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AI in Addiction: A Social Work-Informed Approach from Risk Assessment to Intervention

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Abstract

This study examines addiction via biopsychosocial and structural determinants and, from a social work perspective, positions AI-supported tools across risk assessment, monitoring/early warning, and psychosocial intervention. It is a conceptual review of empirical and theoretical studies (2010–2025) on addiction, AI, and decision-support systems. The reviewed literature indicates that AI-supported tools may help combine clinical and social data to estimate risk and relapse, identify vulnerable groups through social media content and digital footprints, enable monitoring and alerts via wearables and mobile apps, personalize interventions through chatbots and digital therapeutics, and strengthen case management through hybrid models. Yet structural risks also emerge, including privacy and dynamic consent concerns, algorithmic bias and stigma, covert surveillance, the digital divide, limited generalizability from small samples, and the relative neglect of behavioral addictions.

Keywords: Addiction, Artificial intelligence, Risk assessment, Psychosocial intervention, Human-Centered AI

Bağımlılıkta Yapay Zekâ: Risk Değerlendirmeden Müdahaleye Sosyal Hizmet Temelli Bir Yaklaşım

Özet

Bu çalışma, bağımlılığı biyopsikososyal ve yapısal belirleyiciler üzerinden ele almakta ve sosyal hizmet perspektifiyle yapay zeka (YZ) destekli araçların bağımlılık alanında risk değerlendirme, izlem/erken uyarı ve psikososyal müdahale basamaklarındaki konumunu tartışmaktadır. Çalışma, bağımlılık, YZ ve karar destek sistemleri kesişiminde 2010–2025 yılları arasında yayımlanan ampirik ve kuramsal araştırmalara dayanan kavramsal bir derleme niteliğindedir. İncelenen literatür, yapay zekâ destekli araçların, risk ve nüksü tahmin etmek için klinik ve sosyal verileri birleştirmeye, sosyal medya içeriği ve dijital ayak izleri aracılığıyla savunmasız grupları belirlemeye, giyilebilir cihazlar ve mobil uygulamalar aracılığıyla izleme ve uyarılar sağlamaya, sohbet robotları ve dijital terapiler aracılığıyla müdahaleleri kişiselleştirmeye ve hibrit modeller aracılığıyla vaka yönetimini güçlendirmeye yardımcı olabileceğini göstermektedir. Bununla birlikte, mahremiyet ve rıza, algoritmik önyargı ve damgalama, örtük gözetim, dijital uçurum, küçük örneklemlerden kaynaklanan sınırlı genellenebilirlik ve davranışsal bağımlılıkların görece ihmal edilmesi gibi yapısal risk alanları öne çıkmaktadır.

Anahtar Kelimeler: Bağımlılık, Yapay zeka, Risk değerlendirme, Psikososyal müdahale, İnsan merkezli yapay zekâ

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INTRODUCTION

Addiction is characterized by a compulsive drive toward a substance or behavior, loss of control, and continued engagement despite harmful consequences. As a chronic, relapsing disorder, it disrupts daily functioning and produces adverse social, economic, and psychological outcomes; individuals may place the addictive object above other life domains (Moroianu et al., 2023). Beyond an individual-level concern, addiction has broad societal, economic, and public health implications shaped by genetic, psychological, and social factors, underscoring the need for awareness and effective interventions (Fakhoury, 2015). In DSM-5, addiction is conceptualized via criteria such as impaired control, intense craving, tolerance, withdrawal, impaired social functioning, and hazardous use, encompassing both substance-related and behavioral addictions (Liu et al., 2025; Hasin et al., 2013).

As a biopsychosocial public health problem, addiction affects individuals, their environments, and society, and may increase harms to self and others (Fisher et al., 2016; Torres-Berrío et al., 2018). It includes substance addiction—compulsive psychoactive substance uses with withdrawal—and behavioral addiction, such as internet addiction, gambling disorder, and compulsive buying, which undermine functioning and social life (Sussman & Sussman, 2011; Fedrigolli & Ratković, 2021).

