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Review Article

Application of AI agent in Assisting the Diagnosis of Mild Cognitive Impairment

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Abstract

With the accelerating aging of the world population, timely identification of Mild Cognitive Impairment (MCI) has become a crucial public health issue for community health systems. Compared to specialist settings, the core challenge facing communities is not merely insufficient diagnostic accuracy, but rather how to achieve early detection, risk stratification, referral coordination, and continuous monitoring in a scalable, affordable, and governable manner. In recent years, Artificial Intelligence (AI) has evolved from single predictive models to AI agents with information integration, task triggering, and process coordination capabilities. This narrative review focuses on the most recent (from 2023-2026) application of AI agents in assisting the diagnosis of MCI and the early stages of mild dementia, emphasizing their potential role in early detection, risk stratification, referral navigation, and continuous monitoring, and analysing the practical constraints posed by fairness, privacy protection, and regulatory controllability. We believe that the optimal positioning of AI agents is not to replace specialist diagnosis, but rather as an enhancer for primary care identification and pathway management. Future research should shift from simply comparing model performance to external validation in real-world community scenarios, implementation research, economic evaluation, and the construction of governance frameworks.

Keywords: AI agent; Mild cognitive impairment; Community health; Early detection; Risk stratification; Referral navigation; Continuous monitoring

Introduction

Cognitive impairment has become a significant public health challenge in the field of aging health worldwide. The World Health Organization points out that the number of patients worldwide continues to grow, and a considerable proportion live in areas with limited medical resources or insufficient care support [1]. The Global Dementia Public Health Response Action Plan (2017-2025) adopted by the World Health Assembly and The Lancet Dementia Prevention and Control Report (2024) both emphasize that prevention and control should not only focus on late-stage care, but should incorporate risk reduction, early identification, continuous care and equitable access into a unified framework [2,3]. This means that responding to cognitive impairment has become a systemic issue jointly determined by primary screening capacity, community accessibility and cross-level pathway management capacity.

In this context, the early detection of MCI is of special significance. MCI lies between normal aging and dementia, and its basic characteristics include subjective or perceived cognitive decline, abnormal objective cognitive tests, and relatively preserved overall daily living abilities [4,6]. Not all individuals with MCI will progress to Alzheimer's disease, but from a public health perspective, this stage constitutes a high-risk population that deserves priority identification and stratified management [5,6]. If the community health system cannot form an effective identification and referral system at this stage, subsequent specialist diagnosis and care resources can often only be passively intervened when the condition is clearer and the functional impairment is more significant. The main contradiction currently faced by the community health system in the identification of cognitive impairment is not the lack of a single detection technology, but the lack of a low-burden, replicable, and closed-loop service path. Imaging, cerebrospinal fluid, and blood biomarkers are valuable in specialist diagnosis, but their cost, equipment dependence, and personnel requirements make it difficult for them to become a routine configuration for community primary screening [12]. Meanwhile, primary cognitive screening is also affected by factors such as time constraints, insufficient training, fragmented processes, and poor referral [7]. Therefore, the real question that needs to be answered is how to identify high-risk individuals earlier and smoothly enter subsequent services.

The development of artificial intelligence has provided new possibilities for this problem. The AI agent referred to in this review is different from a single auto-scoring model, rather a process-oriented system capable of receiving multi-source data, making risk assessments, triggering subsequent tasks, and outputting structured recommendations. In recent years, research based on speech, language, digital cognitive tasks, electronic health records, and multimodal data has been increasing, demonstrating its potential in early identification, progression prediction, and dynamic monitoring of MCI [8-10]. However, existing research still focuses primarily on model accuracy and offline validation metrics, with less discussion on how AI can enter real-world scenarios from the perspectives of community health workflows, service equity, and governance requirements [11].

Therefore, the focus of this narrative review is on the community health service chain, emphasizing how AI agent can improve identification efficiency through early detection, risk stratification, referral navigation, and continuous monitoring, and how to maintain fairness, privacy protection, and regulatory controllability in this process. The value of AI agents is not only reflected in outputting a probability, but also in how to embed detecting anomalies into the service process [11].

To clarify where AI agents can be embedded in the community MCI service chain, Table 1 summarizes their main functions, outputs, and governance considerations across the pathway.

