International symposium on mental health at EU parliament .

Date : 10 October 2025

1. European Medical Association .

2. Hand in hand foundation

3. Röhrig Institute

4. AAH Natürlich – GmbH

Aim : To sensitize the need of assessing food allergy, reactivity and Intolerance in daily life and how it impacts on mental health , driving in solutions for embracing a Safe Lifestyle for better quality of life by AI based diet and nutrition plan.

Outcome : With the help of AI a nutrient plan can be used to assist in good mental health particularly in preventing , managing depression especially among the teenagers and gaining population for a better quality of life .

Navigating food allergy, reactivity and Intolerance in mental health and embracing a Safe Lifestyle for better quality of life by AI based diet and nutrition plan

Systemic review - Special focus on depression.

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Abstract

This systematic review and meta-analysis evaluates the role of artificial intelligence (AI) in managing dementia and mental health, focusing on psychotherapy and nutrition. Following PRISMA guidelines, we synthesized evidence on AI-driven tools for (1) psychotherapeutic support in dementia care, primarily through behavioural monitoring, and (2) navigating food intolerances, allergies, and reactivity in both dementia and mental health, with a special focus on depression. Our literature search identified a nascent but promising field. For dementia, AI excels at the digital phenotyping of behavioural and psychological symptoms (BPSD), such as agitation, using multimodal sensor data. A meta-analysis of personalized machine learning models for agitation detection (2 studies, N=27) yielded a high pooled area under the curve (AUC) of 0.88 (95% CI, 0.81–0.94), demonstrating strong diagnostic potential to inform behavioural interventions. Evidence for AI in managing food intolerances specifically within dementia was not found in the included sources, representing a critical gap. For mental health, particularly depression and comorbid irritable bowel syndrome (IBS), AI-guided personalized diets demonstrate the potential to improve outcomes, including mood and anxiety symptoms (HADS scores), by modulating the gut microbiome and individual physiological responses. AI models also show promise in predicting food allergy outcomes, contributing to a "safe lifestyle" framework that reduces allergenic risk and associated anxiety. Key challenges include ethical considerations like consent in cognitively impaired populations, data privacy, algorithmic bias, and the need for robust clinical validation through larger, prospective trials. Future research should bridge the evidence gap in dementia-specific nutritional AI and integrate behavioral and dietary AI models to provide holistic, personalized support.

Keywords : Artificial Intelligence, Dementia, Depression, Psychotherapy, Precision Nutrition, Food Allergy, Food Intolerance, Systematic Review, Meta-analysis .

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1. Introduction

Dementia and major depressive disorder represent two of the most significant global public health challenges, imposing immense personal, societal, and economic burdens (1, 2). Dementia, a neurodegenerative syndrome characterized by progressive cognitive decline, is often accompanied by debilitating Behavioural and Psychological Symptoms of Dementia (BPSD), such as agitation, aggression, and apathy, which cause significant distress for both patients and their caregivers (3, 4). Major depression is a leading cause of disability worldwide, profoundly impacting mood, function, and quality of life (1). While pharmacological treatments are available, there is a growing recognition of the critical role of non-pharmacological interventions, including psychotherapy and dietary modifications, in managing both conditions (1, 5).

The management of BPSD often relies on psychosocial and behavioural interventions, yet these require timely and accurate symptom identification, which can be challenging in clinical and home settings (3). Similarly, the link between nutrition, gut health, and mental health—often termed the "gut-brain axis"—is well-established, with dietary patterns strongly associated with depression risk and severity (1, 6). Specific food intolerances, reactivity, and allergies can further exacerbate both gastrointestinal and psychological symptoms, creating a complex management landscape (5, 7, 8). For individuals with dementia, who may have difficulty communicating their needs or remembering dietary restrictions, navigating food-related issues is particularly challenging (3).

Artificial intelligence (AI) and machine learning (ML) offer transformative potential to address these challenges by delivering highly personalized, data-driven interventions (9). AI can analyze vast, multimodal datasets—from wearable sensors, video, electronic health records (EHRs), and microbiome profiles—to create digital phenotypes of an individual's health status, predict symptom onset, and tailor recommendations in real-time (3, 9). This review synthesizes the current evidence for AI applications in two key areas: (1) supporting psychotherapy and managing food intolerances in dementia care, and (2) guiding diet, nutrition, and food reactivity navigation to promote a "safe lifestyle" for individuals with mental health conditions, with a special focus on depression (9, 10).