Addressing addiction is a complex, long-term process requiring sustained rehabilitation, monitoring, and social support to prevent relapses (Ayub et al., 2023; Vieira, 2025). Service delivery is constrained by geographic inequities, cost barriers, limited awareness and capacity, acute-focused responses, lack of individualized care, misdiagnosis and delayed diagnosis, stigma, limited family readiness for early intervention, inadequate regulation and enforcement, and restricted infrastructure in developing countries. Against these constraints, AI has emerged as a promising tool across diagnosis, prevention, and recovery (Khakpaki & Sepehri, 2025). Mobile apps and wearables can track physiological and behavioral data to support treatment guidance (Poudel et al., 2024) and integrating biological and behavioral data can facilitate personalized protocols (Lee, 2024). This article delineates AI-supported applications in addiction from risk assessment to psychosocial intervention and grounded in s ocial work theory and ethics, critically examines associated opportunities and risks.

Background

Addiction treatment is a comprehensive process requiring coordinated, multidisciplinary teamwork, within which social workers hold a pivotal role. Guided by the aim of strengthening the well-being of individuals, families, and communities, social workers contribute a complementary and holistic perspective at both clinical and societal levels. Social work practice in addiction commonly seeks to enhance quality of life, foster social integration, and provide crisis intervention and ongoing support (Estreet et al., 2017). Social workers also play an important role in addressing co-occurring psychiatric disorders that frequently accompany addiction.

Addiction is significantly associated with psychiatric disorders, and comorbidity is common: psychiatric conditions may increase vulnerability to addiction, while addiction may precipitate or exacerbate psychiatric

symptoms. In this context, the use of artificial intelligence (AI) in addiction treatment is increasingly salient for clarifying individual-level dynamics and examining links with psychiatric comorbidity. Addiction is also meaningfully correlated with social exclusion and poverty, which appear to operate in mutually reinforcing ways. As individuals are marginalized and disengage from social bonds, the likelihood of problems such as substance dependence increases (Yue et al., 2022). Likewise, poverty may heighten susceptibility to substance use as constrained resources increase stress and encourage relief- or escape-oriented use (Nadeem et al., 2024). People living in poverty also face barriers to accessing social services, further elevating addiction risk (Motte-Kerr et al., 2020; Adjei et al., 2022).

Within families, psychological and material strains can adversely affect mental health, and childhood adversities and traumatic experiences increase the probability of developing addiction (Bager et al., 2022; Plett et al., 2024). Individuals may develop dependence on a substance or behavior as a coping strategy for current hardships or unresolved trauma; however, withdrawal and addiction-related life consequences may also generate new traumatic experiences, complicated recovery and undermining sustained change.

Overall, the interrelationship among addiction, poverty, social exclusion, and family dynamics has become central to contemporary responses to addiction. These factors interact in complex ways and may operate as triggers and/or maintaining mechanisms. AI may support the analysis and management of this complexity by processing data on individuals' prior experiences, current social circumstances, and family dynamics to generate insights into these interconnected pathways.

METHOD

This study is a social work–oriented conceptual literature review that positions the use of artificial intelligence (AI) in the addiction field across three stages: risk assessment, monitoring and early warning, and psychosocial intervention. It does not produce primary empirical data; instead, it offers a holistic synthesis by integrating existing empirical, theoretical, and practice-based research.

Study Design: The interdisciplinary review and conceptual analysis are organized around three axes: (i) AI-supported risk assessment and prediction in addiction, (ii) AI applications in monitoring and early warning systems, and (iii) the integration of these technologies into psychosocial intervention and social work practice. This structure also guides the subsequent findings and discussion.

Literature Search Process: The search was conducted across databases in medicine, psychiatry, psychology, social work, public health, information systems, and ethics, primarily using PubMed, Web of Science, Scopus, PsycINFO, and Google Scholar. Searches were expanded with keywords related to addiction, digital addiction, and social work. Turkish and English keywords covered: addiction-related terms (e.g., "addiction", "substance use disorder", "behavioral addiction", "digital addiction"); AI and digital technology terms (e.g., "artificial intelligence", "machine learning", "natural language processing", "digital phenotyping", "decision support systems"); and social work/ethics terms (e.g., "social work", "psychosocial intervention", "case management", "algorithmic bias", "privacy", "dynamic consent", "human-centered AI"). Terms were combined with

"AND/OR" and, when necessary, narrowed using more specific concepts such as "risk assessment", "relapse prediction", "early warning", "monitoring", and "decision support system." The temporal scope primarily targeted studies published after 2010, with particular emphasis on 2015–2025; selected earlier conceptually relevant studies -especially on early warning, monitoring, and policy infrastructures- were also included.

