Computers in Human Behavior Reports 21 (2026) 100963

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

Review

Digital technologies and artificial intelligence in eating disorders: A scoping review of prevention, screening, and treatment approaches

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ARTICLE INFO

Keywords:
Digital health
Eating disorders
Clinical psychology
Feeding disorders
Digital psychotherapy
AI in mental health

ABSTRACT

Eating disorders (EDs) are prevalent and often underdiagnosed, and digital interventions may reduce barriers to prevention, early detection, and care. This scoping review mapped research published in 2015–2025 on digital health and artificial intelligence (AI) applications for ED prevention, screening/assessment, prediction/monitoring, and treatment. Searches were run on 29 December 2025 via the University of Catania Primo VE discovery service, covering collections including Scopus, PubMed, PsycArticles, and others. Records were deduplicated and screened using a human-in-the-loop workflow with Large Language Model prioritization used only to order citations for manual screening; study data were charted with a standardized form and synthesized descriptively. The search retrieved 9390 records; 1845 duplicates were removed, leaving 7545 unique records. Screening focused on the top 500 prioritized citations; 191 full texts were assessed and 40 studies were included. Included evidence split evenly between digital technologies (n = 20; mainly web/app cognitive-behavioral programs, screening/triage platforms, and virtual reality interventions) and AI (n = 20; mainly machine learning and natural language processing approaches for risk detection and prediction, plus emerging chatbot-based supports). Evidence was heterogeneous and often early-stage, with limited external validation and uneven reporting of safety and implementation. Future work should emphasize workflow-integrated evaluations, engagement and equity, and governance frameworks for automated tools.

1. Introduction

Eating disorders (EDs) represent a spectrum of conditions characterized by dysfunctional eating behaviors and are classified under "Feeding and Eating Disorders" (FEDs) in the DSM-5-TR (American Psychiatric Association, 2022). These disorders are among the most prevalent mental health issues affecting youth, with a noticeable surge in cases following the COVID-19 pandemic (Devoe et al., 2023; He & Xie, 2023). EDs exert a profound impact on physical health and psychosocial functioning, and they are often accompanied by significant psychiatric comorbidity (Devoe et al., 2023). Despite these challenges, EDs remain frequently underdiagnosed and untreated, with patients enduring long waiting periods for treatment (Burnette et al., 2022; Hamilton et al., 2022).

Self-report questionnaires can be administered at low cost (including online), but pathways that rely on clinician-led interviews and specialist services can be time- and resource-constrained (Berg et al., 2012; Schaefer et al., 2021; Tournayre et al., 2024). As a result, many sufferers (particularly those with binge eating disorder) experience diagnostic delays of three years or more (Gill & Kaplan, 2021), with treatment-seeking delays averaging over five years (Hamilton et al., 2022). Factors such as gaps in awareness among both patients and physicians, persistent stigma, and the overshadowing of ED symptoms by comorbid conditions contribute to this delay, ultimately leading to increased healthcare costs both before and after diagnosis (Citrome, 2017; Linville et al., 2010; Watson et al., 2018).

Early detection is critical for improving outcomes, and digital self-screening tools offer promising avenues for timely identification and referral to healthcare providers. Online screening methods can facilitate earlier intervention, a factor that has been shown to enhance recovery rates and improve overall quality of life (Bryant et al., 2020; Leti et al., 2020). Furthermore, contemporary awareness campaigns on social media not only promote engagement in screening initiatives among adolescents but also challenge the harmful stereotypes perpetuated by diet culture (Mazzeo et al., 2024).

Traditional psychotherapeutic treatments remain the cornerstone of ED management and are widely recognized as "best practices" (Trea-

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https://doi.org/10.1016/j.chbr.2026.100963
Received 10 March 2025; Received in revised form 13 January 2026; Accepted 3 February 2026

sure et al., 2020). However, these interventions often yield inconsistent outcomes, as evidenced by high rates of dropout and relapse (Leichsenring et al., 2019). In response, integrating evidence-based treatments with technological innovations has emerged as a promising strategy to address these limitations.

The field of digital health, which encompasses the use of technology to deliver healthcare services, has seen substantial advancements in recent years (Gentili et al., 2022). Beyond intervention delivery, digital health increasingly includes tools that support the measurement of eating-related behaviors in daily life; in the broader health domain, food-recognition and dietary-monitoring pipelines have been reviewed and applied to image-based dietary monitoring tasks, illustrating the maturation of computer-vision approaches for food and intake-related logging (Allegra et al., 2020; Battiato et al., 2021). Developments in artificial intelligence (AI), virtual reality (VR), and chatbots have opened new possibilities for mental health interventions (Caponnetto & Casu, 2022; Casu et al., 2024; Torous et al., 2021). In the context of EDs, digital interventions have the potential to reduce barriers to help-seeking, enhance traditional treatments, mitigate symptoms, and prevent relapse. For instance, interactive self-help applications have demonstrated the ability to improve motivational stages and reduce psychopathology, as shown in an Asia-Pacific internet-based program (Leung et al., 2013). Similarly, the online motivational therapy ESS-KIMO has been effective in boosting motivation, self-esteem, and symptom reduction when compared to control conditions (Hötzel et al., 2013). Although these digital tools are often adaptations of conventional psychological treatments, yielding outcomes comparable to face-to-face therapy (Fuller-Tyszkiewicz et al., 2024), they underscore the importance of maintaining clinician contact to ensure effective care (National Institute for Health and Care Excellence, 2017; Wilson & Zandberg, 2012). Recent advances in AI, particularly in machine learning (ML) and Natural Language Processing (NLP), have introduced innovative approaches useful for understanding and managing EDs. AI-driven tools can analyze behavioral patterns (Sheta, 2021), predict relapse risks (Curtis et al., 2023; Liang, 2022), and deliver personalized interventions (Schork, 2019; Udegbe et al., 2024). However, their psychological impact, ranging from user trust in algorithmic guidance to ethical concerns about autonomy, remains underexplored. In light of these challenges and opportunities, this scoping review synthesizes insights from recent studies to provide a wide analysis of digital health and AI interventions for eating disorders. Our goal is to map and synthesize the current literature and identify digital tools that can support the prevention, diagnosis, and management of EDs.

Finally, the paper is structured as follows: Section 1 introduces the context of eating disorders and the emerging role of digital technologies and artificial intelligence in addressing prevention, screening, and treatment challenges. Section 2 outlines the scoping review methodology, detailing the literature search strategy, eligibility criteria, LLM-assisted prioritization approach, and data charting procedures. Section 3 presents findings from the 40 included studies, organized thematically across prevention, screening and early detection, digital and AI-enhanced treatment interventions, social media implications, methodological considerations, and ethical and safety issues. Section 4 synthesizes the evidence, discusses implications for design and implementation including lived experience and co-production, and acknowledges limitations. Section 5 summarizes key insights and identifies priorities for future research.

2. Methodology

2.1. Design

This study was designed as a scoping-oriented narrative synthesis (Arksey & O'malley, 2005; Aromataris et al., 2024) to map and characterize the literature on digital technologies and artificial intelligence applications in the context of EDs. Chatbot-based systems were examined as a distinct subcategory within the AI domain. Reporting follows the PRISMA-ScR recommendations, ensuring transparent documentation of information sources, search strategies, record management, and selection procedures (Tricco et al., 2018).

2.2. Eligibility criteria

Eligibility criteria followed the PCC (Population, Concept, Context) framework (Arksey & O'malley, 2005; Aromataris et al., 2024; Peters et al., 2020). We included English-language, peer-reviewed journal articles and conference papers published in 2015–2025. This time window was selected to capture the expansion of scalable web- and app-based interventions and the acceleration of ML/NLP/VR applications in mental health, while keeping the evidence base manageable for a scoping synthesis. The English-only restriction was applied to ensure consistent screening and data charting, and to reduce translation-related ambiguity in technical (AI) and clinical (ED) terminology. For completeness, arXiv was searched; however, preprints were excluded at screening because their content may change prior to formal publication.

