Clinical and Pharmaceutical Sciences Journal

Research article

Artificial Intelligence in Eating Disorders: A Narrative Review of Detection, Digital Interventions, and Implementation Challenges

Marwa Mohammed[1*], Amany Mohammed Abdel El Hafez[2], Mohamed I Mabrouk[3], Taha Hussein Musa[4]

[1,3]Department of Physiotherapy, Faculty of Allied Medical Sciences, Applied Science Private University, Amman, Jordan
[2]Military Medical Academy, Egypt
[4]School of Medicine, Darfur University College, Nyala, Sudan

*Corresponding Author: m_elbelbessy@asu.edu.jo

Received: 31 May 2026 | Revision: 24 June 2026 | Accepted: 30 June 2026

Abstract

Eating disorders (EDs) are severe psychiatric conditions with rising prevalence, yet access to specialised care remains limited due to resource-intensive assessments. This narrative review critically evaluates the evidence for AI-driven detection and intervention, discusses the significant barriers to real-world deployment, and outlines future directions for the safe, equitable, and effective integration of these powerful tools into clinical practice for individuals with EDs. A systematic search of PubMed, PsycINFO, Scopus, IEEE Xplore, and Google Scholar (inception–March 2026) identified 43 peer-reviewed English-language articles, including original studies, systematic reviews, and policy reports. Data were thematically synthesised across four domains: (1) AI-based screening/risk prediction, (2) comorbidity detection, (3) digital interventions, and (4) ethical/implementation challenges. AI shows promise in early ED screening through electronic health records, linguistic analysis, and social media data. However, detection of psychiatric comorbidities such as depression, anxiety, and obsessive-compulsive disorder remains variable and requires further validation. Chatbot-assisted interventions and smartphone-based monitoring are emerging as scalable tools for symptom tracking and delivering cognitive-behavioural content, potentially improving care continuity. Major implementation barriers persist, including data privacy concerns, algorithmic transparency issues, and low clinician acceptance due to liability fears, lack of interpretability, and poor workflow integration. AI holds considerable potential to enhance ED care through earlier detection and expanded access to digital interventions. Realising this potential requires rigorous prospective validation, clear ethical guidelines, and collaborative frameworks involving clinicians in AI design and oversight to ensure these tools complement, not replace, clinical judgment.

Keywords: Artificial Intelligence; bulimia nervosa; chatbots; eating disorders; machine learning.

Introduction

Eating disorders (EDs) are serious psychiatric disorders characterised by disturbed eating behaviours and psychological distress and associated with elevated economic and societal burdens, in addition to elevated rates of mortality and comorbidity [1]. EDs lead to loss of healthy life years because of disability and associated complications [2]. The main EDs are anorexia nervosa (AN), bulimia nervosa (BN), and binge eating disorder (BED). EDs substantially disturb eating behaviours and emotional regulation. Recent research showed that ED prevalence was 15.3% during the COVID-19 pandemic [3]. Studies have detected that children and adolescents are mostly vulnerable during this period [3]. Males with EDs are less frequently identified in clinical settings, despite evidence of their existence; recognition in males is more challenging than in females, likely due to both the general stigma surrounding mental disorders and the perception of EDs as predominantly distressing females. A systematic review estimated the worldwide prevalence of EDs was 8.4% for women and 2.2% for men, while in men, AN, BN, and BED were 0.2%, 0.6%, and 1.0%, respectively [4].

Despite the prevalence of EDs, fewer than one in four persons with these conditions have evidence-based treatment [5]. This gap primarily refers to a shortage of trained mental health professionals, resulting in increased wait

times and inadequate service availability [6]. Executive burdens further reduce the time available for direct patient care. Additional barriers include financial constraints, geographic inaccessibility, and clinical complexities. These factors together delay care and lead to poorer clinical outcomes [6]. Subsequently, there is an increasing need for novel approaches to enhance service accessibility and deliver appropriate interventions.

In response, there has been growing interest in using digital tools and artificial intelligence (AI) to address these barriers [4]. AI tools can provide patients with consistent, on-demand support by delivering treatment materials curated by clinicians. These tools facilitate the practice of therapeutic skills outside of formal sessions through personalised feedback and reminders [7]. AI also enables self-monitoring, promotes progress, and issues homework reminders between appointments. Due to their flexibility and accessibility, AI-based interventions represent a valuable adjunct to traditional treatment, potentially expanding reach and reducing costs for individuals with EDs [7].

However, the potential of AI extends far beyond being a supportive treatment tool. AI-driven methods like natural language processing (NLP) are being researched to analyse social media content, offering an unprecedented opportunity to detect signals of ED symptoms and identify at-risk individuals who may otherwise go undiagnosed [8]. Similarly, machine learning (ML) models applied to clinical datasets have demonstrated improved predictive performance compared to traditional statistical methods, for instance, in identifying youth at risk of a complex clinical course of illness [9]. Furthermore, the integration of AI with smartphone technology, through digital phenotyping and analysis of behavioural data from sensors, presents promising avenues for early risk prediction and real-time symptom detection [10].

While existing reviews have explored digital health interventions for EDs more broadly [11], a dedicated and critical review of these emerging AI applications encompassing detection, digital interventions, and implementation challenges is urgently needed. This narrative review aims to fill this gap by synthesising the current state of research on AI across three interconnected domains: (1) early detection and risk prediction through ML, NLP, and digital phenotyping; (2) AI-enhanced digital interventions that extend beyond traditional treatment adjuncts; and (3) the critical implementation challenges surrounding data quality, algorithmic bias, clinical integration, and ethical governance. By distinguishing itself from previous literature that has primarily focused on AI as a treatment adjunct, this review critically evaluates the evidence for AI-driven detection and intervention, discusses the significant barriers to real-world deployment, and outlines future directions for the safe, equitable, and effective integration of these powerful tools into clinical practice for individuals with EDs.

Materials and Methods

Materials

The materials used in this narrative review consisted of peer-reviewed scientific literature retrieved from PubMed, PsycINFO, Scopus, IEEE Xplore, and Google Scholar. Publications considered for inclusion covered the period from database inception through March 2026 and included original research articles, systematic reviews, meta-analyses, policy documents, and guideline reports relevant to the application of artificial intelligence (AI) in eating disorders (EDs). Eligible studies addressed AI-based approaches for screening, detection, diagnosis, intervention, and management of ED-related mental health conditions. Additional relevant articles were identified through manual searches of reference lists from included studies and pertinent review articles.

Methods

Study design

This study employed a narrative review design to examine the current state of AI applications in ED screening, detection, digital interventions, and implementation challenges. A narrative approach was selected to accommodate the heterogeneous nature of the available literature, which spans clinical, technical, ethical, and regulatory domains, and to provide a broad, integrative overview of challenges and future directions in this emerging field. Although a structured search strategy was employed to identify relevant literature, thereby enhancing transparency and reproducibility, this review did not follow the formal methodological requirements of a systematic review, such as review registration, dual independent screening as a mandatory requirement, or quantitative risk-of-bias assessment. Instead, the structured search served as a rigorous foundation for the narrative synthesis, enabling comprehensive mapping of the evolving landscape of AI applications in EDs while maintaining the flexibility necessary to interpret diverse forms of evidence, including clinical studies, technical reports, ethical analyses, and policy documents.