Search timing and review scope: The literature search was finalized in January 2026 to capture newly published studies within the 2010–2025 timeframe. This study was designed as a conceptual literature review rather than a full systematic review or meta-analysis. Accordingly, the search process aimed to identify conceptual and empirically relevant literature across medicine, psychiatry, psychology, social work, public health, information systems, and ethics, and synthesize this literature within a social work framework. The review should therefore be read as an analytically structured conceptual synthesis rather than as an exhaustive effect-size review of intervention efficacy.

Inclusion and Exclusion Criteria: Inclusion criteria were: direct relevance to addiction; engagement with an AI-based approach (e.g., machine learning, deep learning, natural language processing, decision-support systems, digital phenotyping, or large language models); explicit reference to at least one stage of the addiction process; publication as a peer-reviewed article, book chapter, report, systematic review, or comprehensive review; and availability in English or Turkish. Exclusion criteria were superficial treatment of addiction despite mentioning AI; narrowly technical computer science studies focused only on algorithmic performance without psychosocial or ethical dimensions; and conference abstracts, posters, letters, or methodologically limited brief notes lacking full-text access.

Data Analysis: Included studies were analyzed through descriptive classification and thematic analysis. Descriptively, studies were grouped by addiction type, AI method, target population, and intervention stage (risk assessment, monitoring/early warning, or psychosocial intervention). The thematic and conceptual analysis evaluated opportunities and risks associated with AI applications through the lens of core social work values.

Figure 1 summarizes the article's conceptual framework by positioning AI use in addiction across three interrelated stages: risk assessment, monitoring/early warning, and psychosocial/hybrid intervention. The framework is embedded within a social work lens that emphasizes biopsychosocial assessment, family and environmental context, and micro–mezzo–macro practice. Across all stages, ethical safeguards such as privacy, dynamic consent, algorithmic fairness, accountability, and human oversight remain foundational.