Inclusion criteria. Records were included if they met all of the following criteria based on title, abstract, and keywords:

- **Population (ED-relevant):** The study addressed eating disorders or ED-relevant phenomena, including clinical ED samples (e.g., AN, BN, BED, ARFID, OSFED, atypical AN, transdiagnostic EDs), individuals with elevated ED symptoms/risk, and community or non-clinical samples used to test ED-related mechanisms or risk markers (e.g., body image disturbance, restrictive eating, binge eating, purging/compensatory behaviors, compulsive exercise, ED-related cognitions). Studies in ED-adjacent clinical groups (e.g., high body weight/obesity) were eligible when the explicit aim was ED-relevant screening, risk detection, phenotyping, or characterization of disordered eating patterns.
- **Concept (Technology):** The study involved digital technologies (e.g., eHealth/mHealth, apps, web programs, virtual reality, EMA/ESM, JITAI, wearables/sensors, online self-help/guided self-help, social-media-based interventions) or artificial intelligence (e.g., ML/DL, chatbots, NLP, computer vision, predictive models, detection/classification, social media mining) in an ED/ED-relevant context. Telehealth platforms were eligible only when they delivered structured digital content that was automated and/or self-guided beyond synchronous clinician-led sessions.
- **Context (Health/behavior relevance):** The technology was used for ED-relevant prevention, screening/risk detection, diagnosis/assessment, treatment/support, monitoring, relapse prediction, or other clinically/behaviorally relevant outcomes; proof-of-concept/mechanism testing, method validation, phenotyping/profiling, or model development were eligible when the intended use case was explicitly linked to ED-related prevention, screening, monitoring, or intervention.

Exclusion criteria. Records were excluded if they met any of the following conditions:

- **Virtual delivery of traditional therapy:** Records involving traditional psychological therapies delivered remotely via digital platforms (e.g., videoconference-based CBT, telehealth consultations with a clinician, family-based treatment via telemedicine) without a self-guided or automated digital intervention component were excluded, as these do not constitute digital interventions per se but rather traditional care enabled by communication technology.
- **Outside time window:** Records published before 2015 or after 2025 were excluded.

- **Not ED-focused:** The population/target was not eating disorders (e.g., obesity/weight loss or diet/fitness without ED framing; generic mental health without ED-specific focus).
- **No technology concept:** The record concerned EDs but did not involve digital technology or AI (e.g., purely clinical, pharmacological, or epidemiological work without a technology component).
- **No ED context:** The record involved digital technology/AI but did not target ED populations or ED-relevant use cases (e.g., purely technical methods or non-ED clinical domains).
- **Non-human/non-health context:** Animal studies or technology work not connected to human health/behavior care.

2.3. Information sources

Searches were executed via the University of Catania discovery service (Primo VE[1]). The "simple search" interface was utilized to query multiple indexed collections simultaneously, including Scopus, PubMed, Health & Medical Collection, Wiley, PsycArticles, and arXiv. All citations were exported in BibTEX format for subsequent processing.

2.4. Search strategy

Three complementary search strings were designed to capture both broad domains, while ensuring high sensitivity for chatbot-related research.

- **Search A (Digital Technologies in EDs)**:

  ("eating disorder" OR "eating disorders" OR anorexi* OR bulimi* OR "binge eating" OR ARFID OR OSFED) AND ("digital health" OR eHealth OR mHealth OR telehealth OR "mobile app*" OR smartphone OR "internet-based" OR "web-based" OR online OR "virtual reality" OR VR OR "social media" OR "self-help" OR "guided self-help" OR "just-in-time" OR JITAI OR "ecological momentary" OR EMA)

- **Search B (AI in EDs, excluding chatbots)**:

  ("eating disorder" OR "eating disorders" OR anorexi* OR bulimi* OR "binge eating" OR ARFID OR OSFED) AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR NLP OR "computer vision" OR "predictive model*" OR classification OR detection OR "social media") NOT (chatbot* OR "conversational agent*" OR "dialog system*")

- **Search C (Chatbots in EDs)**:

  ("eating disorder" OR "eating disorders" OR anorexi* OR bulimi* OR "binge eating" OR ARFID OR OSFED) AND (chatbot* OR "conversational agent*" OR "virtual agent*" OR "dialog system*" OR "conversational AI")

The final search was conducted on 29 December 2025. Search details, active filters (Year, Language, Source Type), and contributing collections were logged to ensure reproducibility (Aromataris et al., 2024).

2.5. Record management and deduplication

Retrieved citations were aggregated and deduplicated. Initial deduplication employed a conservative rule-based algorithm (matching DOIs where available; otherwise matching normalized titles, years, and first authors). The dataset was subsequently imported into Rayyan for a second pass of duplicate detection, where flagged records were manually verified and resolved.

[1] https://www.sida.unict.it/content/primo-ve

2.6. Screening and prioritization strategy

Given the volume of retrieved literature, a two-step screening process assisted by Large Language Models (LLM) was adopted to balance efficiency and rigor.

LLM-assisted prioritization. An offline LLM[2] was deployed to rank the deduplicated corpus based on title, abstract, and keywords. The model provided a relevance score used strictly to *order* records for human screening; it did not autonomously exclude studies. This "human-in-the-loop" workflow aligns with emerging guidance on AI in evidence synthesis, treating the LLM as a decision-support tool rather than a replacement (Flemyng et al., 2025; Hamel et al., 2021; O'Mara-Eves et al., 2015; Sanghera et al., 2025).

Selection and validation. The top-ranked records were screened manually at the title/abstract level against the PCC eligibility criteria by the primary reviewer. To verify and strengthen the selection process, all title/abstract decisions for the prioritized set were independently rescreened in a blinded manner by two co-authors. Disagreements (n = 140) were adjudicated by an additional co-author who was not involved in the initial screening decisions; this adjudicator manually reviewed each conflicting record and validated the final inclusion/exclusion decision.

All records retained after title/abstract screening, including the set of concordant inclusions, underwent full-text assessment, with full-text eligibility decisions independently verified by the same adjudicating co-author. In addition, to evaluate the risk of missing eligible literature in the non-prioritized pool, two sequential blinded quality-control audits were conducted by a separate co-author who had not participated in the Primo VE search, nor in the screening/validation of the prioritized set. The audit outcomes are reported in the Results section.

2.7. Data charting and synthesis

Data were extracted using a standardized form capturing: bibliographic details, population/context, technology type, study aim, and primary outcomes. Included studies were categorized into two macro-classes: digital technologies and artificial intelligence, with chatbots as a sub-category. Findings were synthesized descriptively to map the landscape of technological applications in EDs and identify research gaps.

3. Results

3.1. Selection of sources of evidence

The systematic search across Primo VE collections yielded a total of 9390 records. After the removal of 1845 duplicates, 7545 unique records were identified for title and abstract screening. To manage this extensive corpus, the LLM-assisted prioritization strategy (described in Section 2) was applied, and human screening was focused on the top 500 ranked citations.

Within the prioritized set (n = 500), 309 records were excluded at title/abstract screening. The remaining 191 reports were sought for retrieval and all were successfully obtained for full-text assessment. After full-text review, 151 reports were excluded for the following reasons: virtual delivery of traditional therapy without a distinct digital/AI-enabled intervention component relevant to the review scope (n = 9); lack of a clear digital or AI-enabled intervention component (n = 2); redundant or overlapping reports of the same intervention/dataset (n = 89); out of scope for the review framework (e.g., wrong population, wrong concept/intervention, wrong context, wrong outcomes/aim) (n = 13); non-empirical (n = 38).