The rationale for selecting a narrative review design over a systematic or scoping review was threefold. First, the literature on AI applications in EDs is highly heterogeneous and rapidly evolving, making it difficult to apply a uniform quality assessment framework. Second, the review aimed to provide an integrative synthesis across diverse domains, including clinical, technical, ethical, and regulatory aspects, rather than to answer a narrowly defined research question. Third, the field lacks established reporting standards and validated outcome measures that would facilitate

quantitative meta-analysis or systematic comparison. Therefore, a narrative review informed by a structured search strategy was considered the most appropriate methodology for mapping the current landscape, identifying key challenges, and proposing future directions.

Sources of data and search strategy

A literature search was conducted across PubMed, PsycINFO, Scopus, IEEE Xplore, and Google Scholar. The search covered publications from database inception through March 2026. Search term categories were combined using the Boolean operator AND, whereas synonyms within each category were combined using OR. A fully reproducible search strategy was developed and adapted for each database according to its specific syntax requirements.

The following search string was used for PubMed: ("artificial intelligence" OR "AI" OR "generative AI" OR "machine learning" OR "natural language processing" OR "NLP" OR "large language model" OR "LLM" OR "chatbot" OR "conversational agent" OR "digital phenotyping" OR "predictive analytics") AND ("eating disorder" OR "anorexia nervosa" OR "bulimia nervosa" OR "binge eating disorder" OR "BED" OR "body image disturbance" OR "disordered eating" OR "emotional eating") AND ("screening" OR "detection" OR "diagnosis" OR "risk prediction" OR "early identification" OR "assessment" OR "intervention" OR "treatment" OR "management").

For PsycINFO and Scopus, the search string was adapted to account for database-specific syntax: (("artificial intelligence" OR "AI" OR "generative AI" OR "machine learning" OR "natural language processing" OR "NLP" OR "large language model" OR "LLM" OR "chatbot" OR "conversational agent" OR "digital phenotyping") AND ("eating disorder" OR "anorexia nervosa" OR "bulimia nervosa" OR "binge eating disorder" OR "body image" OR "disordered eating" OR "emotional eating") AND ("screening" OR "detection" OR "diagnosis" OR "risk prediction" OR "early identification" OR "intervention" OR "treatment")).

For IEEE Xplore, the search focused primarily on technical and engineering literature: ("artificial intelligence" OR "machine learning" OR "natural language processing" OR "NLP" OR "large language model" OR "chatbot" OR "digital phenotyping") AND ("eating disorder" OR "anorexia" OR "bulimia" OR "binge eating") AND ("screening" OR "detection" OR "diagnosis" OR "intervention").

For Google Scholar, a simplified search string was used because of platform limitations: ("artificial intelligence" OR "AI" OR "machine learning" OR "NLP" OR "chatbot") AND ("eating disorder" OR "anorexia" OR "bulimia" OR "binge eating") AND ("screening" OR "detection" OR "intervention"). Reference lists of included studies and relevant systematic reviews were manually searched to identify additional eligible studies not captured during the electronic database search.

Literature selection process

The literature selection process followed a structured approach to enhance transparency and reproducibility. The initial search identified 1,247 records across all five databases (PubMed: 412, PsycINFO: 287, Scopus: 356, IEEE Xplore: 98, and Google Scholar: 94). After duplicate removal (n = 186), 1,061 records remained for title and abstract screening. Following title and abstract screening, 923 records were excluded because they were irrelevant to AI applications in EDs (n = 547), focused exclusively on general mental health without ED-specific applications (n = 206), consisted of conference abstracts lacking sufficient methodological detail (n = 98), represented opinion pieces without empirical or substantive policy content (n = 52), or were non-English language publications (n = 20).

The remaining 138 full-text articles were assessed for eligibility. Of these, 95 articles were excluded because of insufficient focus on AI applications relevant to EDs (n = 41), duplicate publication of the same findings (n = 18), insufficient methodological information to evaluate relevance (n = 22), or exclusive focus on general digital health without AI-specific components (n = 14). Ultimately, 43 articles met the inclusion criteria and were included in the final narrative review. A PRISMA-style flow diagram summarizing the study selection process is presented in Figure 1.

Study selection was independently performed by two reviewers (Author Initials) to minimize bias and ensure consistency. Titles and abstracts were screened independently according to the predefined eligibility criteria. Any disagreements were resolved through discussion and, when necessary, consultation with a third reviewer. Full-text articles were subsequently assessed independently by the same reviewers. Inter-rater agreement was evaluated using Cohen's kappa coefficient ($\kappa = 0.87$), indicating strong agreement. This dual-reviewer approach enhanced the reliability and transparency of the selection process.

Studies were eligible for inclusion if they were original research articles, including randomized controlled trials, cohort studies, case-control studies, and cross-sectional studies; systematic reviews; meta-analyses; or relevant policy and guideline documents published from database inception through March 2026. Eligible studies focused on the application of AI to identify, screen, detect, or manage mental health issues associated with EDs and involved AI technologies such as machine learning, natural language processing, large language models, chatbots or conversational agents, digital phenotyping, predictive analytics, or computer vision for body image analysis. Only English-language publications were included.

Studies were excluded if they consisted solely of conference abstracts lacking sufficient methodological information, opinion articles, editorials, or commentaries without substantive empirical or policy content, studies focusing exclusively on general digital health interventions without AI-specific components, studies addressing AI applications for other mental health conditions without clear relevance to EDs, or non-English publications.

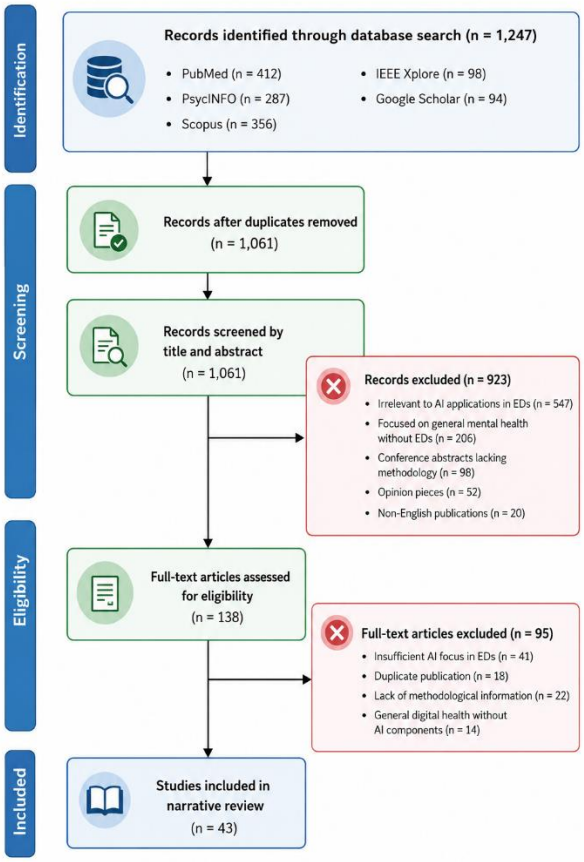

Figure 1. PRISMA-style flow diagram summarizing the literature search and study selection process.