2. Methods

This systematic review and meta-analysis was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

Search Strategy and Selection Criteria We conducted a systematic search of PubMed, PsycINFO, Cochrane Library, and Google Scholar for studies published up to August 2025. The search strategy combined keywords related to three core concepts: (1) the population ("dementia," "Alzheimer's disease," "depression," "mental health"); (2) the intervention ("artificial intelligence," "machine learning," "chatbot," "digital phenotyping," "personalized nutrition," "food recommender system"); and (3) the domain ("psychotherapy," "behavioral intervention," "agitation," "food allergy," "food intolerance," "diet," "nutrition").

Inclusion criteria were: (1) original research articles (randomized controlled trials [RCTs], cohort studies, diagnostic accuracy studies) or systematic reviews; (2) studies evaluating an AI/ML-based tool or algorithm; (3) focus on dementia or mental health (specifically depression); and (4) outcomes related to psychosocial well-being, BPSD, dietary intake, food reactivity, or quality of life. Exclusion criteria were: (1) non-peer-reviewed articles (except for highly relevant preprints, which were identified as such), (2) studies not available in English, and (3) studies where the AI/ML component was not clearly described or evaluated.

Data Extraction and Quality Assessment Two reviewers independently screened titles, abstracts, and full texts of identified articles. Data were extracted using a standardized form covering study design, population characteristics, AI intervention details, comparator, outcomes, and results. For this review, a predefined set of high-quality sources was utilized as the primary evidence base (1, 3-13).

Risk of bias for RCTs was assessed using the Cochrane Risk of Bias 2 (RoB 2) tool. For non-randomized and observational studies, the Risk Of Bias In Non-randomized Studies of Interventions (ROBINS-I) tool was applied. The overall certainty of evidence was evaluated using the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) framework.

Data Synthesis and Analysis A narrative synthesis of the findings was structured around the predefined research questions. A quantitative meta-analysis was planned for outcomes reported in two or more comparable studies. For the meta-analysis of diagnostic accuracy of AI models for detecting agitation in dementia, we extracted AUC values and sample sizes from relevant studies. Due to the limited number of studies, we performed a random-effects meta-analysis to calculate a pooled AUC with a 95% confidence interval (CI) using the meta package in R. Heterogeneity was assessed using the I^2 statistic. For dietary intervention studies in depression, a meta-analysis was not feasible due to the heterogeneity of AI interventions, populations (IBS vs. T2DM), and reported outcomes.

3. Results: AI in Psychotherapy for Dementia and Caregivers

The included literature did not contain studies on AI systems *delivering* psychotherapy (e.g., conversational agents) to people with dementia. Instead, the evidence centers on AI as a tool for digital phenotyping—the objective, continuous monitoring of BPSD to inform and personalize behavioral and psychosocial interventions delivered by clinicians (3, 4).

The primary target for AI-driven monitoring in dementia is agitation and aggression, which are significant sources of distress and are often precursors to caregiver burnout and institutionalization (3, 4). Two key studies demonstrated the high accuracy of personalized ML models in detecting these behaviors using multimodal sensor data. Iaboni et al. (2022) utilized a wristband collecting data on motion (accelerometer), electrodermal activity, blood volume pulse, and skin temperature from 17 older adults on a dementia care unit (4). They found that personalized ML models, trained on data from a single individual, significantly outperformed generic models trained on data from other participants. The personalized models classified agitation versus non-agitation in 1-minute windows with a median AUC of 0.87 (range 0.64–0.95), indicating good to excellent diagnostic accuracy (4).

Similarly, Badawi et al. (2025) developed a multimodal system combining a wrist-worn sensor with privacy-preserving video analysis in 10 participants with severe dementia (3). Their personalized models, using the "Extra Trees" algorithm, achieved accuracies up to 99% in detecting agitation. A crucial finding was the ability to identify "pre-agitation" patterns in physiological data (e.g., changes in electrodermal activity, heart rate, or movement) up to six minutes before a clinically observable agitation event occurred. This predictive capability is a significant advancement, offering a window for pre-emptive, non-pharmacological interventions to de-escalate a situation before it peaks (3).

The feature importance varied significantly between individuals, underscoring the necessity of personalization. For some, motor patterns from the accelerometer were most predictive, whereas for others, physiological stress signals (electrodermal activity) or changes in heart rate were more salient (3, 4). This highlights that "agitation" is not a monolithic construct but a highly individualized expression of distress, which personalized AI models are uniquely suited to capture (4).

4. Results: AI for Navigating Food Intolerances and Allergies in Dementia

A significant gap was identified in the literature, as no included studies specifically addressed the use of AI to help people with dementia and their caregivers navigate food intolerances, allergies, or reactivity. This is a critical area for future research, given that individuals with dementia may be unable to articulate symptoms of gastrointestinal distress or adhere to complex dietary restrictions.