[2] https://ollama.com/library/nemotron-3-nano

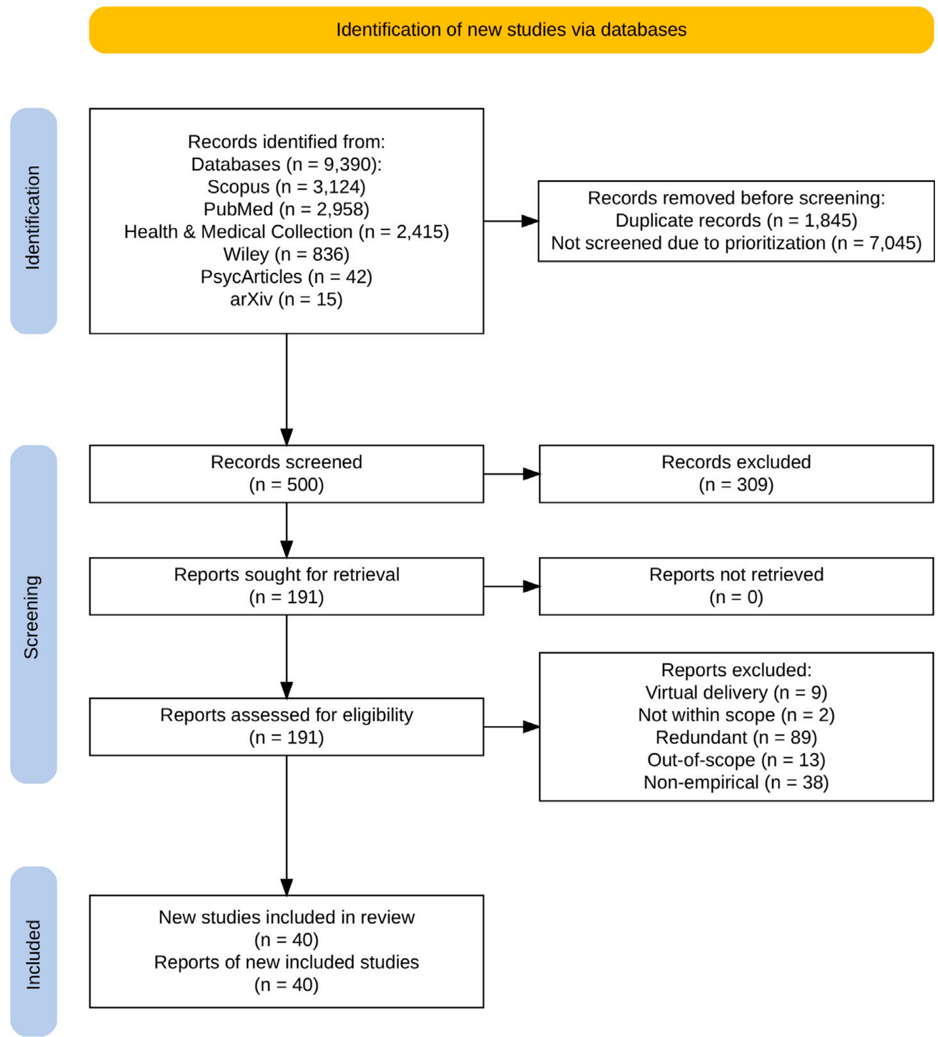

Fig. 1. Adapted PRISMA 2020 flow diagram (Page et al., 2021), generated using the Haddaway et al. (2022) PRISMA2020 tools.

Overall, 40 studies met all eligibility criteria and were included in the final synthesis. The complete selection process, including the prioritization step and the handling of the non-prioritized pool, is summarized in the PRISMA 2020 flow diagram (Fig. 1).

Validation of the prioritization strategy. To rigorously evaluate the risk of missing eligible literature within the non-prioritized pool (n =7 ,045), two sequential blinded audits were conducted by an independent co-author:

- **First Audit (QC1):** A random sample of 100 records was manually screened. 99 records were confirmed as excludable, while 1 was identified as potentially eligible (1% inclusion rate).
- **Second Audit (QC2):** An additional random sample of 50 records was screened, with 100% agreement on their exclusion (0% inclusion rate).

These results indicate a very low prevalence of eligible studies in the non-prioritized set. Using a conservative estimate based on the first audit (7,045 ×1%), approximately 70 potentially relevant records might remain in the pool, while a combined estimate (7,045 ×0.67%) suggests roughly 47. Given the scoping nature of this work and the high sensitivity of the top-ranked set, this reflects a robust and low-bias selection process.

3.2. Characteristics of included studies

The 40 included studies were grouped into two main technological domains: digital technologies (n = 20) and artificial intelligence (n = 20), with chatbot-based systems representing a notable sub-cluster within the AI domain. The full data-charting/extraction table for all included studies is reported in the Appendix (Table A.2). For a concise overview of key study characteristics (population/phenotype, primary use-case, technology family, design, and setting/data source), see Table 1. An evidence map summarizing the distribution of studies across technology families and primary clinical use-cases is shown in Fig. 2. The results are then synthesized narratively and thematically to map the current landscape of digital and AI-driven tools for eating disorders and to highlight major trends and gaps.

3.3. Critical appraisal within sources of evidence

No critical appraisal of individual sources of evidence was conducted, as this scoping review aimed to map and characterize the existing literature rather than to assess risk of bias or certainty of evidence.

3.4. Prevention, screening, and early detection

Early identification of individuals at risk of developing or maintaining EDs is a key step to reduce their burden. Traditional screening often

Table 1
Characteristics of included studies (grouped by primary use-case).

Citation	ED pop./phenotype	Use-case	Tech family	Design	Setting/data
Prediction					
Espel-Huynh et al. (2021)	Mixed ED (clinical)	Prediction	ML/NLP	Secondary analysis	Residential clinic
Forrest et al. (2023)	BED + obesity (clinical)	Prediction	ML/NLP	Secondary analysis	RCT dataset
Funk et al. (2020)	Mixed ED (college; clinical)	Prediction	ML/NLP	Technical development	University; program text
Krug et al. (2023)	AN/BN + controls (clinical)	Prediction	ML/NLP	Technical development	Multi-center clinic
Levinson et al. (2023)	Mixed ED (EMA sample)	Prediction	EMA/JITAI	Technical development	Daily life; smartphone EMA
Linardon et al. (2022)	Binge eating (community/online)	Prediction	ML/NLP	Technical development	Remote/online
McClure et al. (2025)	Binge eating (community)	Prediction	ML/NLP	Observational	Remote/online survey
Monthuy-Blanc et al. (2023)	Community (DE continuum)	Prediction	ML/NLP	Observational	Community survey
Perko et al. (2019)	Mixed ED (app users)	Prediction	EMA/JITAI	Secondary analysis	App dataset
Ryall et al. (2025)	Youth ED (clinical)	Prediction	ML/NLP	Technical development	Clinic; multi-level care
Prevention					
Levinson et al. (2025)	AN/atypical AN (clinical)	Prevention	Web/App	Feasibility/pilot	Clinic; post-treatment
Gutiérrez-Maldonado et al. (2016)	Non-clinical (undergrads)	Prevention	VR/Immersive	Feasibility/pilot	Lab
Meschberger-Annweiler et al. (2023)	Non-clinical (college women)	Prevention	VR/Immersive	Feasibility/pilot	Lab
Reddy and Reddy (2025)	Users of AI assistants	Prevention	Platform	Technical development	Synthetic evaluation
Screening					
Fitzsimmons-Craft et al. (2019)	High risk (college students)	Screening	Platform	Observational	University
Aragon et al. (2021)	Social media users (AN)	Screening	ML/NLP	Secondary analysis	Reddit
Aragón et al. (2025)	Social media users (AN-related)	Screening	ML/NLP	Secondary analysis	Reddit
Iceta et al. (2021)	Obesity (screen DE risk)	Screening	ML/NLP	Observational	Hospital
Moessner et al. (2018)	Social media users (pro-ED)	Screening	ML/NLP	Secondary analysis	Reddit
Schnepper et al. (2025)	Simulated cases (AN/BN vignettes)	Screening	ML/NLP	Technical development	Vignette-based
Yan et al. (2019)	Social media users (ED posts)	Screening	ML/NLP	Secondary analysis	Reddit
Treatment					
Blomberg et al. (2025)	AN (inpatients)	Treatment	Web/App	RCT	Inpatient
Chubinidze et al. (2025)	Restrictive AN (clinical)	Treatment	ML/NLP	Feasibility/pilot	Outpatient
Ferrer-García et al. (2017)	BN/BED (clinical)	Treatment	VR/Immersive	RCT	Clinic
Grammer et al. (2023)	Binge-type ED + high weight	Treatment	Web/App	RCT	Remote/online
Hamatani et al. (2025)	BN (outpatients)	Treatment	Web/App	RCT	Clinic outpatient
Hartmann et al. (2024)	BN (self-referred adults)	Treatment	Web/App	RCT	Remote/online
Hildebrandt et al. (2017)	BN/BED (clinical)	Treatment	Web/App	RCT	Clinic
Keizer et al. (2016)	AN + controls (clinical)	Treatment	VR/Immersive	Observational	Lab
Linardon et al. (2024)	Binge eating (community/online)	Treatment	Web/App	RCT	Remote/online
Melisse et al. (2023)	BED/OSFED-BED (clinical)	Treatment	Web/App	RCT	Specialist clinic
Monaco et al. (2024)	Mixed ED (clinical)	Treatment	Platform	Technical development	Clinical network
Ohsako et al. (2023)	BN/BED (outpatients)	Treatment	Web/App	Feasibility/pilot	Hospital outpatient
Paslakis et al. (2017)	AN/BN (clinical)	Treatment	VR/Immersive	Feasibility/pilot	Inpatient
Porras-Garcia et al. (2021)	AN (clinical)	Treatment	VR/Immersive	RCT	Day-patient clinic

(continued on next page)

Table 1 (*continued*).