Quality measurement and evidence synthesis

As this study was conducted as a narrative review, a formal quantitative risk-of-bias assessment using standardized instruments, such as the Cochrane Risk of Bias tool, was not performed. Nevertheless, a systematic qualitative approach was adopted to evaluate evidence quality and address conflicting findings. Methodological rigor was assessed according to study design, clarity of objectives and research questions, appropriateness of methods, strength of evidence (including sample size, duration of follow-up, and use of validated outcome measures), and relevance to the review objectives. Greater emphasis was placed on peer-reviewed studies, reports issued by the World Health Organization, national health agencies, and official policy documents from reputable international organizations.

When conflicting findings emerged, methodological quality was critically appraised, and greater weight was assigned to evidence supported by multiple high-quality studies. Potential sources of heterogeneity, including differences in study populations, AI technologies, outcome measures, and clinical settings, were also examined. Conflicting findings were reported transparently, highlighting both areas of agreement and disagreement while acknowledging methodological limitations. This approach aligns with best practices for evidence synthesis in narrative reviews by emphasizing transparency and critical appraisal rather than quantitative aggregation.

Results and Discussion

Diagnosis of EDs

Since EDs can become long-lasting and bring both physical and psychological challenges, the first consultations should focus on encouraging patients to begin treatment. It is important to share thorough information about EDs and their risks in a way that reassures them rather than alarms them. For those with AN, be mindful of possible cognitive difficulties caused by severe weight loss. Patients should learn about what causes the disorder, how it may progress, and the potential complications and related conditions that can arise [12]. AN is characterised by self-induced malnutrition leading to significant weight loss. Diagnosis is based on body weight that is low enough to endanger health, defined as

a body mass index (BMI) below 17.5 kg/m2 for adults and below the 10th BMI-for-age percentile for children and adolescents. Early onset in children is particularly harmful, affecting bone strength, growth, and brain development [13]. A preliminary diagnosis of AN in young women is often more straightforward than diagnosing BN or BED, primarily due to the pronounced underweight status of patients with AN.

Key indicators of BN include female sex, a peak onset age of 18 years, significant weight fluctuations, and an intense preoccupation with body weight, eating behaviours, and exercise. BN is defined as consuming a larger amount of food than others in a distinct period while experiencing loss of control [LOC] and compensatory strategies at least once per week for the past 3 months [13]. People with BN often have periods of overeating followed by strict fasting, vomiting, or using laxatives and diuretics. In contrast, BED is typically not diagnosed unless it is associated with being overweight or obese, particularly when the disorder is perceived as hindering the individual's efforts to lose weight. BED is defined by recurrent episodes of consuming significantly more food than is typically consumed in a short period. Individuals may eat rapidly, beyond fullness, or when not hungry, often in isolation. Feelings of loss of control, shame, and guilt commonly follow these episodes. BED is diagnosed when such episodes occur at least once a week for three months [14].

When evaluating someone for possible EDs, it is vital to look closely at their physical health, searching for warning signs like malnutrition or compensatory actions such as self-induced vomiting, misuse of laxatives or diet pills, or excessive exercise. It is equally important to assess neurodevelopmental conditions and mental health challenges that often accompany EDs, such as autism spectrum disorder, depression, anxiety, self-harm, and obsessive-compulsive disorder, as well as any signs of alcohol or substance misuse. If compensatory behaviours are suspected, checking fluid and electrolyte balance becomes essential. For those at risk of heart problems due to rapid weight loss, intense exercise, or severe purging, consider whether an electrocardiogram (ECG) is needed. Always keep in mind the possibility of emergency care for individuals whose physical health is severely compromised or who may be at risk of suicide [15].

EDs should be assessed in the context of each person's home, education, work, and social environment, including the influence of the internet and social media. Family members, caregivers, teachers, and peers are encouraged to support individuals in treatment and may also require support for their own well-being. Confidentiality must be maintained in accordance with multidisciplinary team requirements [16]. The guidance recommends that consent for assessments and treatments involving children under 16 years of age should be obtained in accordance with Gillick competence, which is a clinical determination of the child's capacity to provide consent to medical treatment equivalent to that of an autonomous adult [17].

Current Management of EDs

Treatment for EDs should be guided by diagnosis according to ICD-10 criteria [18]. When establishing a diagnosis of EDs, physicians must consider key factors reported by family or caregivers, such as remarkably low or high BMI or body weight, considering age, sudden weight loss, dieting or restrictive eating behaviours and changes in eating patterns. In addition, physicians should monitor children and adolescents for signs of faltering growth, delayed puberty, or restricted height [15].

Psychological treatments stand at the forefront for adults, children, and young people facing EDs, offering a diverse toolkit of therapeutic approaches tailored to individual needs [15]. Medication alone is not enough to treat EDs. The guideline committee also found that physical therapies such as transcranial magnetic stimulation, acupuncture, weight training, yoga, and warming therapy should not be included in treatment plans, as there is little reliable evidence that they help people recover. However, if someone is facing severe electrolyte imbalance, malnutrition, dehydration, or signs of organ failure, they should receive urgent medical care [15].

Cognitive behaviour therapy for EDS (CBT-EDs) is considered the first-line treatment for BN and BED. In contrast, for AN, no level A evidence-based psychotherapeutic treatment exists; however, treatment guidelines recommend manualized psychotherapeutic interventions [19]. Resistance to change and high comorbidity reduce treatment effectiveness and increase relapse rates [20]. Treatment for EDs usually tries to reduce symptoms by using main strategies: helping people eat regular, balanced meals and working on problems like low self-esteem, perfectionism, and trouble handling emotions. Treatment also helps people learn what sets off their EDs symptoms, like wanting to exercise too much, vomiting, or skipping meals, by keeping track of their own behaviour. Even with these strengths, research shows that less than half of people with EDs who get proven treatments will fully recover [21]. This calls for innovative diagnostic and treatment approaches that truly reflect the unique needs of every patient.

All people with AN should get support from different types of professionals, including learning about the disorder, checking their weight, mental and physical health, and any risks. They should also get advice about food and eating, but the guidelines do not say exactly what kind. The main goal is to help the person with AN reach a healthy weight or BMI for their age [15]. The guideline says that everyone with BED should be offered a self-help program focused on BED. If this is not suitable, not recommended, or does not work, group or one-on-one CBT-ED should be offered. People with BN should be told that therapy does not have much effect on body weight. Adults should be offered a self-help program

for BN that uses cognitive behavioural self-help materials for EDs. This self-help should include a series of short support sessions. The guidelines suggest 4 to 9 sessions, each lasting 20 minutes, over 16 weeks, starting with weekly sessions. If self-help is not suitable, not recommended, or does not work after 4 weeks, adults with BN should be offered one-on-one CBT-ED [15]

Application of AI in Identifying Mental Health Issues Associated with EDs

AI is becoming more common in healthcare, with new tools being created to help prevent diseases, find health problems, and suggest treatments [22]. Harnessing AI leads to earlier disease detection and diagnosis, opening the door to timely interventions that can help prevent serious outcomes. However, AI technology is not yet extensively used in clinical practice for EDs or mental health conditions [23] This is reasonable because AI research and technology are still in their early stages, and much still needs to be learned about their capacities.