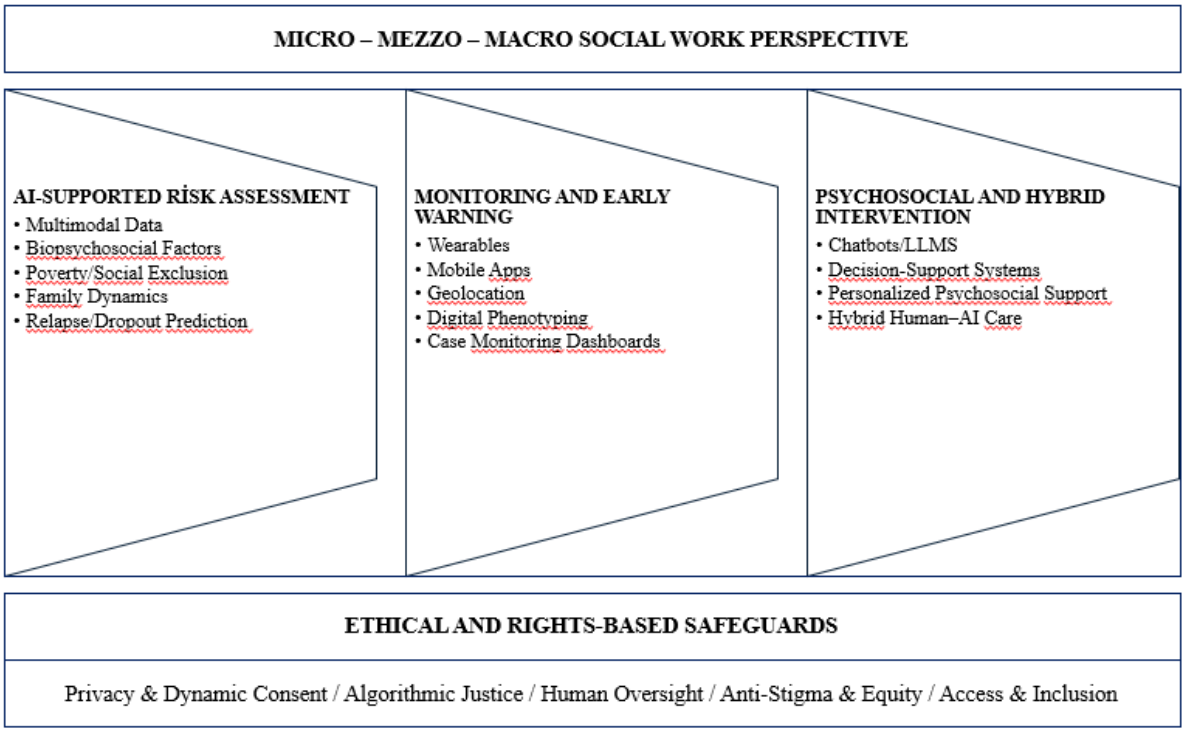

Figure 1. A Social Work-Informed Three-Stage Framework for AI in Addiction

FINDINGS

This section synthesizes the reviewed literature by classifying AI-related applications in addiction across three analytically defined stages: risk assessment, monitoring and early warning, and psychosocial intervention. Rather than presenting uniform evidence of clinical effectiveness, the section maps the main areas in which AI has been discussed or tested in the literature and evaluates these developments through a social work lens, with particular attention to psychosocial context, ethical challenges, and the evolving roles of social workers.

AI in the Risk Assessment Stage

AI is increasingly central to addiction risk assessment because it can process large, complex, and multimodal datasets for early detection and relapse prediction. By analyzing interactions across psychological, social, and physiological domains, AI can estimate vulnerability and support the optimization of intervention strategies. Machine-learning models can assess risk using variables such as personal histories, socioeconomic conditions, and environmental factors (Khakpaki & Sepehri, 2025). These tools also enable analysis of social exclusion and poverty, identification of comorbidity risk clusters, and development of individualized treatment plans based on medical history, behavioral patterns, and treatment outcomes (Suva & Bhatia, 2024).

Digital phenotyping further illustrates how AI has been explored in risk assessment and in identifying treatment barriers. For example, one line of evidence includes deep-learning studies using digital footprints such as social media language to estimate 90-day treatment dropout risk among patients with substance use disorders, including models based on Bidirectional Encoder Representations from Transformers (BERT) (Suva & Bhatia,

2024; Chen et al., 2025). Similarly, machine-learning and natural language processing systems have been used to detect substance-use-related signals among homeless youth, with one reported study indicating an Area Under the Receiver Operating Characteristic Curve (ROC-AUC) of 0.77 based on social media posts (Suva & Bhatia, 2024; Chen et al., 2025). These studies should be interpreted as examples of emerging predictive evidence rather than as definitive proof of stable clinical utility across settings.

AI models can also estimate relapse probability. Liang's model examined risk factors relevant to predicting post-examination relapses (Liang, 2002). AI-related tools have also been discussed in relation to relapse-sensitive environments. Applications such as Addicaid and Sober Grid are better understood not as clinically proven relapse-prevention systems, but as digital platforms with geolocation-triggered support functions and analytic potential that may assist self-monitoring, timely alerts, and feasibility-level intervention planning (Suva & Bhatia, 2024). Their significance, therefore, lies more in development-stage capacity and real-time support possibilities than in well-established clinical effectiveness.

Despite these advantages, AI introduces ethical and social risks. Limited representativeness and non-homogeneous data can yield inaccurate or biased outputs that may exclude groups. Chatbots based on large language models can reflect incomplete, outdated, biased, or distorted training data, producing misleading narratives and misinformation (Wei et al., 2023). Self-report data may also be affected by social desirability and response biases. A further concern -particularly for vulnerable groups- is that predicted risk may translate into labeling and stigma when AI infers psychological profiles and future risk from sensitive data (Gezgin & Efeoğlu, 2025). From a social work perspective, such risk output must be used non-punitively, treated as fallible, and directed toward supportive intervention. Privacy, data security, false positive/negative alerts, and access inequities remain key concerns, underscoring the need for transparency, respect for users' rights, and human-centered, case-oriented approaches.