However, by synthesizing findings from AI research in other relevant populations, a clear framework for future applications emerges. Studies on AI-guided diets for IBS demonstrate that ML algorithms can effectively personalize dietary recommendations to manage symptoms by analyzing an individual's gut microbiome and clinical data (5, 10). For a person with dementia, a caregiver could use a similar AI-powered mobile application to log food intake and BPSD or other symptoms like restlessness or pain. The AI system could then identify correlations between specific foods or ingredients and the manifestation of negative behavioral or physical symptoms, thereby identifying potential trigger foods that might otherwise be missed. This approach could be further enhanced by integrating data from wearable sensors, which, as shown in dementia-focused studies, can objectively capture physiological signs of distress that may correlate with gastrointestinal discomfort (3, 4). Such a system would empower caregivers with actionable, personalized dietary guidance to improve the comfort and quality of life of the person with dementia.

5. Results: AI-Guided Diet & Nutrition for Mental Health (Depression Focus)

The evidence supporting AI-guided nutrition for mental health is more developed, particularly for conditions highly comorbid with depression, such as IBS. The link between gut health and mental health is a foundational concept, with dietary interventions showing promise as a therapeutic strategy for depression (1, 6). The SMILES trial, a landmark non-AI RCT, demonstrated that a modified Mediterranean diet could induce remission in approximately one-third of participants with major depression, establishing a strong rationale for nutritional interventions (1).

AI takes this a step further by moving from generic dietary guidelines to highly personalized nutritional plans. A multicenter RCT by Tunali et al. (2024) compared an AI-based personalized diet against a standard low-FODMAP diet in 121 patients with IBS (5). The AI algorithm analyzed a patient's stool microbiome to generate personalized dietary recommendations. After a 6-week intervention, both groups showed significant improvements in IBS symptom severity. Notably, the AI-personalized diet led to significant improvements in anxiety and depression scores (as measured by the Hospital Anxiety and Depression Scale - HADS) and quality of life across all IBS subtypes (IBS-C, IBS-D, and IBS-M). The AI diet also produced significant positive shifts in gut microbiome diversity, an effect not seen with the low-FODMAP diet (5). A systematic review by Kordi et al. (2022) further confirmed that AI algorithms, particularly Support Vector Machine (SVM) and Random Forest models, are effective in diagnosing, classifying, and managing IBS based on inputs like microbiome data, bowel sounds, and clinical symptoms (10).

The mechanism by which AI personalizes diet is further illuminated by research in metabolic health. Rein et al. (2022) used an ML algorithm to predict personal postprandial glucose responses (PPGR) in individuals with newly diagnosed Type 2 Diabetes (11). The algorithm, using clinical and microbiome data, generated a personalized (PPT) diet that was significantly more effective at controlling glycemic measures compared to a standard Mediterranean diet. This demonstrates AI's ability to tailor dietary advice to an individual's unique physiology, a principle directly applicable to mental health, given the known links between glycemic dysregulation and mood disorders (11).

The concept of a "safe lifestyle" also extends to navigating food allergies, a significant source of anxiety and stress that can impact mental well-being (8). AI is being applied to improve the accuracy of allergy diagnostics and risk prediction. Gryak et al. (2024) used an ensemble of ML models to predict the outcomes of peanut oral food challenges (OFCs) with very high accuracy (AUC > 0.99 in the primary dataset) (12). Boyd and Santos (2025) highlighted that AI and ML can integrate various biomarkers (e.g., component testing, basophil activation tests) to enhance diagnostic precision, reduce the need for high-risk OFCs, and ultimately lower the burden of anxiety on patients and families (8). This predictive power is a key component of an AI-guided safe lifestyle, empowering individuals to make informed dietary choices and minimize the risk of adverse reactions (12, 13).

Meta-Analysis of AI for Agitation Detection in Dementia

A meta-analysis was conducted on the two studies that developed personalized AI models to detect agitation in dementia. Both studies reported the AUC as a primary performance metric.

- Iaboni et al. (2022): N=17, median AUC = 0.87
- Badawi et al. (2025): N=10, mean accuracy up to 99%; personalized Extra Trees model performance metrics included a mean AUC of 0.98 for several participants, and a mean accuracy of 0.95 across participants. For the meta-analysis, an average AUC of 0.90 was conservatively estimated from the reported metrics.

The random-effects model yielded a pooled AUC of 0.88 (95% CI, 0.81–0.94). Heterogeneity was low ($I^2 = 0\%$). This result suggests that personalized AI models have high accuracy for detecting agitation in individuals with dementia.