Advances in technology, especially in AI, are ready to transform how mental health care is delivered. AI refers to computer systems capable of tackling responsibilities that require human intelligence, such as problem-solving, language understanding, pattern recognition, decision-making, and planning [24]. New technology, particularly AI, might change how mental health care is given. AI can help individuals to solve difficult problems in mental health, as able to detect how an illness will develop, helping with diagnosis and treatment choices, and sorting or organising patient reports. Popular language models that can have real-time conversations (like ChatGPT) can write up observations about patients, suggest possible diagnoses from health records, and give support resources to individuals seeking help. AI can be designated as computer systems that do tasks that usually need human intelligence, such as solving problems, understanding language, observing patterns, making findings, and planning [25]. AI stands ready to revolutionise mental health care, update diagnoses, guide treatment choices, and ease administrative burdens. Embracing this technological wave is essential for the speciality to move forward.

ML models have demonstrated strong performance in diagnostic classification for EDs. A study using regularised logistic regression incorporating psychosocial data achieved AUC-ROCs of 0.92 (95% CI: 0.86–0.97) for AN and 0.91 (95% CI: 0.85–0.96) for BN, even when excluding BMI from the analysis. These models also demonstrated high transdiagnostic potential, accurately classifying major depressive disorder and alcohol use disorder from healthy controls (AUC-ROCs: 0.75–0.93). Shared predictors across disorders included neuroticism, hopelessness, and symptoms of attention-deficit/hyperactivity disorder [26].

In longitudinal risk prediction, ML models exhibited moderate performance in predicting the development of future EDs symptoms (AUC: 0.71, 95% CI: 0.67–0.75), depressive symptoms (AUC: 0.64, 95% CI: 0.60–0.68), and harmful drinking (AUC: 0.67, 95% CI: 0.64–0.70) in adolescents aged 14 to 19 years [26]. Natural Language Processing models applied to social media data have demonstrated feasibility in detecting ED symptoms at scale. Fine-tuned large language models such as MentalBERT achieved an accuracy of 98.9% and an F1-score of 98.8% for early risk assessment of anorexia from social media posts [27] . Research supports the feasibility of harnessing social media data to identify individuals with ED symptoms, though these systems are not transparent and show room for improvement [8].

AI proves substantial capability in the prevention and treatment of EDs and body image disturbances [28]. Current research indicates that AI can accelerate the assessment of emotional eating, defined as eating in response to negative emotions, among individuals with obesity. This method has the potential to enable large-scale assessment. The AI model integrated a comprehensive set of clinical variables to inform its algorithms [29]. Three major variables were maintained, each consistent with established clinical understanding and reports. The first, “I eat to forget my problems,” underlines the effect of anxiety and stress in substance-use disorder [29]. The second, “I eat more when I am alone,” relates to loneliness and avoiding social isolation [29]. The third item, “I eat sweets or comfort food,” measures consumption frequency, which may reflect addiction severity. These items are closely linked to BED and emotional eating. Further research should validate the FAST nomogram in large sample-size populations, focusing on sensitivity, specificity, and relevance for EDs.

A recent study examined clinician and community perspectives regarding the application of AI in EDs management. Results indicated that 59% of clinicians, most of whom use ChatGPT, integrate AI systems into their practice. In contrast, 18% of community participants employ these tools for educational or support purposes [7]. Only one-third of participants in both groups believe that the benefits of AI outweigh its risks in treatment. These findings indicate ongoing caution and uncertainty concerning the broad implementation of AI in EDs care [7].

AI Applications for Detecting Specific Psychopathological Manifestations in EDs

EDs are frequently complicated by comorbid psychiatric conditions that significantly impact treatment outcomes and prognosis. Recent AI research has increasingly focused on detecting these specific psychopathological manifestations using various computational approaches. Depression and anxiety are the most prevalent comorbidities in EDs, affecting over 50% of individuals with EDs [26]. ML models have been developed to detect depressive symptoms

from ecological momentary assessment data, with GPT-4o demonstrating 100% accuracy in identifying worsening depression patterns and 83% accuracy for worsening anxiety patterns in psychiatric digital phenotyping data [30]. These models can process multidimensional data streams to identify early warning signs of symptom deterioration.

Despite the elevated mortality risk in EDs, particularly in AN where mortality rates are approximately six times higher than the general population [26] , AI detection of suicidality in ED populations remains under-researched. Current approaches primarily rely on NLP analysis of social media text or clinical notes to identify suicidal ideation, but specific applications for ED populations require further investigation. Obsessive-Compulsive Symptoms (OCD) frequently co-occur with EDs, particularly AN. While AI models have been developed for OCD detection from social media data and clinical text, their application specifically to ED populations represents an emerging area requiring dedicated research. AI-driven analysis of ecological momentary assessment (EMA) data has demonstrated utility in detecting emotional dysregulation patterns. A proof-of-concept study using autoencoder-based analysis of high-dimensional EMA data from EDs patients identified distinct symptom phenotypes anchored in eating anxiety, with the Mistakes Exposure module producing the largest shifts in eating-related anxiety [31] . The AI model achieved Root Mean Square Error (RMSE) = 0.25 and $R^2 = 0.8$ in reconstructing symptom patterns, and a four-cluster solution yielded distinct, interpretable symptom phenotypes [31].

The pervasive nature of ED-related content on social media platforms offers an unprecedented opportunity to detect signals of ED symptoms. Content tags, topic modelling, and NLP have been researched as methods to identify individuals with ED symptoms. However, social media platforms' automated detection systems for moderating harmful content are not transparent and show room for improvement, highlighting the importance of ED experts' involvement [8]. Psychological research has identified specific linguistic patterns and behavioural markers associated with anorexia, making social media data a promising tool for early detection. Digital phenotyping uses sensor data collected via smartphones to derive real-time behavioural, social, or environmental metrics that can be analysed to infer mental states [10]. Sophisticated capabilities like digital phenotyping and natural language processing may aid the detection of EDs in new ways while also informing the development of closed-loop, adaptive interventions [10].

Digital Solutions for EDs Patients

Several studies have developed digital solutions for patients with EDs, improving treatment accessibility and cost-efficiency. Examples include an app for monitoring and addressing depression and EDs symptoms, a decision tree chatbot for psychoeducation and body image coping skills, and a conceptual app for BED and BN that delivers just-in-time adaptive interventions based on predicted behaviours [32]. Furthermore, the implementation of an embodied question-answering system for EDs treatment and a reinforcement learning-based remote coaching intervention for weight loss resulted in significant cost reductions in remote coaching [33].

A smartphone tool integrated with AI systems

Individuals with EDs may benefit from smartphone application-based interventions and monitoring tools, given that the ego-syntonic characteristics of these conditions frequently result in ambivalence toward behavioural change [34]. These applications enable users to participate in treatment at their own pace, supporting autonomy and control throughout the therapeutic process [35]. The scalability, flexibility, and affordability of these applications suggest they are promising solutions for addressing barriers inherent in traditional clinical services.

Recent research indicates increasing interest in smartphone-based intervention and monitoring tools among individuals with EDs [36].With global smartphone ownership nearing 90% and internet access more common on smartphones than computers, smartphone tools offer impressive scalability [37]. Recent studies showed that convinced individuals desire digital tools over conventional face-to-face methods, especially for symptom management and progress tracking outside formal therapy [38]. Physicians have also shown openness to using apps as assistants to treatment to support engagement between sessions [39]. The results indicate a moderate level of excitement and acceptability involving smartphone technology among individuals with EDs, underscoring its capacity to complement traditional treatment methods and broaden access to supplementary support options.