AI in the Monitoring and Early Warning Stage

By analyzing behavioral, physiological, and environmental data, AI can support monitoring and early warning and may predict treatment course and relapse risk more accurately than conventional psychometric assessments, enabling timely intervention (Morii et al., 2024). AI may also optimize clinical communication and workflows to support more efficient monitoring (Kuponiyi, 2023). Continuous tracking through wearables and mobile applications provides extensive data streams that can support follow-up and timely response (Yang et al., 2021; Liu et al., 2023). Wen et al. developed a model using mobile response patterns to passively detect reflective behaviors and collect data relevant to predicting digital addiction outcomes (Wen et al., 2021). Wearables can also enable real-time monitoring of mood and stress. In addition, AI can analyze neurobiological change in substance dependence using data from Electroencephalography (EEG) and Magnetoencephalography (MEG), which capture neural activity with high temporal resolution (Liu et al., 2006; Nobukawa et al., 2024; Verney & Ellwanger, 2013), helping clarify neurological dynamics (Nilawati et al., 2024).

AI and data analytics increasingly support case management and preventive program planning by integrating indicators across health, education, psychosocial conditions, and economic domains. Machine learning has been used to enhance clinical decision-support systems (Oonsivilai et al., 2018). Decision-support dashboards for monitoring high-risk individuals and families can provide rapid, reliable integrated data and help prioritize interventions (Oparah, 2025; Buragadda, 2024). While monitoring and surveillance may appear similar, monitoring focuses on continuous tracking for individuals or small groups to inform individualized intervention, whereas surveillance tracks broader population-level trends (Burke et al., 2020). AI can enhance risk prediction and intervention effectiveness in both.

AI in the Psychosocial Intervention Stage

AI contributes to psychosocial intervention by addressing access gaps and strengthening effectiveness through personalized insights. By processing large datasets, AI-supported systems can inform interventions aligned with individual risk profiles using factors such as mood, behavior, and environmental conditions. Deep learning approaches analyzing social media content can detect health-related signals, identify psychological risk factors, and support more responsive psychosocial support (Staccini & Lau, 2024). Chatbots and large language models may also provide direct support and reduce barriers related to limited clinician access, while offering lower-cost counselling options.

AI applications in psychopharmacology and psychological research have been discussed in relation to their potential to transform mental health services (Salemi et al., 2025). AI can generate moment-to-moment assessments of stress and mood from biometric data to inform intervention strategies. Explainable outputs may support professional use and improve intervention effectiveness, while strengthening trust and transparency (Rahimi et al., 2022). Integrating emotional intelligence into AI-enabled decision-support systems has been proposed to improve decision-making and incorporate emotional support alongside person-centered care (Tretter, 2024). Overall, AI integration may increase accessibility and enable individualized approaches that can improve treatment trajectories.

Hybrid models combine AI with conventional or human-centered strategies, integrating AI's analytical strengths with human ethical oversight and therapeutic depth. AI-supported decision-support systems may facilitate personalized treatment plans and more effective responses, potentially increasing access to effective methods and reducing relapse risk (Ahn et al., 2014). Through decision-support systems, AI can help professionals interpret data more rapidly, strengthening decision-making and effective intervention. It is positioned as a support tool rather than a replacement for social workers; multidisciplinary approaches highlight its potential to enhance social worker effectiveness (Hughes et al., 2024). AI may also improve social workers' understanding of clients' needs by accelerating information flows (Droubay & Butters, 2019). Nonetheless, algorithmic recommendations may not align with human judgment and may overlook context and individual differences, requiring practitioners to manage misunderstandings and ethical challenges. Given

error margins and the necessity of professional judgment when AI outputs conflict with professional ethics, AI alone is insufficient for addressing addiction.

Ethics, Human Rights, and Professional Boundaries

Integrating artificial intelligence (AI) into the addiction field offers transformative opportunities for assessment and intervention, but it also raises ethical and legal challenges that require rigorous scrutiny. From a human rights perspective, this section addresses privacy and consent issues related to the processing of sensitive addiction data, risks of algorithmic bias and discrimination, and the potential pressures that technology-mediated guidance may exert on individual autonomy. It further highlights how technological change reshapes professional boundaries through transparency, accountability, and social justice, emphasizing social work's supervisory and rights-based responsibilities in this digital ecosystem.