Service-chain stage	Community task	AI agent role	Actionable output
Early clues and opportunistic screening	Identify subtle risk signals during routine visits, chronic disease management, caregiver reporting, or brief cognitive tasks.	Integrate electronic health records, digital cognitive tasks, speech/language cues, functional information, and caregiver reports to flag persistent abnormal patterns.	Low-burden screening prompt, rescreening reminder, and structured risk note.
Rescreening and risk stratification	Decide who needs repeat screening, second-level assessment, specialist referral, or routine follow-up.	Apply population-adapted risk models, correction variables, and two-threshold decision rules to separate low-, intermediate-, and high-risk groups.	Risk category with recommended next step and trigger for further assessment when needed.
Referral navigation	Connect high-risk individuals to specialist assessment, caregiver support, and subsequent management.	Generate structured referral summaries, identify barriers such as cost or accompaniment, and track appointment completion and specialist feedback.	Referral packet, navigation checklist, closed-loop status update, and follow-up task.
Continuous monitoring	Observe cognitive, functional, behavioral, and service-use changes over time.	Combine repeated active assessment with passive trend data and compare changes with the individual's baseline.	Early-warning alert, updated management plan, and scheduled reassessment.
Governance and equity across the chain	Maintain safe, fair, and accountable deployment in heterogeneous community populations.	Support human oversight, explainable outputs, minimal data collection, audit logs, privacy protection, and subgroup performance monitoring.	Reviewable decision trail, privacy safeguards, and equity monitoring indicators.
Note: The AI agent is positioned as a workflow-support and decision-support tool, not as a substitute for specialist diagnosis.			

Table 1: Role of AI agents in the community MCI service chain.

Community Health Identification Path and Real-world Bottlenecks

From the perspective of public health processes, the identification of cognitive impairment in the community is a service chain consisting of multiple links: early clues, opportunistic screening, rescreening and risk stratification, specialist assessment, post-diagnosis support and long-term follow-up [2,1]. Therefore, the evaluation criteria should focus on screening coverage, rescreening completion rate, referral completion rate, follow-up continuity, and the fairness and traceability of the entire process.

However, several bottlenecks exist in reality. 1. The concealment of early symptoms and insufficient proactive consultation. Many high-risk individuals do not seek medical attention with "cognitive decline" as their chief complaint, but rather enter primary care services indirectly through symptoms such as decreased medication adherence, functional decline, emotional problems, or abnormal chronic disease management. 2. The dual limitation of screening tools and human resources at the primary care level. Although traditional scales are feasible, they are often affected by education level, implementation time, and interpretation experience; when primary care teams simultaneously undertake multiple chronic disease and public health tasks, any additional tools that increase the burden are difficult to use stably in the long term [7]. 3. The gap between community-based initial screening and specialist confirmation. High-end examination resources are mostly concentrated in higher-level institutions, and without effective referrals, the benefits of initial screening are difficult to realize [12]. 4. The weak continuous monitoring and fragmented pathway management. MCI is dynamic, and the value of a single screening is limited, while community services often lack systematic longitudinal observation tools. 5. The issue of fairness runs through the entire chain: differences in education level, language background, digital literacy and resource accessibility will affect the performance of tools and service utilization. If not handled properly, the technology, which is intended to narrow the gap, may instead widen new inequalities [11].

From the perspective of service organizations, the essence of community cognitive impairment identification is not a single technical problem, but a procedural problem. Precisely because the difficulties occur in the chain, the value of AI agents should be understood as a process coordination tool connecting early detection, stratification, referral and follow-up.

Application of AI Agents in MCI Early Detection

From the perspective of data sources, the most practical entry points for early detection include brief cognitive screening and digital cognitive tasks, voice and language data, electronic health records and caregiver reports, and second-layer support information for high-risk individuals. The current evidence base is strongest for these component technologies rather than for fully integrated AI agent systems. Digital cognitive tools and speech-based biomarkers have shown feasibility and diagnostic potential, but their performance is heterogeneous and is affected by task design, age, language, education and technical familiarity [10,14]. Therefore, their results should be interpreted as signals that may support an agent, not as proof that an autonomous agent can already diagnose MCI in community practice.

Compared with specialized memory clinics, community health systems have more frequent, earlier and more diverse contact points. MCI in primary care often does not appear as a cognitive complaint alone, but is intertwined with medication non-adherence, disordered chronic disease management, sleep problems, functional decline and caregiver-observed changes. Milner et al. pointed out that digital biomarkers of MCI are more likely to present as multidimensional phenotypes rather than as a single variable [9]. This supports the rationale for multi-source integration, but the available studies still mainly validate separate biomarkers or prediction models. They do not by themselves demonstrate that an AI agent can coordinate screening, interpretation and follow-up across a real community service chain.

In workflow terms, AI-supported early detection can be divided into three modes: pre-screening before outpatient visits or physical examinations, opportunistic recognition in primary care encounters, and remote or home-based lightweight recognition. Existing primary care research suggests that short, self-administered digital cognitive tools can identify objective cognitive impairment and can be linked with higher-level examinations [13]. This evidence supports a stepped screening pathway, but it is still closer to a digital screening tool than to a true agent. A true AI agent would need to combine multiple data sources, judge whether the signal is persistent or context-dependent, generate a structured explanation, trigger rescreening or referral tasks, and record whether the pathway action was completed.