Smartphones are now used at different stages of EDs treatment. As self-management tools, apps help participants to monitor their symptoms, practice coping strategies, and reinforce healthy behaviours between or outside therapy sessions [40]. They are increasingly integrated into traditional treatment structures. For example, patients may utilise applications in conjunction with psychotherapy to improve adherence to treatment plans, complete assigned tasks, and record emotions and behaviours in real time. This approach enables more focused and effective therapeutic dialogues [39]. Aftercare represents a implying application, as digital applications can offer ongoing access to resources and monitoring after discharge from intensive treatment, thereby supporting relapse prevention [41].

Emerging hybrid models of care progressively utilise smartphone data to inform medical decision-making. Real-time passive and active data streams can alert contributors to early indicators of symptom deterioration, enabling timely involvement [42]. Monitoring EDs symptoms through smartphones has been extensively explored using EMA devices

[43]. Smartphones are a natural fit for this approach because they travel everywhere with us, are always within reach, and can quietly gather information as people go about their habits. This allows EMA to overcome the major drawbacks of conventional assessments, which often miss the real-world context, rely on imperfect memories, and overlook the ups and downs of daily experiences.

Chatbots and EDs

Clinical studies on chatbots are rapidly increasing, given the substantial potential of this area. Chatbots can open doors to inexpensive or even free treatment support, reaching more populations with proven help and serving as a vital first step to connect individuals with the care they require. By combining these interventions with mobile sensing technology, support can be designed and delivered directly to those most at hazard [44]. By tapping into the rhythms of our mobile phone use, this approach discovers each person's distinct patterns of risk and recovery as they progress. Will this daring vision for healthcare truly open the door to mental health prevention for anyone with a smartphone, or are we chasing a dream that technology cannot yet deliver? The real answer will emerge only as a new generation of robust studies, using creative tools like digital control groups, such as chatbots that offer unrelated advice, to put these ideas to the test. While early studies without such controls will still play a vital role as pilots, the future lies in research that pushes the boundaries of feasibility and explores placebo-controlled outcomes to help us decide which chatbots deserve to lead the way [45].

Deciding when to bring chatbots into treatment teams remains a complex challenge, as does keeping their software up-to-date to protect the well-being of actual humans [20]. AI is still finding its base in the mental health field, falling short of replacing the vital role of human staff. Just recently, the National Eating Disorders Association (NEDA) pulled its chatbot from the help hotline after it was found giving advice that could do more harm than good [46]. At first, NEDA brushed off the advocate's claims, only to quietly erase their statement once evidence began to back up the allegations [46]. The study also recounted the heartbreaking case of a Belgian man who took his own life following conversations with an AI chatbot on the Chai app [46].

When a widely distributed ED chatbot gave troubling advice, it was unclear whether the team behind it had fully considered these risks before allowing users to interact with it. A further complication is that chatbots often stray from precise rules, occasionally missing warning signs in users' language and reacting inappropriately [20]. An individual cannot simply assume the outcomes from rule-based chatbots to carry over to AI chatbots, nor can one count on an AI chatbot behaving the same way after a software upgrade [47]. Attacking these challenges calls for fresh momentum in both clinical research and the evolution of AI technology for healthcare. Clinically, any chatbot, whether rule-based or AI-driven, must be backed by strong scientific evidence. On the technology front, developers and their multidisciplinary teams should openly recognise limitations and capability biases [20]. Multidisciplinary teams assume the vital duty of ensuring ethical, safe care, even as they navigate landscapes with few established standards and best-practice protocols.

Safety and Ethical Considerations of The Usage of AI in EDs

LLMs, including ChatGPT and other generative AI systems, have generated considerable interest in mental health applications. These models can assist with tasks such as creating structured summaries of patient information, identifying possible diagnoses using medical data, and offering preliminary support [48]. However, their clinical utility must be critically examined. AI triggers excitement with its potential to transform prevention and treatment services, yet its rapid evolution may be outpacing the ethical measures meant to guard users. Research shows that even as technology and AI become more dominant in the field of EDs, challenges around body image persist, underscoring the ongoing need for ethical and safe practices [20].

Current research on ChatGPT's ability to provide information about EDs reveals both potential and significant limitations. A recent review found that ChatGPT's answers do not always provide definitive results and may lead to confusion in determining the type of ED. Ethical principles must be followed when using these tools, including contributing to society and human well-being and not causing harm [48]. LLMs are known to produce hallucinations as incorrect or fabricated information presented with confidence. In psychiatric digital phenotyping data interpretation, GPT-4o demonstrated instances of hallucination, such as claiming patterns existed in data when none were present [30]. This phenomenon poses significant risks in clinical contexts where accurate information is essential. Generative AI tools present evidence-based risks including inaccuracies, inconsistencies, hallucinations, and the potential to introduce harmful biases into clinical decision-making [48]. No chatbot has been specifically designed to address concerns related to negative body image , and studies have yet to clarify whether chatbots can improve eating disorder psychopathology, depression, and anxiety or detect EDs in advance [48].

A widely publicised incident occurred when a generative AI chatbot, Tessa, delivered harmful dieting advice, prompting significant concern and hesitancy among clinicians, patients, and advocacy groups. This incident involved an unexpected activation of generative AI capabilities within a system originally intended to be rule-based, resulting in conversational outputs that were not clinically appropriate. This case highlights the critical importance of safety,

transparency, and community involvement in developing generative AI-supported ED tools [31]. A balanced perspective recognises that while LLMs may eventually support mental health care by accelerating workflows and handling large datasets, they are not designed to make definitive clinical judgments. Randomised controlled trials are needed to compare the effectiveness of clinicians, generative AI, and the combination of both [48].

With AI-powered inventions advancing at a remarkable pace, we stand on the brink of a future where their precision and capabilities rise. To ensure their successful integration into clinical practice for EDs, it is crucial to explore what might help or hinder their adoption before widespread implementation becomes inevitable across medicine [25]. The way professionals and communities view AI can reveal just how deeply these tools might find their way into clinics or reach those who need them most. For example, if physicians fear AI's accuracy or ethical risks, they may be unwilling to accept these technologies into their daily work. Their doubts about whether AI can truly grasp the unique and obscure nature of EDs could also push them to stick with tried-and-true, human-centred methods for assessment, diagnosis, and treatment [49].

On the other hand, people seeking support might be cautious about AI-driven care and desire warmth, understanding, and reassurance that only a human therapist can provide. Worries about privacy and the risk of AI mishandling sensitive health information may also make many hesitant to use these digital solutions. Sometimes, AI may fall short of putting the patient's needs first. If the system is poorly trained or lacks crucial information, it could respond in ways that miss the mark. Without strong standards to measure how safe and effective these systems are, uncertainty remains. There is also the risk that personal data could be traded or used for marketing by companies [50]. Studies have shown that both clinicians and community members worry that AI might be misused without proper training, and that it introduces fresh challenges for protecting sensitive health data [7]. An additional arrest trend emerged: both groups recognised clear boundaries for AI in treating EDs. Most felt that no matter how advanced technology becomes, it could never exceed human clinicians in the deeply personal skills at the heart of psychotherapy, such as showing empathy, imitating genuine connections, and guiding patients through emergencies [7].