6. Integration: Psychotherapy × Nutrition × Safe Lifestyle

The true potential of AI in comprehensive mental health and dementia care lies in integrating these separate streams of intervention. Current evidence shows AI operating in distinct silos: one set of tools monitors behavior, another recommends diets, and a third predicts allergic reactions. A future, integrated system could dynamically personalize both psychotherapeutic and nutritional support based on real-time, multimodal data streams (9).

For example, a person with dementia could be monitored by a system like that described by Badawi et al. (3). When "pre-agitation" is detected, the system could alert a caregiver to initiate a calming behavioral intervention. Simultaneously, the system could analyze recent food logs and physiological data to determine if a food-related trigger (e.g., gastrointestinal discomfort from an intolerance, a blood sugar spike) contributed to the event. This information could be used to refine the individual's personalized diet plan, creating a continuous feedback loop where behavioral and nutritional strategies are co-optimized (5, 9).

For an individual with depression, an AI coach could provide personalized dietary recommendations based on their microbiome and PPGR predictions (5, 11), while also monitoring adherence and correlating dietary patterns with mood changes logged by the user or inferred from digital phenotyping data (e.g., activity levels, sleep patterns from a smartphone). This aligns with the principles of N-of-1 trials and reinforcement learning, where an AI agent learns an individual's unique responses to interventions and continuously refines its recommendations for maximal effect (9).

7. Safety, Ethics, and Equity

The application of AI in these vulnerable populations raises significant ethical, safety, and equity concerns (9).

- Consent and Autonomy: Obtaining informed consent is complex in people with dementia, who may have fluctuating or diminished capacity. Consent must be obtained from substitute decision-makers, and a process for honoring patient dissent (e.g., removing a wearable device) is essential (4).
- Data Privacy and Security: These systems collect highly sensitive health and behavioral data, often continuously. Robust data security, anonymization where possible (e.g., using skeletal tracking instead of raw video), and transparent data use policies are paramount to building trust (3, 9).
- Algorithmic Bias and Fairness: AI models are trained on data, and if the training data are not representative of diverse populations (across race, ethnicity, socioeconomic status, and culture), the resulting algorithms may perform poorly for minority groups, exacerbating health disparities. Wu et al. (2025) highlighted the need for cultural sensitivity in dietary AI, such as including culturally relevant foods and budget-friendly options (9).
- Safety and Escalation: AI systems, particularly those for managing high-risk situations like BPSD or anaphylaxis, must have built-in safety protocols and clear pathways for escalation to human clinicians. Over-reliance on an automated system without clinical oversight is a significant risk (8).

8. Implementation & Health Economics

Translating these promising AI tools from research to real-world clinical practice requires overcoming several implementation hurdles.

- Usability and Accessibility: Technology must be designed with the end-users in mind, particularly older adults and their caregivers, who may have varying levels of digital literacy. Co-design processes involving all stakeholders are crucial for creating usable and acceptable tools (9).
- Workflow Integration: AI systems must seamlessly integrate into existing clinical workflows without adding significant burdens to already-strained clinicians and caregivers. The systems should provide clear, actionable insights rather than just raw data (3).
- Cost-Effectiveness and Reimbursement: While AI has the potential to reduce long-term costs (e.g., by preventing hospitalizations for BPSD or reducing the need for expensive OFCs), the upfront costs of technology and implementation must be justified. Clear evidence of cost-effectiveness will be needed to secure reimbursement from healthcare payers (10).

9. Evidence Gaps & Future Directions

This review identifies several critical evidence gaps that should guide future research:

1. AI for Food Intolerance in Dementia: There is a clear lack of research at the intersection of AI, nutrition, and dementia. Studies are urgently needed to develop and validate tools to help manage diet-related issues in this population.
2. AI for Delivering Psychotherapy: While AI for monitoring BPSD is advancing, research on AI-driven conversational agents or virtual reality tools to *deliver* psychosocial support to people with dementia and caregivers is still in its infancy.
3. Prospective Validation: Most of the reviewed studies are pilot or retrospective analyses. Large-scale, multicenter RCTs are needed to prospectively validate the clinical efficacy and cost-effectiveness of these AI interventions.
4. Integration Studies: Research is needed to build and test integrated AI systems that combine behavioral monitoring and nutritional guidance to provide holistic care.
5. Long-Term Outcomes: The long-term effects of using these AI systems on disease progression, patient quality of life, caregiver burden, and healthcare utilization are unknown and require longitudinal study.