A rights-based discussion of AI in addiction also needs to be anchored in current international and national governance frameworks. At the international level, UNESCO's Recommendation on the Ethics of Artificial Intelligence frames human rights and human dignity as foundational values and emphasizes transparency, fairness, accountability, privacy, data protection, and human oversight as core principles of ethical AI governance. In the Turkish context, this discussion also has a direct legal dimension under the Law on the Protection of Personal Data (KVKK), which treats health, biometric, and genetic data as special categories of personal data subject to stricter protection. Accordingly, AI systems used in addiction-related assessment, monitoring, or intervention should be evaluated not only for technical performance but also for proportionality, purpose limitation, legal basis, and the adequacy of safeguards in handling sensitive personal data.

AI applications foreground data privacy and informed consent because addiction-related information is highly sensitive and centralized data sharing is difficult to govern. AI systems may process special-category data, including information linked to substance use, psychiatric comorbidity, risk behaviors, and, in some contexts, biometric monitoring. In this field, informed consent cannot be reduced to a one-time clinical form. Data may later be repurposed, used to generate predictive inferences, processed by third-party systems, or collected passively without the person's active awareness. For this reason, unauthorized collection, secondary use, or third-party transfer may directly violate privacy rights and undermine trust in treatment.

The use of sensitive addiction data in AI entails serious risks. As Amedior notes, patients' data may be used independently of their preferences, creating privacy risks (Amedior, 2023). Third-party processing and passive data collection without explicit consent can further intensify ethical concerns in treatment settings. Risk assessment and prediction models may also amplify algorithmic bias and discrimination, particularly when outputs correlate with poverty, ethnicity, gender, or migration status. Bias embedded in training data can yield inequitable recommendations and may drift toward automated "criminalization." Predictive models may insufficiently account for cultural context, producing erroneous outputs across populations; replication across diverse settings remains inadequate (Suva & Bhatia). Harm reduction requires bias-minimizing design to

protect equity (Chin et al., 2023) and stronger ethical standards and oversight to increase transparency and comprehensibility (Prakash et al., 2022).

AI may support self-determination in addiction treatment, yet it can also exert invisible pressure by shaping decision-making. Mahmood et al. emphasize that AI can influence healthcare decisions and may threaten professional autonomy (Mahmood et al., 2024). Although AI does not replace human judgment, its recommendations may steer choices; therefore, transparent use should be paired with approaches that guide without intruding on decision-making. Frameworks that support autonomy and reduce invisible pressures may strengthen treatment processes, making a balance between AI recommendations and self-determined decisions essential.

The risks of confabulation and misinformation remain major ethical and practical concerns, and responsibility for accuracy ultimately rests with human actors (Bunnell et al., 2025). Erroneous outputs can cause harm—for instance, misleading recommendations may generate serious misunderstandings about health status and reduce treatment engagement (Ifenthaler et al., 2024). AI-supported decision-making can also introduce biases that overlook social determinants, complicating fair and equitable clinical decisions; thus, ethics should be embedded throughout development and implementation (Bernstein et al., 2023). When AI supports social work practice, robust ethical oversight is critical to ensure interventions remain safe, equitable, and rights based. Core domains include rights protection, service quality and professional accountability, algorithmic justice and inequity prevention, public trust, and continuous improvement.

DISCUSSION

A substantial share of artificial intelligence (AI) research has relied on relatively small and culturally homogeneous samples, limiting reliable replicability and constraining the generalizability of findings across contexts. Studies that re-test results across diverse geographic regions, cultural backgrounds, and socioeconomic strata remain insufficient. Moreover, much of the literature is grounded in language learning and pattern recognition and focuses primarily on predictive models, while trials of AI-based interventions or service delivery systems have not yet been conducted. The evidence base also concentrates largely on substance use disorders, leaving AI's potential in behavioral addictions -such as online gaming disorder and problematic internet use- largely unexplored despite their emergence as public health concerns (Suva & Bhatia, 2024). Accordingly, while AI shows highly validated effects in some addiction-related applications, other areas remain early-stage and lack robust evidence, particularly for behavioral addictions.

