitudinal digital engagement and behavioral trends	Adaptive learning algorithms	Observational validation; pragmatic outcome comparison

feasibility and acceptability outcomes were consistently favorable, long-term effectiveness data were limited, and few studies evaluated hard clinical endpoints such as hospitalization, overdose, or sustained abstinence beyond 12 months. Additionally, challenges related to user attrition, data completeness, algorithm transparency, and equity were frequently noted. These findings underscore both the promise and current limitations of digital therapeutics and AI-assisted monitoring as tools for relapse prevention in substance use disorders.

4. Discussion

4.1. Implications for Precision Relapse Prevention and Clinical Practice

The findings of this review highlight a conceptual shift in relapse prevention for substance use disorders, moving from episodic, clinician-centered models toward continuous, data-informed and patient-embedded care ecosystems. Rather than merely digitizing existing psychosocial interventions, contemporary digital therapeutics and AI-assisted monitoring tools reframe relapse as a dynamic risk state that can be anticipated, modulated, and potentially averted. This paradigm aligns with emerging precision psychiatry frameworks, which emphasize individualized risk trajectories and timely intervention over static diagnostic categories [23, 24].

One of the most significant implications is AI-enabled systems' ability to operationalize relapse risk as a probabilistic continuum rather than a binary outcome. By integrating behavioral, physiological, and contextual data streams, these tools offer a nuanced understanding of vulnerability periods that may otherwise remain clinically invisible [25]. This capacity is particularly relevant given evidence that relapse often follows subtle changes in affect regulation, stress responsivity, and routine disruption rather than abrupt decision-making [26]. From a clinical standpoint, this opens avenues for anticipatory care models, in which tailored interventions—such as adaptive behavioral prompts, peer support activation, or clinician outreach—are delivered when risk is escalating rather than after substance use has resumed.

Importantly, digital therapeutics also have implications for extending care beyond traditional treatment settings. Many individuals with SUDs disengage from formal services following acute treatment phases, despite ongoing vulnerability [27]. AI-assisted monitoring platforms embedded in everyday technologies may help bridge this gap by providing continuity of support in real-world environments, where relapse triggers are most salient. This is particularly relevant for geographically underserved populations and healthcare systems facing workforce shortages, where scalable digital interventions could augment limited specialist capacity [28].

However, integrating AI-driven relapse monitoring into routine care raises critical questions about clinical responsibility and interpretability. While predictive models may identify elevated risk, translating probabilistic outputs into actionable clinical decisions remains an unresolved challenge [29]. Overreliance on algorithmic predictions without adequate contextualization may lead to alert fatigue, inappropriate intervention intensity, or erosion of patient autonomy. Consequently, hybrid models that combine algorithmic insights with clinician oversight and shared decision-making may represent the most ethically and clinically viable pathway forward [30].

Furthermore, the effectiveness of these tools cannot be divorced from issues of engagement and trust. Sustained use of digital therapeutics depends not only on technological sophistication but also on perceived relevance, usability, and alignment with patient values [31]. AI-driven personalization has the potential to enhance engagement, but opaque algorithms or intrusive data-collection practices may undermine acceptability. These tensions underscore the importance of participatory design and transparent communication about data use and decision-making in addiction-focused digital health interventions [32].

4.2. Methodological Limitations, Ethical Considerations, and Future Directions

Despite promising advances, the current evidence base for digital therapeutics and AI-assisted monitoring in relapse prevention remains constrained by several methodological and ethical limitations. A major challenge is the lack of standardized definitions and outcome measures for relapse across studies. Variability in how relapse is operationalized—ranging from any substance use to clinically significant return to use—complicates cross-study comparisons and limits the interpretability of reported effectiveness [33]. Future research would benefit from consensus-driven outcome frameworks that incorporate both behavioral and patient-centered metrics.