Schroeder et al. (2024)	AN-R + controls (clinical)	Treatment	VR/Immersive	Observational	Lab
Serino et al. (2019)	AN (clinical)	Treatment	VR/Immersive	Feasibility/pilot	Outpatient clinic
Sharp, Dwyer, Randhawa, et al. (2025)	ED waitlist (mixed)	Treatment	Chatbot	RCT	Outpatient waitlist
Thompson, Calissano, et al. (2023)	AN (clinical)	Treatment	VR/Immersive	Feasibility/pilot	Outpatient
Treasure et al. (2025)	AN + carers (clinical)	Treatment	Web/App	RCT	Transition to community

Notes. Studies are grouped by primary use-case for display; multi-purpose studies may span more than one use-case/technology category.
Abbreviations. AN: anorexia nervosa; BN: bulimia nervosa; BED: binge-eating disorder; DE: disordered eating; EMA: ecological momentary assessment; JITAI: just-in-time adaptive intervention; RCT: randomized controlled trial.

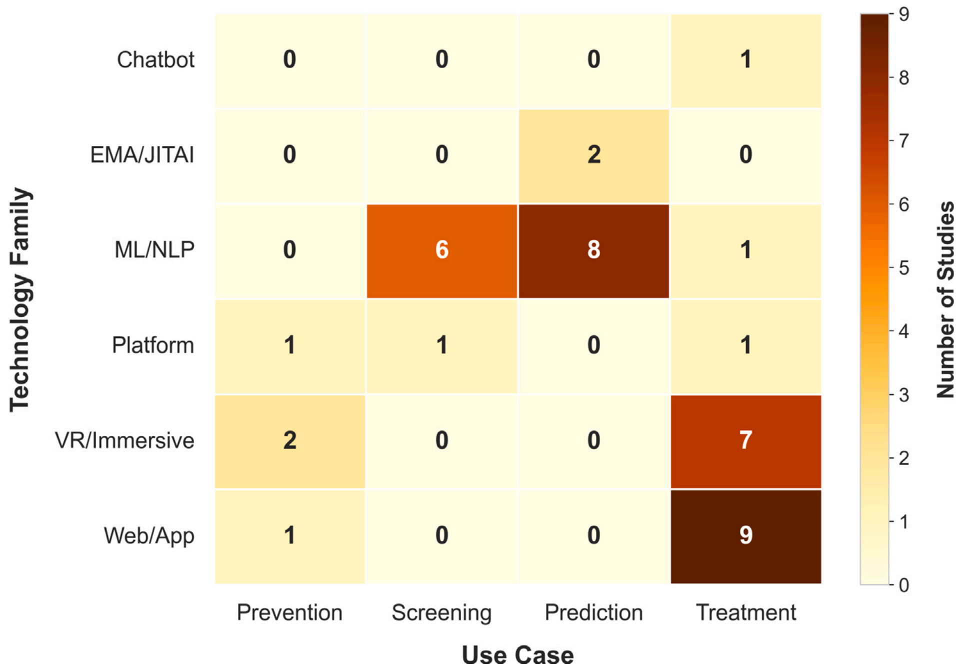

Fig. 2. Evidence map heatmap illustrating the research density across technology families and use cases. The matrix reveals that ML/NLP technologies are predominantly applied to prediction (n = 8) and screening (n = 6), whereas VR/Immersive (n = 7) and Web/App (n = 9) technologies are primarily focused on treatment interventions.

relies on retrospective self-report and cross-sectional assessment, which may miss the dynamic and multifactorial nature of ED risk and symptom trajectories. Recent digital and AI approaches aim to improve early detection by leveraging intensive longitudinal data, user-generated content, and scalable screening infrastructures. In this section, we summarize evidence across four areas: ML-based risk prediction, social media analysis, AI-assisted screening tools, and integrated screening and intervention platforms.

3.4.1. Machine learning for risk prediction

Machine learning can model nonlinear relationships, higher-order interactions, and high-dimensional predictors without prespecifying a small set of variables. Evidence to date suggests strong performance when rich within-person longitudinal data are available, but mixed results when relying mainly on baseline self-report predictors.

Using ecological momentary assessment (EMA), Levinson et al. (2023) trained a neural network to predict binge eating, restriction, and purging in a transdiagnostic ED sample (four assessments/day for 25 days), reporting high accuracy (up to 0.90) and using SHAP values to examine predictor importance across behaviors and time horizons. In contrast, McClure et al. (2025) compared nine ML classifiers to predict onset and persistence of binge eating over 8 months using baseline self-report predictors and found uniformly poor performance, with no advantage over generalized linear models. Ryall et al. (2025) reported that prediction of complex clinical course in youth improved when models incorporated both intake and discharge variables, and that random forests benefited from broader feature sets rather than only the top predictors. Finally, Krug et al. (2023) applied LASSO and prediction rule ensembles to childhood risk factors, showing good discrimination for ED versus non-ED status and more limited differentiation between anorexia nervosa and bulimia nervosa.

3.4.2. Social media analysis and early detection

Social media text provides large-scale signals that may support early identification and triage, but also raises issues around generalizability and clinical validation. Moessner et al. (2018) analyzed posts from Reddit's pro-ED forum using topic modeling, identifying recurrent themes including social support and weight-related discussions. Aragon et al. (2021) proposed fine-grained emotion representations (BoSE and Δ-BoSE) to detect anorexia- and depression-related language patterns from posting histories. Focusing on intervention needs, Yan et al. (2019) developed NLP classifiers to flag ED-related posts potentially warranting immediate support, using clinician-evaluated labels and a semi-supervised approach to reduce the need for large annotated datasets.

3.4.3. AI-assisted screening tools

AI-assisted screening aims to reduce respondent burden while preserving clinically useful information, typically through feature selection or short-form tools. Iceta et al. (2021) derived a reduced-item ML-based screening tool in a tertiary obesity setting to identify disordered-eating risk indicators linked to food addiction and emotional eating (indexed against the Yale Food Addiction Scale). Complementing item reduction, Funk et al. (2020) outlined an NLP framework for extracting information from user-generated text (e.g., diary entries) within digital interventions, moving beyond fixed questionnaires toward language-based behavioral signals.

3.4.4. Screening and intervention platforms

At the service level, integrated platforms can combine screening, triage, and delivery of tailored interventions or referrals. Fitzsimmons-Craft et al. (2019) described a university-wide implementation of an online screening and intervention platform, embedding standardized assessment with automated risk stratification and linkage to appropriate resources. These models illustrate how digital infrastructures can support population-level early detection while operationalizing referral pathways.

3.5. Digital and AI-enhanced treatment interventions

Digital interventions for EDs increasingly translate evidence-based psychotherapy into web- and app-based formats, while AI is entering the field both through predictive/precision architectures and through automated patient-facing supports (including chatbots and emerging generative-AI–assisted practices). Overall, effects appear more consistent for binge-type symptoms when interventions preserve core CBT mechanisms (e.g., self-monitoring, regular eating, relapse-prevention) and include enough structure to sustain engagement.

3.5.1. Cognitive-behavioral digital interventions

Web-based guided self-help (GSH) Enhanced Cognitive-Behavioral Therapy (CBT-E) can produce robust improvements in BED when compared with a delayed-treatment control. In a two-arm randomized controlled trial (RCT; $n = 180$), guided self-help CBT-E reduced objective binges markedly (Cohen's $d = 1.0$ between groups) and 48% achieved abstinence at end of treatment (Melisse et al., 2023).

For bulimia nervosa (BN), an unguided web-based CBT self-help intervention reduced binge eating and global ED symptoms compared with a waiting list, but showed limited impact on compensatory behaviors, suggesting that unguided formats may not fully address the behavioral breadth of BN (Hartmann et al., 2024). In contrast, culturally adapted guided internet-based CBT in Japan suggests that adding clinician support can be feasible and clinically relevant: a pilot mixed BN/BED (where BED stands for *binge-eating disorder*) outpatient study reported acceptability and safety, with a 25% abstinence rate and no adverse events (Ohsako et al., 2023), and an RCT in Japanese women found superior reduction in the combined frequency of binge eating and compensatory episodes versus usual care (Hamatani et al., 2025).