Addiction cases typically involve multiple systems, including healthcare, social services, justice, education, and community-based support networks. AI can strengthen inter-institutional integration and offer strategic opportunities for social workers, educators, and policymakers to address the social, economic, and health dimensions of addiction. Given that social work practice requires risk assessment, early intervention, continuity of follow-up, case management, and interagency coordination, AI -through data analytics and predictive modeling- can support decision-making, monitoring, and intervention capacity. AI-supported tools

may expand follow-up and enable timely intervention by identifying, at an early stage, environmental, behavioral, biopsychosocial, and socioeconomic factors associated with heightened addiction risk, thereby allowing preventive interventions to be targeted more accurately.

AI applications in addiction entail significant opportunities but also structural risks that may threaten ethical and social justice principles, typically linked to data quality, ethical governance, and broader societal consequences. Digital structural inequalities may prevent services from reaching vulnerable groups despite AI's potential benefits. Geographic constraints, financial barriers, exclusion driven by limited training data, and erroneous outputs for minority populations due to insufficient data can produce uneven distribution of benefits. Inaccurate outputs and algorithmic bias may also result in unjust labeling and ethical violations. Harms arising from AI-processed data and outcomes cannot be attributed directly to AI systems; therefore, minimizing adverse consequences and ensuring accountability elevates the importance of human-centered AI—systems that empower individuals, protect privacy, support human decision-making, and minimize ethical risks. A human-centered approach is thus necessary for responsible and equitable implementation.

Limitations and Future Research

Although AI research in addiction has progressed, major limitations persist, particularly regarding social science perspectives and ethical implementation. A key challenge is that correlation-based approaches common in AI-driven addiction research provide an insufficient account of causality, risking misinterpretation and flawed intervention inferences; distinguishing correlation from causation is crucial for understanding addiction-related psychological and social dynamics (Vaghefi et al., 2016; Rahayu et al., 2020). Developing causality-based models is therefore central, and future work should advance methods for examining cause–effect relations through AI, with an emphasis on causal inference and graphical models (AlSaad et al., 2025). Addressing data privacy and security concerns and reducing inequities in access to healthcare services are also critical for ethical and effective implementation (Wu et al., 2024; Meder et al., 2025), and collaboration between policymakers and researchers is recommended.

Most studies draw on treatment data, Electronic Health Records (EHR), clinical measures, and neuroimaging datasets, which leaves core social determinants -poverty, family environment, trauma history, housing insecurity, discrimination, social isolation, and broader disadvantage- underrepresented. Limited clinical samples and insufficient inclusion of social determinants may impede effective and inclusive deployment; broader datasets, multi-center integration, and attention to social context are therefore essential to strengthen applicability. Clinically, improving explainability is also vital: when users and providers can understand AI decision processes, trust is likely to increase, and Explainable Artificial Intelligence (XAI) may be an effective strategy (Meder et al., 2025).

At the national level, data on minority populations are limited, and in Türkiye field data often overlook minority groups. The absence of shared data infrastructure across social work, healthcare, judicial, and educational institutions further constrains AI's functional capacity, while ethical and legal frameworks remain

insufficient, leaving governance and regulatory gaps. Finally, effective governance-level implementation requires aligning healthcare infrastructure and resource availability with standard requirements for the effective use of AI tools (Suva & Bhatia, 2024).

Future research should move beyond proof-of-concept prediction studies and prioritize real-world, ethically governed implementation research. First, there is a need for longitudinal and multi-site studies that test AI-supported tools across diverse cultural, socioeconomic, and service settings in order to strengthen external validity. Second, behavioral addictions, including problematic internet use, online gaming disorder, and related emerging forms of dependency, should be addressed more systematically, as the current evidence base remains disproportionately centered on substance use disorders. Third, future studies should evaluate hybrid intervention models in which AI functions as a decision-support and follow-up tool under professional supervision rather than as an autonomous substitute for human care. Fourth, participatory and rights-based research designs should include service users, families, and frontline professionals in the development and evaluation of AI systems, particularly to address concerns related to stigma, privacy, dynamic consent, and algorithmic bias. Finally, implementation studies should examine not only predictive accuracy but also fairness, interpretability, service accessibility, user trust, and the effects of AI integration on professional roles within social work and interdisciplinary addiction services. From a social work perspective, the next phase of scholarship should investigate whether AI-supported systems improve not only relapse prediction and treatment adherence, but also social inclusion, continuity of care, family functioning, and equitable access to services.