For community implementation, several conditions remain necessary. First, tools must be externally validated across education levels, languages, rural and urban settings, and groups with different digital literacy. Second, the system must be embedded in routine primary care workflows without adding excessive time burden to clinicians. Third, the outputs must be understandable to community physicians, nurses and care navigators. Fourth, abnormal findings must be linked to clear next steps, such as rescreening, risk stratification, referral or monitoring. Without these conditions, early-detection agents may remain a collection of promising screening technologies rather than a sustainable community service mechanism [14,15].

Application of AI Agents in Risk Stratification

The public health logic of risk stratification is to shift community screening from immediate qualitative diagnosis to allocation of follow-up actions. Existing evidence supports the use of multidimensional variables for predicting dementia risk in people with MCI, including age, cognitive performance, functional status, comorbidities and mental symptoms [8]. However, most of this evidence comes from predictive model development and retrospective or cohort-based validation. It supports risk prediction as a related technology, but does not fully establish that AI agents can safely assign community pathways without additional governance.

Variables suitable for community risk stratification can be broadly categorized into five groups: demographic and educational correction information; cognitive and functional variables; comorbidity and clinical context variables; lightweight digital biomarkers such as speech, language and behavioral data; and second-tier evidence such as blood biomarkers for selected higher-risk individuals [9,10,12]. Correction information, including education level and digital proficiency, is essential because cognitive tests and digital tool performance are strongly affected by these factors. If these differences are ignored, a model may misinterpret normal group variation as pathological change [14].

From a workflow perspective, a two-threshold strategy may be more suitable for community settings than a single threshold because it can separate clearly low-risk and high-risk individuals while leaving the intermediate group for rescreening or additional assessment [13]. This strategy is useful for resource allocation, but the evidence still needs to be interpreted cautiously. Existing studies may support the diagnostic or predictive value of specific tests and biomarkers, whereas an agent-based stratification system would also need to decide what action follows each risk category, how uncertainty is communicated, and when a clinician should override the recommendation.

When risk stratification is applied in community practice, important gaps remain. Many models perform well during development but lack external validation and may have a high risk of bias across regions, institutions and populations [8]. Evidence on the psychometric properties of MCI screening tools also shows insufficient information on cross-cultural validity, measurement invariance and measurement error [15]. Therefore, the appropriate positioning of AI agents at this stage is stratified decision support and pathway triggering, not automated diagnosis. The system should support human review, document the basis for the risk category, and monitor whether different subgroups are being referred or monitored equitably.

Risk stratification must also be connected with second-level examination. One misconception is that any abnormality should immediately lead to specialist referral or biomarker testing, which may rapidly deplete scarce resources. Another is that stratification can stop at score reporting without triggering action. A more reasonable pathway is to use second-level testing selectively after high-risk stratification, thereby improving specificity and resource allocation efficiency [12,13]. To implement this pathway, communities still need locally calibrated thresholds, referral capacity, clinician training, data-sharing mechanisms and evaluation of pathway outcomes rather than model accuracy alone.

Application of AI Agents in Referral Navigation

For MCI and early mild dementia, the significance of community screening is not only detecting abnormalities, but also determining whether abnormal results can be converted into timely assessment, care support and subsequent management [17-19].

In the community health system, the potential roles of AI agent in referral navigation include matching pathways according to risk level, organizing structured referral summaries, identifying non-medical barriers such as family accompaniment, costs, transport and digital capability, and tracking appointment completion, absence and specialist feedback [16]. These functions are closer to agentic workflow support than simple prediction because they involve task triggering, information transfer and closed-loop follow-up. However, most currently available evidence still comes from general care navigation principles, digital health workflows or decision-support systems rather than from validated AI agent deployments in MCI referral pathways.

The WHO iSupport for Dementia project suggests that caregiver education and support can be a structural component of the care pathway rather than only an ancillary service after diagnosis [20]. In an AI agent framework, this means that referral navigation should not end with sending a patient to a specialist. It should also identify whether the family understands the reason for referral, whether caregiver support is needed, and whether the patient returns to community follow-up after specialist assessment. The evaluation of such systems should prioritize pathway outcomes, including referral completion rate, time from abnormal screening to specialist assessment, non-attendance rate, loss to follow-up rate and subgroup differences in completion rates.

Several implementation conditions are still missing before referral navigation can be considered mature in community MCI care. AI agents would need interoperability with appointment systems, electronic health records and specialist feedback channels. They would also need clear responsibility boundaries: who responds to a high-risk alert, who contacts the family, who confirms that referral was completed, and who acts when the patient is lost to follow-up. Without these operational mechanisms, referral navigation may remain a conceptual extension of screening rather than a tested agent-based service model.