Mobile tools can strengthen core CBT processes by reducing friction in daily self-monitoring. In an RCT ($n = 66$; BED or BN), a smartphone-assisted CBT-GSH condition produced a greater reduction in objective bulimic episodes relative to traditional CBT-GSH, while remission rates were not significantly different; importantly, the smartphone-assisted arm showed higher meal/snack adherence, and regular meal adherence mediated effects on objective bulimic episodes (Hildebrandt et al., 2017).

3.5.2. Combined digital interventions for high body weight

When binge-type EDs co-occur with high body weight, digital programs have explored combining CBT for ED symptoms with behavioral weight loss (BWL) content, but short-term weight change remains difficult to obtain. In young adults ($n = 60$), an online guided self-help CBT+BWL intervention reduced ED psychopathology, but did not yield superior weight outcomes versus CBT-only, indicating that symptom change and weight loss may require different (or longer) digital optimization (Grammer et al., 2023).

3.5.3. Virtual reality and immersive technologies

VR interventions target ED mechanisms by combining controlled exposure, embodiment, and measurement-rich behavioral readouts in ecologically plausible contexts. Embodiment-based approaches in anorexia nervosa (AN) include VR Full Body Illusion protocols improving body size estimation (Keizer et al., 2016) and "body swapping" approaches aiming to update distorted body representations (Serino et al., 2019); extending these principles to treatment, a randomized trial (AN-VR-body-exposure) found that VR-based body exposure reduced fear of gaining weight and body image disturbances relative to treatment-as-usual (Porras-Garcia et al., 2021).

For binge-type EDs, VR has been used to support cue exposure by eliciting and reducing craving with virtual food stimuli; validation work suggests both immersive and lower-cost non-immersive systems can be viable for craving reduction (Gutiérrez-Maldonado et al., 2016). In treatment-resistant BN/BED, VR cue exposure has also been tested as a second-level approach, showing advantages over additional CBT on key outcomes such as binge/purge abstinence and craving/anxiety reductions (Ferrer-García et al., 2017).

Recent immersive paradigms also target specific ED-relevant processes beyond eating episodes. For example, VR "jogging" exposure has been proposed to habituate the acute urge to be physically active in ED patients, supporting symptom-focused management of compulsive exercise drives (Paslakis et al., 2017). VR has additionally been integrated with eye-tracking in an attentional bias modification task (ABMT), showing preliminary ability to reduce attentional bias toward weight-related body areas (Meschberger-Annweiler et al., 2023), while motion-tracking tasks provide objective evidence of persistent avoidance tendencies toward virtual food in restrictive AN (Schroeder et al., 2024).

Finally, avatar-based relational techniques are being adapted from psychosis to AN: a case series testing AVATAR therapy (externalizing and dialoguing with an eating-disorder avatar) found feasibility, acceptability, and safety, with preliminary improvements in distress related to the eating-disorder voice and self-compassion (Thompson, Calissano, et al., 2023).

3.5.4. AI-powered personalization and prediction

AI in ED care is currently most visible in proposals that integrate heterogeneous clinical and real-world data streams to support precision approaches (risk modeling, treatment planning, relapse prediction), potentially coupled with patient-facing chatbot support (Monaco et al., 2024). Empirical comparisons of ML versus traditional regression for predicting ED outcomes suggest that incremental gains can be small and that predictive performance may remain limited for some outcomes, questioning whether model complexity alone solves clinical prediction constraints (Espel-Huynh et al., 2021; Forrest et al., 2023).

Beyond prediction, AI-mediated interventions can also serve as scalable bridges to care. A recent RCT evaluated a rule-based chatbot delivering a single-session intervention (ED ESSI) for people on waitlists, reporting greater reductions in ED pathology and distress symptoms versus a control condition and higher subsequent treatment uptake (Sharp, Dwyer, Randhawa, et al., 2025). In parallel, early clinical work is exploring generative AI as a tool for expression and engagement: an AI-assisted visual elicitation protocol using DALL·E 3 was piloted in AN qualitative case studies to support emotional externalization and therapeutic engagement within a therapist-led structure (Chubinidze et al., 2025).

3.5.5. Specialized digital applications

Beyond CBT translations, skills-based smartphone programs can disseminate structured therapeutic content at scale for binge-spectrum problems, though sustained engagement remains a limitation. In a large remote RCT for recurrent binge eating, a self-guided Dialectical-Behavior Therapy skills app produced greater reductions than waitlist in objective binge episodes and global ED psychopathology at 6 weeks, with maintenance/improvement at follow-up but substantial dropout and declining engagement (Linardon et al., 2024).

In AN, not all mobile cognitive-training approaches show additive benefit. In an inpatient RCT, smartphone-based approach–avoidance bias modification training for food cues did not outperform sham or treatment-as-usual on ED psychopathology, BMI, or fear of food (Blomberg et al., 2025). Finally, ML-based clustering has been used to derive multi-dimensional "eater profiles", offering a path toward matching digital components to cross-diagnostic patterns rather than only DSM categories (Monthuy-Blanc et al., 2023).

3.6. Social media: Risk amplification and intervention opportunities

Social media exposure is increasingly recognized as a contextual risk factor for disordered eating, with effects that extend beyond adolescence. In a sample of middle-aged women, overall frequency of use was not the primary correlate of eating psychopathology; rather, appearance- and body-related social comparison processes showed robust associations with multiple indicators of disordered eating, with Instagram emerging as the platform most specifically linked to dietary restriction (Thompson et al., 2023b). This pattern aligns with a broader view in which core maintaining processes (e.g., restriction and binge-related dynamics) are central nodes within eating-disorder symptom networks, suggesting that interventions should prioritize these mechanisms over platform-specific exposure metrics (Perko et al., 2019). At the same time, social media can function as a scalable channel for support and recovery-oriented engagement. Pro-recovery communities on TikTok show heterogeneous representations of recovery across diagnosis-specific hashtags, combining peer support with narratives that may also shape expectations and social comparison (e.g., implicit control strategies vs explicit critique of diet culture) (Greene et al., 2023).

AI methods further extend the intervention and monitoring space by enabling detection of risk signals from user-generated content. Language-model approaches have been used to identify anorexia-related patterns and to support cross-condition detection, suggesting potential utility for surveillance, triage, and progress monitoring, while also raising requirements for transparency, validation on clinical datasets, and ethical governance (Aragón et al., 2025).

3.7. Methodological considerations and comparative effectiveness

Across studies that use AI/ML to predict eating-disorder outcomes, a recurring finding is that greater model complexity does not automatically yield clinically meaningful gains over traditional statistical approaches. In adults with binge-eating disorder and obesity, machine-learning models (e.g., elastic net, random forest) achieved predictive performance that was broadly comparable to regression models, with early response and psychosocial variables (e.g., emotion regulation and stigma-related factors) among the most informative predictors (Forrest et al., 2023). Similarly, in residential treatment samples, machine-learning models did not clearly outperform simpler regression approaches when relying mainly on baseline clinical variables and early symptom change, implying that benefits may depend on larger datasets and richer longitudinal/process information (Espel-Huynh et al., 2021).

This emphasis on process data is particularly relevant for digital interventions, where engagement traces can be directly measured. In self-guided digital interventions, prediction of uptake, adherence, and dropout from baseline variables alone was weak, whereas incorporating intervention-usage variables substantially improved prediction of engagement outcomes, supporting the integration of digital phenotyping and in-treatment markers into predictive pipelines (Linardon et al., 2022). Consistently, comparative work on delivery modality indicates that shared recovery markers (e.g., improvements in eating-disorder-specific quality of life and anxiety-related factors) may generalize across online and face-to-face CBT, while some predictors appear modality-specific, underscoring the need for personalization when choosing digital versus traditional care pathways (Matherne et al., 2022).

3.8. Ethical, safety, and bias considerations

The clinical deployment of AI in eating disorders requires explicit attention to fairness, safety engineering, and accountability. Large language models can reproduce biases in assessment-like outputs; for example, gender-related bias has been observed in mental health quality-of-life estimates generated from eating-disorder case vignettes, highlighting risks of inequitable downstream decision support (Schnepper et al., 2025). In parallel, safety failures in health-adjacent chatbots illustrate that harm can occur without robust guardrails; a modular approach combining deterministic filters with in-line LLM policy checks has been proposed to enforce fail-closed behavior and escalation pathways aligned with governance frameworks (Reddy & Reddy, 2025).