Upcoming Guidelines to Address AI Challenges

Exploring how clinicians and societies distinguish and utilise AI in clinical care for EDs can help recognise barriers, build trust in empirically validated AI tools, and drive the development of innovations that integrate effortlessly into clinical systems [51]. Proactively distributing accessible training and educational resources on AI, including its strengths, challenges, and legal considerations associated with widely used systems, can enhance clinician trust and confidence during acceptance. Implanting this content into current curricula offers a practical pathway to initial knowledge, allowing clinicians to stay informed without mastering every technical detail of AI [7].

Several priorities emerge for the responsible integration of AI into clinical practice. First, the development of robust privacy and data security protocols is essential. This includes establishing clear and practical guidelines for clinicians managing sensitive patient data with AI tools while ensuring that AI systems comply with the highest international privacy standards, including the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) [23]. Regulatory and professional bodies should collaborate closely with AI developers to establish clear standards for obtaining informed patient consent and ensuring that data are appropriately anonymised or encrypted before use. In parallel, clinician training programs should emphasize the critical importance of protecting patient confidentiality and increase awareness of the risks associated with entering sensitive information into AI systems. To address current implementation challenges, AI technologies must demonstrate transparency and accountability, supported by clearly defined operational and ethical standards. Safeguarding data privacy and security should remain a central priority, while empowering patients to retain control over their personal health information [50]. Regular auditing and monitoring are also necessary to ensure the reliability, accuracy, and trustworthiness of AI systems. Furthermore, multidisciplinary collaboration among clinicians, AI developers, ethicists, and policymakers is essential to enhance the effectiveness and integrity of healthcare chatbots, particularly in settings with limited technological resources [50]. Digital literacy programs may empower patients to engage more effectively with AI-enabled healthcare tools, while user-friendly interfaces can improve accessibility for individuals with limited technological experience. Finally, multilingual support is crucial to ensure equitable access and facilitate effective communication across diverse patient populations [50].

Future research should reconsider current practices and perspectives, following their development as AI technology develops and becomes more widely adopted in mental health care. As AI capabilities advance rapidly, such studies can yield new insights into how evolving technology shapes the integration and effectiveness of AI in ED research and clinical practice [7]. AI intended for human interaction must be developed with safety as a priority. Chatbots designed for EDs and body image concerns must meet this standard, given the significant risk of harm from AI responsibility [24]. Establishing a collaborative learning environment that draws on past errors can help reduce future mistakes [20]. Considerate collaboration between clinicians and AI researchers, coupled with the mindful development of AI models, can yield powerful, transparent, and equitable tools that empower clinicians in emergency departments

and catalyse new medical discoveries. Finally, exploring how clinicians and communities view and use AI in clinical care for EDs helps uncover obstacles, spark greater trust in AI tools once proven effective, and inspire innovations that fit seamlessly into clinical routines [51]. Developers and researchers must pull back the shade on their chatbot training methods and data sources, since the internet is still flooded with harmful content that could easily steer these systems in the wrong direction [52].

The research and development team must carefully consider the intended end-users of any AI resource and ensure authentic representation of the target community to prevent exclusion. Attentiveness to factors such as gender, language, race, age, and comorbidities during the development process facilitates the creation of inclusive and reasonable answers [53]. Each member of a multidisciplinary team contributes unique expertise that reinforces the success of an AI resource. The findings and recommendations presented here establish a foundation for responsible AI use during the transition toward a more technologically integrated research environment. Given the rapid evolution of generative AI, these guidelines should be reviewed and updated at least annually to remain aligned with emerging technologies, ethical standards, and the evolving needs of the field. Future efforts may benefit from the development of closed, secure AI platforms specifically designed for the EDs research community or the broader research subdivision. Such platforms would enable field-wide analyses that exceed the capabilities of individual research teams, institutions, or investigators.

The ED field can draw on lessons from other domains to evaluate smartphone technology that leverages AI to enhance personalisation. Realising the potential of these tools requires addressing challenges related to engagement, trust, data governance, and clinical integration [10]. Future large-scale, collaborative efforts aimed at transforming ED care are needed [54]. Future research should prioritise developing robust privacy and data security protocols, establishing clear standards for informed patient consent, and ensuring data anonymisation or encryption before use [48]. Clinician training must emphasise the importance of protecting patient confidentiality and highlight risks associated with inputting sensitive information into AI tools [48].

Conclusion

Artificial intelligence (AI) holds considerable promise for improving eating disorder (ED) care through earlier detection, enhanced diagnostic support, and scalable digital interventions. However, despite encouraging findings, the current evidence remains limited by methodological weaknesses, insufficient external validation, and significant ethical and governance challenges. While rule-based digital tools appear feasible for clinical implementation under appropriate supervision, more advanced AI technologies, particularly generative AI, require rigorous validation and robust safeguards before routine clinical use. Future research should prioritize multicenter validation studies, transparent regulatory frameworks, multidisciplinary collaboration, and the development of ethically designed AI systems to ensure that these technologies complement rather than replace clinical judgment in ED care.

Acknowledgment

The authors would like to express their sincere gratitude to all researchers, clinicians, and professional organizations whose published work contributed to the development of this review. The authors also acknowledge colleagues and experts in the fields of eating disorders, digital health, and artificial intelligence whose scholarly contributions have advanced understanding in this rapidly evolving area.

Declarations

Author contribution : M.M., M.I.M., and A.M.A. contributed to the conception and design of the study, as well as to the acquisition, analysis, and interpretation of data. M.M. and T.H.M. drafted the manuscript and critically revised it for important intellectual content. M.M., M.I.M., A.M.A., and T.H.M. reviewed and approved the final version of the manuscript for publication. All authors agree to be accountable for all aspects of the work and to ensure that any questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Funding statement : No external funding was received for the preparation of this review. The authors did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest : The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics Declaration : Ethical approval was not required for this study because it is a narrative review based exclusively on previously published literature and did not involve human participants, animals, or identifiable personal data.

Additional information : The authors confirm that all statements and interpretations presented in this review are based on the available published literature and represent the authors' independent scholarly synthesis.

Informed Consent Statement

Not applicable. This study did not involve human participants or the collection of identifiable personal information.

Data Availability Statement

No new data were generated or analyzed in this study. All data supporting the findings of this review are derived from previously published studies, which are appropriately cited throughout the manuscript.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors acknowledge the use of DeepSeek Proofreader solely for English language editing and improvement of manuscript readability. All AI-generated suggestions were critically reviewed, revised, and verified by the authors to ensure the accuracy, integrity, and scientific validity of the manuscript. The authors take full responsibility for all content presented in this work.

ORCID for Authors

Marwa Mohammed[1], ORCID: https://orcid.org/0000-0003-1666-2167
Mohamed I Mabrouk[3], ORCID: https://orcid.org/0009-0009-9191-1240
Taha Hussein Musa[4], ORCID: https://orcid.org/0000-0003-4452-1943

References

[1] M. Solmi *et al.*, "Outcomes in people with eating disorders: a transdiagnostic and disorder-specific systematic review, meta-analysis and multivariable meta-regression analysis," *World Psychiatry,* vol. 23, no. 1, pp. 124-138, doi:10.1002/wps.2118220.