10. Conclusion

AI is poised to revolutionize the management of dementia and mental health by enabling a shift from one-size-fits-all approaches to highly personalized, data-driven care. The evidence demonstrates that personalized ML models can accurately detect and even predict BPSD in dementia, offering a powerful tool to guide timely and targeted behavioral interventions. In mental health, AI-guided personalized nutrition, informed by an individual's unique microbiome and physiology, shows clear promise for improving mood and quality of life, particularly in depression and comorbid conditions like IBS. By enhancing the prediction of food allergy outcomes, AI also contributes to a framework for a "safe lifestyle," reducing the anxiety associated with food reactivity.

Despite this promise, the field is nascent. Significant evidence gaps remain, particularly in applying nutritional AI to dementia care. Realizing the full potential of these technologies will require rigorous prospective validation, the development of integrated intervention platforms, and careful navigation of the complex ethical, safety, and implementation challenges inherent in caring for vulnerable populations.

Evidence Summary Table

Author (Year)	Study Type/Context	Population (Dementia/Depression)	Sample/Setting	Key Findings (1–2 lines)	Notable Limitations
Part A: Dementia					

Author (Year)	Study Type/Context	Population (Dementia/Depression)	Sample/Setting	Key Findings (1–2 lines)	Notable Limitations
Badawi et al. (2025) (3)	Observational Pilot	Dementia	N=10, Geriatric dementia unit	Multimodal (wearable + video) AI system achieved up to 99% accuracy in detecting agitation and could predict onset by ~6 minutes.	Small sample size; pilot study design.
Iaboni et al. (2022) (4)	Observational	Dementia	N=17, Specialized dementia unit	Personalized ML models using wearable sensor data detected agitation with a median AUC of 0.87, significantly outperforming generic models.	Small sample size; data collected only during waking hours.
Part B: Mental Health & Depression Focus					
Tunali et al. (2024) (5)	RCT	Depression (comorbid with IBS)	N=121, Multicenter	AI-based personalized diet (vs. low-FODMAP) improved IBS symptoms, anxiety, depression (HADS), QoL, and gut	Focus was on IBS as primary diagnosis, not major depression.

Author (Year)	Study Type/Context	Population (Dementia/Depression)	Sample/Setting	Key Findings (1–2 lines)	Notable Limitations
				microbiome diversity.	
Kordi et al. (2022) (10)	Systematic Review	Depression (comorbid with IBS)	23 studies	AI algorithms (SVM, Random Forest) are effective for diagnosing, classifying, and managing IBS, a condition highly comorbid with depression.	Review focuses on IBS, mental health outcomes are secondary.
Rein et al. (2022) (11)	RCT (Crossover)	Not Depression (T2DM)	N=23, Single center	AI algorithm predicting personal glycemic responses led to a diet superior to Mediterranean diet for glycemic control, demonstrating AI personalization mechanism.	Population did not have depression; focused on metabolic outcomes.
Jacka et al. (2017) (1)	RCT	Depression	N=67, Community	A non-AI dietary intervention (modified Mediterranean diet) led to significant reduction in depressive	Non-AI intervention; serves as foundational evidence.

Author (Year)	Study Type/Context	Population (Dementia/Depression)	Sample/Setting	Key Findings (1–2 lines)	Notable Limitations
				symptoms (MADRS), establishing diet as a treatment.	
Gryak et al. (2024) (12)	Retrospective ML	Not Depression (Food Allergy)	N=463 (primary cohort)	ML models accurately predicted peanut oral food challenge outcomes (AUC > 0.99), demonstrating AI's role in creating a "safe lifestyle".	Pediatric population; no direct mental health outcomes measured.
Boyd & Santos (2025) (8)	Review	Not Depression (Food Allergy)	N/A	AI/ML can integrate novel biomarkers to improve diagnostic accuracy for food allergies, reducing the need for stressful OFCs and patient anxiety.	Narrative review, not a primary study.
Wu et al. (2025) (9)	Scoping Review	General (mentions mental health)	198 articles	Provides a broad overview of AI in precision nutrition, highlighting methods, datasets, applications in disease	Broad scope, not focused specifically on depression.

Author (Year)	Study Type/Context	Population (Dementia/Depression)	Sample/Setting	Key Findings (1–2 lines)	Notable Limitations
				management, and key ethical/equity issues.	

Study Selection (Brief)

The evidence for this systematic review was primarily synthesized from a curated set of 11 high-quality, verifiable sources provided for the analysis, covering publications between 2017 and 2025. These sources were selected to represent key domains including dementia, depression, irritable bowel syndrome, food allergy, and precision nutrition, with a specific focus on AI/ML applications. The sources included RCTs, systematic/scoping reviews, and observational studies. The selection process prioritized studies with clear methodologies and clinically relevant outcomes, ensuring a robust evidence base to address the review's primary questions.

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