Beyond risk mitigation, digital interventions may support continuity of care, including relapse prevention, when grounded in established mechanisms and delivered with sufficient clinical integration. Exposure-based digital modules adapted from anxiety interventions have been proposed to target eating-disorder fears (e.g., food, weight gain via imaginal exposure, interoceptive cues, and social fears), aiming to improve accessibility and post-discharge support (Levinson et al., 2025). However, effectiveness is not guaranteed: in a large pragmatic evaluation of a digital aftercare augmentation for anorexia nervosa involving patient–carer dyads, adding the intervention to usual care did not yield significant improvements and was not cost-effective, with low adherence emerging as a key implementation bottleneck (Treasure et al., 2025).

4. Discussion

This scoping review maps recent evidence on digital and AI-enabled approaches for eating disorders across prevention, screening, prediction, monitoring, and treatment, highlighting both clinically evaluated interventions and a substantial body of technical and secondary-analytic work (Aromataris et al., 2024; Tricco et al., 2018). An overview of the populations examined across the included studies can be seen in Fig. 3.

4.1. Summary of evidence and interpretation

Across prevention and early detection, the literature converges on two complementary directions: (i) NLP-based models for risk identification using social media and other user-generated text, and (ii) screening infrastructures that integrate assessment, triage, and referral logic in real-world settings (Aragon et al., 2021; Fitzsimmons-Craft et al., 2019; Moessner et al., 2018; Yan et al., 2019). At the same time, AI-assisted screening proposals emphasize feasibility and respondent-burden reduction, but their clinical utility depends on validation, transparency of decision rules, and careful definition of intended use (Funk et al., 2020; Iceta et al., 2021).

For prediction and monitoring, EMA-based and longitudinal modeling illustrates the promise of short-horizon symptom forecasting, yet other prospective settings still report limited performance gains over simpler models, suggesting that data quality, feature richness, and temporal granularity are often more decisive than algorithmic complexity

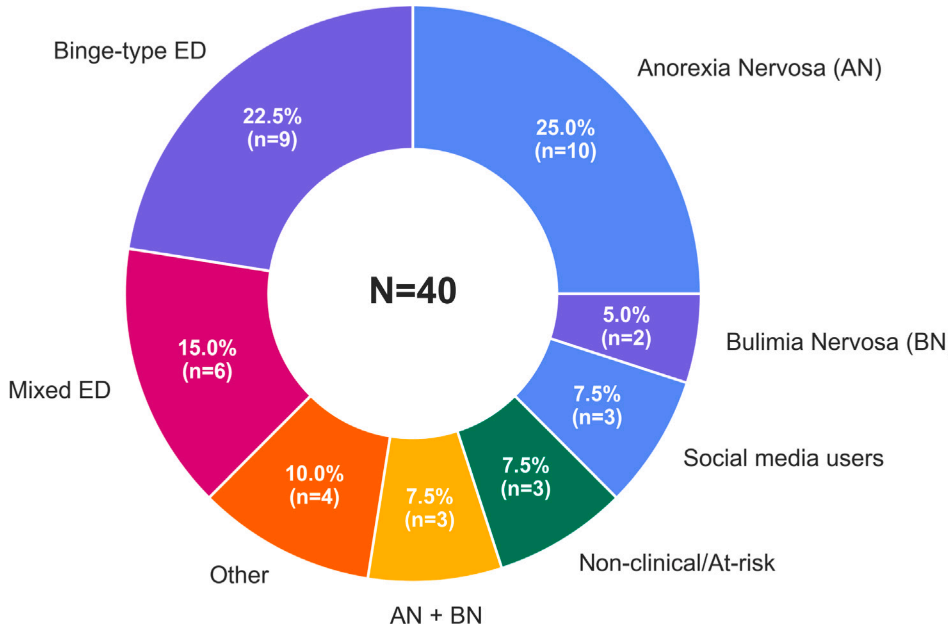

Fig. 3. Donut chart illustrating the eating disorder populations/phenotypes targeted in the included studies. Anorexia Nervosa (25.0%) and Binge-type EDs (22.5%) are the most studied phenotypes, while non-clinical or at-risk populations account for a smaller proportion (7.5%).

alone (Espel-Huynh et al., 2021; Forrest et al., 2023; Levinson et al., 2023; McClure et al., 2025; Ryall et al., 2025). This pattern supports a pragmatic view of AI in ED care as decision support rather than autonomous clinical decision-making (Monaco et al., 2024).

For treatment, evidence is strongest where digital delivery preserves core evidence-based mechanisms (e.g., structured CBT components) and where interventions are evaluated in controlled designs (Hamatani et al., 2025; Hartmann et al., 2024; Hildebrandt et al., 2017; Melisse et al., 2023). Immersive and VR paradigms also show clinically relevant signals for body-image and cue-exposure targets, but require resources and implementation expertise that may limit scalability outside specialist contexts (Ferrer-García et al., 2017; Paslakis et al., 2017; Porras-Garcia et al., 2021; Serino et al., 2019). Finally, patient-facing automation is emerging in both rule-based chatbot trials and early generative-AI–assisted protocols; these directions are promising but should be framed within explicit safety constraints and escalation pathways (Chubinidze et al., 2025; Sharp, Dwyer, Randhawa, et al., 2025).

4.2. Implications for design and implementation

A recurring implementation challenge is engagement: even when symptom improvements are observed, adherence and sustained use can be difficult to maintain in self-guided formats, supporting hybrid models where digital components are paired with clinician or coach support when feasible (Hamatani et al., 2025; Linardon et al., 2024; Ohsako et al., 2023). From a design perspective, integrating acceptance and engagement frameworks (e.g., TAM and persuasive design principles) may help align usability with clinical goals, especially for tools intended for preventive or long-term use (Marangunić & Granić, 2015; McCall et al., 2021; Wang et al., 2023). At the service level, scalable screening platforms illustrate how digital systems can operationalize triage and referral, but they also shift the bottleneck to downstream care capacity and governance (i.e., what happens after identification) (Fitzsimmons-Craft et al., 2019).

4.2.1. Lived experience and co-production

Beyond usability and clinical efficacy, the design and deployment of digital and AI-enabled ED tools should incorporate co-production with people with lived experience of eating disorders, alongside clinicians, researchers, digital experts, and regulators. This is particularly important for defining acceptable risk thresholds, safety features (e.g., crisis escalation and content moderation), and equity-sensitive design choices that can influence uptake and unintended harms. Co-designed evaluation outcomes (e.g., perceived safety, autonomy, and trust) may also improve interpretability of engagement metrics and support workflow-integrated implementation in real-world services.

Beyond usability and clinical efficacy, the design and deployment of digital and AI-enabled ED tools should incorporate co-production with people with lived experience of eating disorders, alongside clinicians, researchers, digital experts, and regulators (Brotherdale et al., 2024; Sharp, Dwyer, Xie et al., 2025). This is particularly important for defining acceptable risk thresholds and safety features (e.g., crisis escalation pathways), and for anticipating and mitigating unintended harms (Lawrence-Sidebottom et al., 2024; Miller et al., 2023; Sharp, Dwyer, Xie et al., 2025). Equity-sensitive design choices (e.g., partnering with diverse stakeholders, addressing digital divide barriers, and monitoring potential bias) can influence both uptake and differential benefit across groups (Brotherdale et al., 2024; Miller et al., 2023). Co-designed evaluation outcomes (e.g., perceived safety, autonomy, and trust), alongside standard engagement metrics, may improve interpretability of real-world use and support workflow-integrated implementation in services (Brotherdale et al., 2024; Miller et al., 2023).

4.3. Limitations

This review has limitations. First, the evidence base is heterogeneous (technical development, secondary analyses, feasibility studies, and RCTs), and we did not conduct a critical appraisal of individual sources, consistent with the aim of mapping and characterizing the field (Tricco et al., 2018). Second, our process constraints (English-only,2015–2025, peer-reviewed sources; preprints screened but excluded) may have reduced coverage of fast-moving AI work (Aromataris et al., 2024). Third, to manage the large corpus we used LLM-assisted prioritization to order records for screening (not to automate exclusion), and although blinded audits suggested a low prevalence of eligible studies in the non-prioritized pool, some eligible literature may still have been missed (Flemyng et al., 2025).

5. Conclusions

Digital and AI-enabled approaches for eating disorders now target prevention, screening, prediction, monitoring and treatment, but many technically sophisticated tools still lack translation into coherent, end-to-end care pathways. The most relevant next steps are to strengthen external validation and reporting, evaluate these tools in pragmatic, workflow-integrated studies, and implement clear safety and governance for automated systems, alongside longitudinal evaluations of engagement, sustainability and costs; where evidence within specific subdomains becomes sufficiently mature, focused systematic reviews should then be considered.