[2] D. van Hoeken and H. W. Hoek, "Review of the burden of eating disorders: mortality, disability, costs, quality of life, and family burden," (in eng), *Curr Opin Psychiatry,* vol. 33, no. 6, pp. 521-527, Nov 2020, doi:10.1097/yco.0000000000000641.

[3] S. Zipfel, U. Schmidt, and K. E. Giel, "The hidden burden of eating disorders during the COVID-19 pandemic," *The Lancet Psychiatry,* vol. 9, no. 1, pp. 9-11, doi:10.1016/s2215-0366(21)00435-1.

[4] M. Galmiche, P. Déchelotte, G. Lambert, and M. P. Tavolacci, "Prevalence of eating disorders over the 2000–2018 period: a systematic literature review," *The American Journal of Clinical Nutrition,* vol. 109, no. 5, pp. 1402-1413, doi:https://doi.org/10.1093/ajcn/nqy342.

[5] R. Striegel Weissman and F. Rosselli, "Reducing the burden of suffering from eating disorders: Unmet treatment needs, cost of illness, and the quest for cost-effectiveness," (in eng), *Behav Res Ther,* vol. 88, pp. 49-64, doi:10.1016/j.brat.2016.09.006.

[6] A. E. Kazdin, E. E. Fitzsimmons-Craft, and D. E. Wilfley, "Addressing critical gaps in the treatment of eating disorders," *International Journal of Eating Disorders,* vol. 50, no. 3, pp. 170-189, doi:10.1002/eat.22670

[7] J. Linardon, C. Liu, M. Messer, Z. McClure, C. Anderson, and H. K. Jarman, "Current Practices and Perspectives of Artificial Intelligence in the Clinical Management of Eating Disorders: Insights From Clinicians and Community Participants," (in eng), *Int J Eat Disord,* vol. 58, no. 4, doi:10.1002/eat.24385.

[8] L. D'Adamo *et al.*, "Detecting Eating Disorders From Social Media Content: What Has Been Done and Where Do We Go Next?," (in eng), *Int J Eat Disord,* vol. 59, no. 1, pp. 35-39, doi:10.1002/eat.24565.

[9] S. Ryall, A. Bradley, K. El Emam, and N. Obeid, "Applying Machine Learning to Predict Complex Clinical Course in Youth With Eating Disorders," *International Journal of Eating Disorders,* vol. 59, no. 1, pp. 134-145, doi:https://doi.org/10.1002/eat.24570.

[10] J. Linardon and J. Torous, "Integrating Artificial Intelligence and Smartphone Technology to Enhance Personalized Assessment and Treatment for Eating Disorders," *International Journal of Eating Disorders,* vol. 58, no. 8, pp. 1415-1424, doi:https://doi.org/10.1002/eat.24468.
[11] M. Casu, L. Marletta, C. V. Ragaglia, P. Caponnetto, and S. Battiato, "Digital technologies and artificial intelligence in eating disorders: A scoping review of prevention, screening, and treatment approaches," *Computers in Human Behavior Reports,* vol. 21, p. 100963, doi:https://doi.org/10.1016/j.chbr.2026.100963.
[12] S. Herpertz, U. Hagenah, S. Vocks, J. v. Wietersheim, U. Cuntz, and A. Zeeck, "The Diagnosis and Treatment of Eating Disorders," *Deutsches Ärzteblatt international,* doi:10.3238/arztebl.2011.0678.
[13] M. Fichter, "Epidemiologie der Essstörungen," in *Handbuch Essstörungen und Adipositas*, S. Herpertz, M. Zwaan, and S. Zipfel, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, pp. 45-55.
[14] A. Sanz Cortés, "Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, Text Revision (DSM-5-TR). American Psychiatric Association, 2022. https://doi.org/10.1176/ appi.books.9780890425787," *Psicooncología,* vol. 19, no. 2, pp. 339-340, doi:10.5209/psic.840452.
[15] M. Vasey, F. Besag, Z. Bronowska, and E. Cini, "The NICE guideline for the recognition and treatment of eating disorders," *Cutting Edge Psychiatry in Practice,* vol. 6, no. 1, pp. 117-127, doi:10.65031/vjcx5272.
[16] R. Griffith, "What is Gillick competence?," *Human Vaccines & Immunotherapeutics,* vol. 12, no. 1, pp. 244-247, doi:10.1080/21645515.2015.1091548.
[17] V. Larcher and A. Hutchinson, "How should paediatricians assess Gillick competence?," *Archives of Disease in Childhood,* doi:10.1136/adc.2008.148676.
[18] WHO, "World Mental Health Report (no date) World Health Organization. ," *Available at: https://www.who.int/teams/mental-health-and-substance-use/world-mental-health-report (Accessed: 01 January 2026).*
[19] A. E. Kazdin, E. E. Fitzsimmons-Craft, and D. E. Wilfley, "Addressing critical gaps in the treatment of eating disorders," (in eng), *Int J Eat Disord,* vol. 50, no. 3, doi:10.1002/eat.22670.
[20] G. Sharp, J. Torous, and M. L. West, "Ethical Challenges in AI Approaches to Eating Disorders," (in eng), *J Med Internet Res,* vol. 25, p. e50696, doi:10.2196/50696
[21] A. M. Monteleone *et al.*, "Treatment of eating disorders: A systematic meta-review of meta-analyses and network meta-analyses," *Neuroscience & Biobehavioral Reviews,* vol. 142, p. 104857, doi:https://doi.org/10.1016/j.neubiorev.2022.104857.
[22] A. González, G. Hernández-Chan, R. Colomo-Palacios, J. Gómez Berbis, A. Garcia Crespo, and G. Alor-Hernández, "Towards an Ontology to Support Semantics Enabled Diagnostic Decision Support Systems," *Current Bioinformatics,* vol. 7, pp. 234-245, doi:10.2174/157489312802460721.
[23] J. Torous and C. Blease, "Generative artificial intelligence in mental health care: potential benefits and current challenges," *World Psychiatry,* vol. 23, no. 1, pp. 1-2, doi:10.1002/wps.21148.
[24] W. Ertel, "Introduction to artificial intelligence " in *Undergraduate Topics in Computer Science*, ed: Springer Fachmedien Wiesbaden, 2024, pp. 1-23.
[25] S. Kolding, R. M. Lundin, L. Hansen, and S. D. Østergaard, "Use of generative artificial intelligence (AI) in psychiatry and mental health care: a systematic review," *Acta Neuropsychiatrica,* vol. 37, doi:10.1017/neu.2024.50
[26] Z. Zhang *et al.*, "Machine learning models for diagnosis and risk prediction in eating disorders, depression, and alcohol use disorder," *Journal of Affective Disorders,* vol. 379, pp. 889-899, doi:https://doi.org/10.1016/j.jad.2024.12.053
[27] L. Fakher and M. Davarkhah, "Harnessing Large Language Models for Early Risk Assessment of Anorexia on Social Media," in *2025 IEEE 4th International Conference on Computing and Machine Intelligence (ICMI)*, 2025, pp. 1-5.
[28] A. K. Graham, J. A. Kosmas, and T. A. Massion, "Designing Digital Interventions for Eating Disorders," *Current Psychiatry Reports,* vol. 25, no. 4, pp. 125-138, doi:10.1007/s11920-023-01415-x
[29] S. Iceta, S. Tardieu, J. A. Nazare, A. Dougkas, M. Robert, and E. Disse, "An artificial intelligence-derived tool proposal to ease disordered eating screening in people with obesity," (in eng), *Eat Weight Disord,* vol. 26, no. 7, pp. 2381-2385, doi:10.1007/s40519-020-01076-2.
[30] M. Flathers *et al.*, "Interpreting psychiatric digital phenotyping data with large language models: a preliminary analysis," *BMJ Mental Health,* vol. 28, no. 1, p. e301817, doi:10.1136/bmjment-2025-301817.
[31] R. Torres, J. Hernandez, A. Gaweda, and C. A. Levinson, "Leveraging artificial intelligence to personalize treatment for eating disorders: A proof-of-concept study," *Journal of Affective Disorders,* vol. 406, p. 121681, doi:https://doi.org/10.1016/j.jad.2026.121681
[32] E. E. Fitzsimmons-Craft *et al.*, "Effectiveness of a chatbot for eating disorders prevention: A randomized clinical trial," (in eng), *Int J Eat Disord,* vol. 55, no. 3, pp. 343-353, doi:10.1002/eat.23662