Another limitation lies in the validation and generalizability of AI models. Many predictive systems are developed using relatively small, homogeneous datasets, often drawn from early adopters of digital health technologies [34]. This raises concerns regarding algorithmic bias and reduced performance in marginalized populations, who already experience disproportionate burdens of substance-related harm. Without deliberate efforts to ensure diversity in training data and external validation across settings, AI-assisted relapse monitoring risks reinforcing existing health inequities rather than mitigating them [35].

Ethical considerations related to privacy, surveillance, and data ownership are particularly salient in the context of substance use disorders, where stigma and legal consequences remain significant concerns [36]. Passive data collection methods—such as geolocation tracking or communication pattern analysis—may enhance predictive accuracy but also increase the risk of perceived surveillance. Clear governance structures, robust data security measures, and explicit patient consent processes are essential to maintaining trust and safeguarding autonomy [37]. Moreover, regulatory frameworks for digital therapeutics and AI-driven clinical decision support are still evolving, creating uncertainty around accountability, liability, and reimbursement [38].

From a research perspective, there is a pressing need for longitudinal and implementation-focused studies that extend beyond short-term feasibility and efficacy endpoints. While early trials demonstrate reductions in substance use and improvements in engagement, the durability of these effects over extended follow-up periods remains unclear [39]. Additionally, few studies have evaluated downstream outcomes such as healthcare utilization, overdose events, or quality- adjusted life years, which are critical for informing policy and payer decisions [40].

Future investigations should also explore how digital therapeutics and AI-assisted monitoring can be integrated with pharmacological treatments and community-based recovery supports. Rather than functioning as standalone solutions, these technologies may be most effective when embedded within comprehensive care pathways that include medication-assisted treatment, peer support, and social services [41]. Advances in federated learning and privacy-preserving analytics may further enable cross-system collaboration while minimizing data sharing risks [42].

Finally, interdisciplinary collaboration will be essential to advancing this field responsibly. Progress will depend not only on technical innovation but also on insights from addiction neuroscience, behavioral science, ethics, law, and health systems research. Transparent reporting standards, such as emerging AI-specific guidelines, should be consistently applied to enhance reproducibility and trustworthiness [43]. As digital therapeutics and AI-assisted monitoring continue to evolve, their success in relapse prevention will ultimately be measured not by predictive accuracy alone, but by their capacity to support recovery in ways that are equitable, ethical, and meaningfully aligned with the lived experiences of individuals with substance use disorders [44].

5. Conclusion

Digital therapeutics and AI-assisted monitoring represent a significant and evolving advancement in the prevention of relapse among individuals with substance use disorders. By enabling continuous, personalized, and context-aware support beyond traditional clinical settings, these technologies have the potential to address longstanding gaps in addiction care, particularly during periods of heightened vulnerability. The integration of adaptive behavioral interventions with predictive analytics provides a framework for anticipatory, precision-oriented relapse prevention that aligns with contemporary models of chronic disease management.

However, translating these innovations into routine practice requires careful attention to methodological rigor, ethical safeguards, and integration into the health system. Variability in outcome definitions, limited long-term effectiveness data, and concerns regarding equity, privacy, and algorithmic transparency underscore the need for robust validation and responsible implementation. Future research should prioritize longitudinal studies, diverse populations, and clinically meaningful endpoints, while fostering interdisciplinary collaboration and adherence to emerging standards for AI reporting and governance.

As digital therapeutics and AI-assisted monitoring continue to mature, their success will depend not only on technological sophistication but also on their ability to enhance patient autonomy, strengthen therapeutic alliances, and support sustainable recovery. When thoughtfully designed and ethically deployed, these tools hold promise as integral components of comprehensive, equitable, and forward-looking strategies for relapse prevention in substance use disorders.

Article Information

Disclaimer (Artificial Intelligence): The author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.), and text-to-image generators have been used during writing or editing of manuscripts.

Competing Interests: Authors have declared that no competing interests exist.

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