CRediT authorship contribution statement

Mirko Casu: Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Lucrezia Marletta:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Claudio Vittorio Ragaglia:** Writing – review & editing, Validation, Supervision. **Pasquale Caponnetto:** Supervision. **Sebastiano Battiato:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation.

Declaration of competing 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.

Appendix. Section

This appendix provides the complete data extraction table for all 40 studies included in the scoping review. Table A.2 summarizes key details for each study, including the paper title, authors and publication year, population and context, technology type and aim, and main outcomes.

Table A.2
Data extraction table summarizing key details from studies included in this review: paper title, authors and year, population and context, technology and aim, and main outcomes. Rows are ordered alphabetically.

Title	Author(s) & Year	Population/Context	Technology & Aim	Main outcomes
A Framework for Applying Natural Language Processing in Digital Health Interventions	Funk et al. (2020)	College women with eating disorders using guided self-help program	NLP framework to extract text features and predict engagement and symptom change in digital health interventions	NLP models modestly predicted binge eating episodes and provided preliminary evidence that text features relate to symptom reductions.
A Randomized Controlled Comparison of Second-Level Treatment Approaches for Treatment-Resistant Adults with Bulimia Nervosa and Binge Eating Disorder	Ferrer-García et al. (2017)	Adults with BN or BED who remained symptomatic after individual CBT in specialist ED centers in Spain and Italy	VR-based cue exposure therapy via immersive food environments as second-level treatment to reduce craving and binge/purge behavior	VR-CET led to higher abstinence from binge eating (53% vs 25%) and purging (75% vs 31.5%), larger reductions in binge frequency, ED symptoms, anxiety, and food craving vs additional CBT
A Virtual Reality Full Body Illusion Improves Body Image Disturbance in Anorexia Nervosa	Keizer et al. (2016)	Adult women with AN in specialist ED treatment and healthy controls in laboratory VR setting	Immersive VR full body illusion with synchronous/asynchronous visuo-tactile stimulation of healthy-BMI avatar to modulate distorted body size experience	AN patients showed reduced overestimation of shoulder, abdomen, and hip size immediately after illusion, partially maintained at ~2h45 follow-up.
A case series to test the acceptability, feasibility and preliminary efficacy of AVATAR therapy in anorexia nervosa	Thompson, Calissano, et al. (2023)	Adults with AN receiving ongoing outpatient treatment or professional check-ins	AVATAR therapy using voice-transformation software to create and dialogue with digital representation of the ED voice to increase autonomy and self-compassion	AVATAR therapy was feasible, acceptable, and safe with high completion rates, significant reductions in voice-related distress, and increased self-compassion but no consistent ED symptom changes.
A dialectical behavior therapy skills training smartphone app for recurrent binge eating	Linardon et al. (2024)	Adults with recurrent binge eating recruited online, enrolled in fully remote RCT	Self-guided DBT-based app delivering skills modules, brief exercises, and digital diary cards to reduce binge eating	Compared to waitlist, app produced medium–large reductions in objective binge episodes and ED psychopathology at 6 weeks, further improvements by 12 weeks, with minimal adverse effects despite high attrition.
A pilot trial of an online guided self-help CBT program for bulimia nervosa and binge eating disorder in Japanese patients	Ohsako et al. (2023)	Female outpatients aged 16–40 with BN or BED in Japanese hospital settings	Internet-based guided self-help CBT program with weekly email support	No serious adverse events; 25% abstinent from bulimic behaviors, 75% with ≥25% binge reduction, 11.1% dropout at 16 weeks.
A proof-of-concept study applying machine learning methods to putative risk factors for eating disorders	Krug et al. (2023)	1402 participants (588 ED patients: AN and BN; 760 healthy controls) from six specialist centers across five European countries	Supervised ML (LASSO, prediction rule ensembles) applied to childhood risk factors to predict ED presence and AN vs BN diagnosis	ML models showed good accuracy for ED vs non-ED and fair accuracy for AN vs BN, achieving more parsimonious models than logistic regression.
AN-VR-BE. A Randomized Controlled Trial for Reducing Fear of Gaining Weight in Anorexia Nervosa through VR Body Exposure	Porras-Garcia et al. (2021)	Adolescent and adult AN patients in day-patient ED programs in Spanish hospitals	Immersive VR embodiment-based body exposure with progressive BMI increases in personalized avatar to target fear of weight gain	VR body exposure plus TAU led to greater reductions in fear of weight gain and body image disturbances than TAU alone, with some effects maintained at 3-month follow-up.
Adapting digital anxiety treatments to reduce anorexia nervosa relapse	Levinson et al. (2025)	Adults with AN/atypical AN in ED specialty care or post-treatment	Digital CBT exposure modules (FED-F) adapted from STAND anxiety program to target ED-specific fears (food, weight gain, social, interoceptive)	Feasibility study demonstrated strong overlap between ED and anxiety fears; adapted modules proposed as scalable digital approach for AN relapse prevention.
Adapting language models for mental health analysis on social media	Aragón et al. (2025)	Reddit users posting about anorexia, depression, gambling disorder, and self-harm	Transformer-based language models (BERT/RoBERTa) adapted with Reddit data to detect early risk of four mental disorders	Domain-adapted models achieved higher F1 than generic models, showed good early-risk detection, and maintained competitive cross-domain transfer.
An Attentional Bias Modification Task through VR and Eye-Tracking to Enhance Anorexia Nervosa Treatment	Meschberger-Annweiler et al. (2023)	Healthy college women in VR lab embodied in personalized avatar	VR with eye-tracking to deliver body-related attentional bias modification task	VR-based ABMT significantly reduced attentional bias after 150-225 trials, with acceptable but improvable usability.

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Table A.2 (*continued*).