[33] E. M. Forman *et al.*, "Using artificial intelligence to optimize delivery of weight loss treatment: Protocol for an efficacy and cost-effectiveness trial," (in eng), *Contemp Clin Trials,* vol. 124, p. 107029, doi:10.1016/j.cct.2022.107029

[34] L. Clausen, M. Lübeck, and A. Jones, "Motivation to change in the eating disorders: A systematic review," *International Journal of Eating Disorders,* vol. 46, no. 8, pp. 755-763, doi:10.1002/eat.22156.

[35] J. Torous *et al.*, "The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality," *World Psychiatry,* vol. 20, no. 3, pp. 318-335, doi:10.1002/wps.20883.

[36] J. Torous *et al.*, "The evolving field of digital mental health: current evidence and implementation issues for smartphone apps, generative artificial intelligence, and virtual reality," *World Psychiatry,* vol. 24, no. 2, pp. 156-174, doi:10.1002/wps.21299.

[37] R. Gelles-Watnick, "Americans' use of Mobile Technology and Home Broadband, Pew Research Center. ," *Available at: https://www.pewresearch.org/internet/2024/01/31/americans-use-of-mobile-technology-and-home-broadband/ (Accessed: 02 January 2026). ,* 2024.

[38] C. Anderson, M. Fuller-Tyszkiewicz, M. Messer, and J. Linardon, "Target-user preferences, motivations, and acceptance for a dialectical behaviour therapy smartphone application for eating disorders," *Eating and Weight Disorders - Studies on Anorexia, Bulimia and Obesity,* vol. 29, no. 1, doi:10.1007/s40519-024-01646-8.

[39] C. Liu and J. Linardon, "Mental health clinicians' practices and perspectives of eating disorder apps," *Psychiatry Research,* vol. 347, p. 116412, doi:10.1016/j.psychres.2025.116412

[40] J. Linardon *et al.*, "A dialectical behavior therapy skills training smartphone app for recurrent binge eating: a randomized clinical trial," *Psychological Medicine,* vol. 54, no. 16, pp. 4646-4657, doi:10.1017/s0033291724002800.

[41] C. Neumayr, U. Voderholzer, J. Tregarthen, and S. Schlegl, "Improving aftercare with technology for anorexia nervosa after intensive inpatient treatment: A pilot randomized controlled trial with a therapist-guided smartphone app," *International Journal of Eating Disorders,* vol. 52, no. 10, pp. 1191-1201, doi:10.1002/eat.23152.

[42] N. Macrynikola *et al.*, "Testing the Feasibility, Acceptability, and Potential Efficacy of an Innovative Digital Mental Health Care Delivery Model Designed to Increase Access to Care: Open Trial of the Digital Clinic," *JMIR Mental Health,* vol. 12, p. e65222, doi:10.2196/65222.

[43] S. Shiffman, A. A. Stone, and M. R. Hufford, "Ecological Momentary Assessment," *Annual Review of Clinical Psychology,* vol. 4, no. 1, pp. 1-32, doi:10.1146/annurev.clinpsy.3.022806.091415.

[44] K. Tzafilkou, A. A. Economides, and N. Protogeros, "Mobile Sensing for Emotion Recognition in Smartphones: A Literature Review on Non-Intrusive Methodologies," *International Journal of Human–Computer Interaction,* vol. 38, no. 11, pp. 1037-1051, doi:10.1080/10447318.2021.1979290.

[45] J. Torous, N. M. Benson, K. Myrick, and G. Eysenbach, "Focusing on Digital Research Priorities for Advancing the Access and Quality of Mental Health," *JMIR Mental Health,* vol. 10, p. e47898, doi:10.2196/47898.

[46] S. Writer, " Neda suspends AI chatbot for giving harmful eating disorder advice %, Psychiatrist.com. ," *Available at: https://www.psychiatrist.com/news/neda-suspends-ai-chatbot-for-giving-harmful-eating-disorder-advice/ (Accessed: 02 January 2026). ,* 2023.

[47] E. E. Fitzsimmons-Craft *et al.*, "Effectiveness of a chatbot for eating disorders prevention: A randomized clinical trial," *International Journal of Eating Disorders,* vol. 55, no. 3, pp. 343-353, doi:10.1002/eat.23662

[48] H. Toklu Baloğlu, "Effect of ChatGPT use on eating disorders and body image," (in eng), *World J Psychiatry,* vol. 15, no. 8, p. 107122, doi:10.5498/wjp.v15.i8.107122.

[49] C. Blease, A. Worthen, and J. Torous, "Psychiatrists' experiences and opinions of generative artificial intelligence in mental healthcare: An online mixed methods survey," *Psychiatry Research,* vol. 333, p. 115724, doi:10.1016/j.psychres.2024.115724.

[50] M. R. Islam, T. J. Urmi, R. A. Mosharrafa, M. S. Rahman, and M. F. Kadir, "Role of ChatGPT in health science and research: A correspondence addressing potential application," *Health Science Reports,* vol. 6, no. 10, doi:10.1002/hsr2.1625

[51] S. Cross *et al.*, "Use of AI in Mental Health Care: Community and Mental Health Professionals Survey," *JMIR Mental Health,* vol. 11, pp. e60589-e60589, doi:10.2196/60589.

[52] S. K. Nutley, A. M. Falise, R. Henderson, V. Apostolou, C. A. Mathews, and C. W. Striley, "Impact of the COVID-19 Pandemic on Disordered Eating Behavior: Qualitative Analysis of Social Media Posts," *JMIR Mental Health,* vol. 8, no. 1, p. e26011, doi:10.2196/26011

[53] K. Gabriels, "Addressing the Soft Impacts of Weak AI-Technologies," presented at the The 2018 Conference on Artificial Life, 2018. Available: http://dx.doi.org/10.1162/isal_a_00093