Practice and Policy Recommendations

Integrating artificial intelligence (AI) into the addiction field requires a comprehensive, multi-layered strategy that goes beyond technical implementation and spans from individuals to public policy. Drawing on social work's person-in-environment perspective and the ecological systems approach, this section frames AI-supported pathways across three connected levels: micro (digital tools to strengthen individuals and families), mezzo (community-based early warning and institutional capacity), and macro (national data integration, ethical standards, and digital justice) to support a sustainable model for combating addiction.

At the micro level, AI can strengthen and personalize individual- and family-focused interventions. AI-supported monitoring, motivation-enhancing tools, and digital guidance may support case management while promoting autonomy and motivation. AI-based follow-up—through digital behavioral tracking, mobile feedback, and early warning algorithms—can enhance continuity by providing ongoing information on risk, behavioral change, and needs, enabling more targeted and evidence-informed interventions. AI may also facilitate low-cost, continuous support, improve access to treatment, and support ongoing monitoring, including relapse-prevention and early warning functions; systematic reviews indicate that AI-supported mobile interventions can increase motivation and improve adherence.

Family-based digital awareness and guidance modules may strengthen families' roles and engagement by reducing risk factors and reinforcing protective factors (Melo & Alarcão, 2012). Literature underscores the importance of family dynamics and support systems, suggesting that family-based programs may be effective in addressing addiction (Thege et al., 2017).

AI can complement community-based social work by enabling early detection of substance use, behavioral addictions, and social risks among youth, adults, and at-risk communities, supporting timely intervention through tracking behavioral tendencies and anticipating risk (Kuss & Griffiths, 2011; Bányai et al., 2017). AI-supported screening and referral systems can also assist NGOs by improving client-flow management, timely outreach, and more efficient distribution of social support services, while contributing to community health infrastructure (Wamuti et al., 2024). Effectiveness depends on continuous improvement and training; staff training may enhance service quality (Lee et al., 2023), and community awareness initiatives can support adoption.

Macro-level priorities guide the integration of AI in addiction through national addiction information systems, an AI ethics framework, inequality-reducing digital access policies, and professional standards and training requirements. National information systems are crucial for collecting, analyzing, and sharing addiction data, and AI can strengthen these functions and inform health policy. Many countries use national monitoring systems to understand trends and plan services; the EMCDDA highlights "national focal point" structures and data integration models linked to early warning systems as central to evidence-informed policy (Fielden & Marsh, 2007). Because access to digital addiction services is shaped by infrastructure, device ownership, digital literacy, and socioeconomic status and the digital divide deepens inequalities (UNESCO, 2022) inequality-reducing digital access policies are needed to ensure AI systems meet different groups' needs, including low-cost/free platforms, stronger rural infrastructure, expanded digital literacy programs, and wider mobile-based support applications.

CONCLUSION

AI has a substantial current and prospective role in addressing addiction, potentially reducing professionals' workload and strengthening prevention and intervention; however, it is not a standalone solution in this complex field. Sustainable outcomes depend on integrating AI with human expertise and relational practice. When AI systems are not adequately regulated or grounded in an ethical framework, they may generate ethical violations, deepen inequality, and cause harm. Because model outputs reflect training data, biases in data collection, representation, or classification can be reproduced, complicating effective intervention for disadvantaged groups and potentially reinforcing labeling and harm.

If AI is deployed without safeguarding a social work orientation, ethical governance, and principles of justice, it risks algorithmic bias, non-consensual surveillance, data-driven stigmatization, and the reproduction of social inequalities. Risk reduction requires AI training, diversified samples to support generalizable inference, and an explicit commitment to human-centered AI. Meaningful benefits are most likely when AI-informed

interventions are designed based on human rights, professional ethics, and an ecological perspective that remains sensitive to social determinants at family and community levels as well as individual risk factors.

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Ethical Considerations

This article doesn't contain any studies with human or animal participants.

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