An advanced AI platform for personalized treatment of Eating Disorders	Monaco et al. (2024)	Individuals with ED treated in Campania Region psychiatric network, centered on Regional Center in Salerno	Integrated AI platform using ML/DL, multimodal data, and chatbot to support personalized diagnosis, treatment planning, and relapse prediction	Anticipated outcomes include more accessible care, enhanced personalization, improved engagement, better waitlist management, and strengthened care coordination.
An AI-derived tool to ease disordered eating screening in people with obesity	Iceta et al. (2021)	Adults with severe obesity hospitalized for metabolic and bariatric assessment	ML-based 3-item nomogram (FAST) to rapidly screen for emotional eating/food addiction risk	Three items on emotional eating predicted positive YFAS diagnosis with acceptable AUC and F1.
An exploratory application of ML to optimize prediction of responsiveness to digital ED interventions	Linardon et al. (2022)	Adults with recurrent binge-eating enrolled in self-guided digital CBT-based interventions	Supervised ML using baseline and usage data to predict uptake, adherence, dropout, and symptom change	Baseline-only models showed poor prediction; adding usage variables improved adherence/dropout prediction but not symptom-change prediction.
Analyzing big data in social media: Text and network analyses of an eating disorder forum	Moessner et al. (2018)	Users of Reddit r/proed forum, a pro-ED online community	Big-data analysis using text mining (LDA) and social network analysis to characterize topics and community structure	LDA identified nine main topics; SNA showed few highly central users driving activity; users' support language was associated with neighbors'.
Application of ML to Prediction of Onset and Persistence of Binge Eating	McClure et al. (2025)	Adults self-selected online, surveyed at baseline and 8-month follow-up	Supervised ML classifiers trained on 39 baseline variables to predict onset and persistence of binge eating	ML models showed poor to fair discrimination (AUC ≈ 0.61 onset, 0.59 persistence), not outperforming regression.
Application of network analysis to investigate sex differences in ED psychopathology	Perko et al. (2019)	Adults with AN, BN, BED, or OSFED using Recovery Record app (N=1348; 50% men)	Smartphone app symptom monitoring analyzed with network analysis to examine sex differences in ED symptom interconnections	Binge eating and restricting were most central in both sexes; network structure was similar but connections were stronger in women.
Applying ML to Predict Complex Clinical Course in Youth With Eating Disorders	Ryall et al. (2025)	Youth aged ≤18 years treated across multiple care levels at CHEO Eating Disorders Program	Supervised ML using intake and discharge data to predict risk of complex clinical course	Random forest showed fair discrimination (AUC ≈ 0.72); inclusion of discharge variables, especially weight change, substantially improved prediction.
AI-assisted visual elicitation in anorexia nervosa	Chubinidze et al. (2025)	Adults with restrictive AN in specialist outpatient therapy; two case studies	AI image-generation (DALL·E v3) to co-create visual metaphors from patients' sensory narratives for therapeutic reflection	AI-assisted visual elicitation was feasible, helped externalize emotions, evoked embodied responses, and appeared to enhance insight and engagement.
Automatic detection of ED-related social media posts that could benefit from intervention	Yan et al. (2019)	Reddit users posting in six ED-related subreddits	ML and NLP classification to flag posts suggesting immediate risk of disordered eating	With only 53 labeled examples, best models identified intervention-worthy posts with 4% error rate in top-50.
Binge Eating, Purging, and Restriction Symptoms: Increasing Prediction Accuracy Using ML	Levinson et al. (2023)	Adults with transdiagnostic EDs completing smartphone EMA over 25 days	Supervised ML applied to intensive longitudinal EMA data to predict behaviors up to 12 h ahead	Models achieved high accuracy (≈ 0.76-0.96) for predicting binge eating, restriction, and purging.
Cue-exposure software for bulimia nervosa and binge eating disorder	Gutiérrez-Maldonado et al. (2016)	Non-clinical undergraduates exposed to food-related VR in laboratory	VR cue-exposure (immersive HMD vs non-immersive 3D laptop) to reduce food craving	One-session VR-CET significantly reduced craving with similar efficacy for both systems.
Detecting Mental Disorders Through Emotional Patterns - Anorexia and Depression	Aragon et al. (2021)	Reddit users with self-declared diagnosed depression or anorexia vs random controls	Emotion-lexicon-based sub-emotion modeling to detect disorders from posts	Fine-grained emotion representations outperformed BoW, BoE, LIWC, and deep models; late fusion achieved competitive F1 scores.
Digital augmentation of aftercare for patients with anorexia nervosa: TRIANGLE RCT	Treasure et al. (2025)	Adults with severe AN and carers during transition from UK inpatient/day services to community	Web-based ECHOMANTRA aftercare with videos, materials, and facilitated online patient-carer group chats	No significant effect on patient distress or outcomes at 12–18 months; higher costs and fewer QALYs than usual care despite positive feedback.
Efficacy of Web-Based Guided Self-help CBT-Enhanced for BED: RCT	Melisse et al. (2023)	Adults with DSM-5 BED or OSFED-BED, BMI 19.5-40, treated in Dutch specialist center	Web-based guided self-help CBT-E with online materials and telephone support	Guided self-help CBT-E significantly reduced binges and EDE scores vs control at 12 weeks, with higher recovery rates; benefits persisted at follow-up.
Evaluation of combined online intervention for binge-type EDs and high body weight	Grammer et al. (2023)	Young adults with binge-type EDs and BMI ≥25 randomized to CBT-only vs CBT+BWL	Online guided self-help CBT via Qualtrics, with/without behavioral weight loss	Both reduced ED attitudes, binges, and compensatory behaviors but produced no significant weight loss.
Exploring Biases of LLMs in Mental Health: Gender and Sexual Orientation in AN and BN	Schnepper et al. (2025)	Case vignettes of adults with AN or BN adapted for gender and sexual orientation	LLMs (ChatGPT-4 and MentaLLaMA) to rate HRQoL and ED measures from vignettes	ChatGPT-4 showed small gender bias in mental HRQoL with lower estimates for males; MentaLLaMA produced unreliable results.
From avatars to body swapping: VR for body-size distortion in anorexia	Serino et al. (2019)	Adult woman with AN in intensive multidisciplinary outpatient treatment, 1-year follow-up	Immersive VR full body illusion with synchronous/asynchronous visuotactile stimulation	VR body swapping partially reduced initial size overestimation, tracked improvements in multisensory integration, showed feasibility as adjunct tool.
Guided Internet-Based CBT for Women With Bulimia Nervosa: RCT	Hamatani et al. (2025)	Japanese female outpatients aged 13-65 with BN, BMI ≥ 17.5	Guided internet-based CBT with asynchronous messaging, culturally adapted modules over 12 weeks	Guided ICBT plus usual care significantly reduced weekly episodes vs usual care (d ≈ 0.7) and yielded higher remission rates.
ML vs traditional regression predicting treatment outcomes for BED from RCT	Forrest et al. (2023)	Adults with BED and obesity in RCT of behavioral weight-loss vs stepped-care treatment	Supervised ML (elastic net, random forests) vs regression to predict outcomes	ML showed minimal advantage over regression, with overall limited accuracy (AUC up to 0.73, low R^2).
Persistent avoidance of virtual food in AN-restrictive type: Motion tracking in VR	Schroeder et al. (2024)	Young female patients with acute AN-R and healthy controls in lab-based VR task	Immersive VR with motion-tracked hand movements in stop-signal task to examine food avoidance vs inhibitory control	AN-R patients showed persistently reduced approach to virtual food and lower stop error rates, indicating generalized avoidance alongside heightened inhibitory control.
Prediction of ED treatment response trajectories via ML vs regression	Espel-Huynh et al. (2021)	Adolescent girls and adult women in residential ED treatment at two U.S. facilities	Supervised ML (SVM, kNN) vs multinomial logistic regression using early monitoring data to predict trajectory class	Logistic regression using three early indicators achieved excellent accuracy (AUC ≈ 0.93), with no gain from ML.

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Table A.2 (*continued*).

Preventing Another Tessa: Modular Safety Middleware for Health-Adjacent AI Assistants	Reddy and Reddy (2025)	Users seeking support for EDs and body image concerns in mental health helpline/chatbot	Modular safety middleware combining lexical gates and LLM policy filter to enforce safety policies	Hybrid middleware achieves perfect interception of unsafe prompts in synthetic evaluations with low cost/latency.
RCT comparing smartphone assisted vs traditional guided self-help for binge eating	Hildebrandt et al. (2017)	Adults with BN or BED from specialty ED clinic treated with CBT-guided self-help	Smartphone app (Noom Monitor) to digitize CBT-GSH self-monitoring and enhance adherence	CBT-GSH+Noom led to greater reductions in binges and higher remission at end-of-treatment, mediated by meal adherence, but benefits not maintained at 6-month follow-up.
Smartphone approach-avoidance bias modification training for AN - RCT	Blomberg et al. (2025)	Inpatients aged ≥16 with AN in specialized inpatient treatment in Germany	Smartphone approach-avoidance bias modification training with food cues as adjunct to TAU	Active ABMT did not outperform sham or no training on ED psychopathology, BMI, or bias.
State-Wide University Implementation of Online Platform for ED Screening and Intervention	Fitzsimmons-Craft et al. (2019)	College students in Missouri public universities in state-wide ED screening initiative	Web- and mobile-based CBT platform integrating screening with tailored interventions and referrals	Reached 2500 students over three years; over half screened at high risk, intervention uptake 44%–51%, app use associated with significant reductions in restrictive eating and binge eating.
The Effectiveness of a Chatbot Single-Session Intervention for People on ED Treatment Waitlists: RCT	Sharp, Dwyer, Randhawa, et al. (2025)	Adolescents and adults (≥16 years) on outpatient waitlists for ED treatment in Australia	Rule-based web chatbot (ED ESSI) delivering 30-minute CBT-E-based single-session with assessment and psychoeducation	Chatbot produced greater reductions in ED pathology, impairment, depression, and anxiety vs web sheets, increased confidence to change, and higher treatment uptake (93% vs 70%).
VR jogging as exposure paradigm for acute urge to be physically active in EDs	Paslakis et al. (2017)	Adult female inpatients with AN or BN in behavioral treatment	Immersive 3D VR jogging exposure to elicit and habituate acute urge to be physically active	Single-session VR exposure was feasible, well accepted, and produced small but significant reduction in urge to exercise.
Web-Based CBT for Bulimia Nervosa: RCT	Hartmann et al. (2024)	Adults (18–65) with BN, German-speaking, recruited via online self-referral	Web-based unguided CBT self-help (12-week modular platform)	Produced moderate reductions in binge-eating episodes, ED symptoms, and impairment vs waiting-list but no significant change in compensatory behaviors or well-being.
When Eating Intuitively Is Not Always Positive: Using ML to Unravel Eater Profiles	Monthuy-Blanc et al. (2023)	317 community participants in Canada during COVID-19 pandemic	ML-based clustering to identify and validate eater profiles along functional-dysfunctional continuum	Seven-cluster model revealed distinct patterns of body dissatisfaction, bulimic/restraint behaviors, and intuitive eating.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.chbr.2026.100963.

Data availability

No data was used for the research described in the article.

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