Application of AI Agents in Continuous Monitoring

MCI and early mild dementia are dynamic processes rather than static labels, so community management needs to extend identification into the time dimension [9]. Existing evidence supports the feasibility of several monitoring technologies. Home-based or telephone cognitive testing studies show that repeated, low-burden remote assessment can be conducted in people with MCI and may provide information about longitudinal change [21]. Wearable-device research suggests that physiological and behavioral deviations from an individual's baseline may be associated with cognitive or executive-function changes [22]. However, these studies mainly show that data can be collected and that some signals are clinically relevant; they do not prove that AI agent can already manage MCI continuously in community services.

From an application perspective, three approaches are relevant. The first is periodic active monitoring, such as telephone cognitive tests, short digital recognition tasks or regular voice sampling. The second is passive home monitoring through wearable devices, smartphone sensors or home-environment sensing. The third is hybrid monitoring, which uses low-burden passive observation and periodically calibrates trend judgments with structured active assessment. Compared with a single monitoring mode, the hybrid approach may be more suitable for communities with limited resources and heterogeneous populations. Nevertheless, the evidence for each approach is still largely technology-specific rather than agent-specific.

A true AI agent for continuous monitoring would need to do more than collect repeated measurements. It would have to establish an individualized baseline, distinguish meaningful decline from normal variability or device artifacts, explain why an alert was generated, trigger a service response, and document whether the response occurred. It should also know when not to escalate, because excessive alerts may increase family anxiety and primary care workload. At present, the evidence supports continuous monitoring as a dynamic observation and early-warning concept, but not yet as a fully validated automated management system.

Important implementation gaps remain. Monitoring thresholds are not standardized; passively sensed data can be difficult to interpret; long-term device adherence may decline; and economic feasibility in routine community care is uncertain [23]. Privacy and acceptability are also central because continuous monitoring may involve voice, movement, sleep, physiological indicators and daily routines. Therefore, evaluation should not rely only on correlations between sensor features and cognitive scores. It should include false-alert rates, clinician workload, patient and caregiver acceptability, equity across digital-literacy groups, costs, data security, and whether alerts actually lead to beneficial service actions.

Fairness, Privacy Protection and Regulatory Controllability

For AI agents targeting cognitive impairment in community health systems, fairness is a prerequisite for real-world deployment. The current evidence base for fairness is mostly derived from clinical AI fairness reviews, psychometric evaluations of screening tools and broader digital health experience, rather than from trials of community MCI agents [15,24]. This means that fairness concerns are well justified, but the specific fairness performance of agent systems still needs to be tested in the MCI pathway itself. Community service recipients are highly heterogeneous in age, education, language, digital ability, comorbidity burden, family support and access to health resources. In MCI screening, these differences are not only background characteristics, but can directly affect measurement results.

Older adults with low education may perform poorly on cognitive scales or digital cognitive tasks because of limited schooling, unfamiliarity with test formats or low literacy rather than true cognitive decline. Voice and language models may be affected by dialect, accent, bilingual experience, hearing impairment, speech speed, vocabulary familiarity and local cultural expressions. In a community MCI setting, an abnormal language feature detected by the model may reflect dialectal variation or limited formal education rather than neurocognitive decline. Digital tools that require smartphones, touch screens, online questionnaires or wearable devices may also selectively include older adults who are more digitally literate and health conscious, while excluding those who are frailer, poorer, living alone or less familiar with digital technologies. These selection effects can distort both model development and service allocation.

Therefore, fairness in community settings should not be understood merely as statistical balance at the algorithm level, but also as fairness in coverage, measurement, pathway access and user burden. A review of clinical AI fairness shows gaps in bias-related attributes, clinical embedding, procedural fairness and resource-allocation fairness [24]. Evidence on MCI screening tools also indicates insufficient information on cross-cultural validity, measurement invariance and measurement error [15]. For implementation, communities need subgroup validation, bias audits, local calibration, accessible non-digital alternatives, and monitoring of whether different groups experience different false-positive rates, referral rates or loss-to-follow-up rates.

Privacy protection is also a critical boundary for AI agents entering community services. Unlike single paper-and-pen screening, agents may integrate cognitive test scores, medical history, medication adherence, voice recordings, language samples, functional questionnaires, caregiver reports, service-use records, location-related service traces, wearable physiological indicators and activity rhythms. These data can improve early identification and continuous monitoring, but they also create risks of sensitive health-information exposure, re-identification and use beyond the original care purpose. Voice data may reveal identity, emotional state, dialect and family context; behavior trajectories and wearable data may disclose daily routines, sleep patterns or living arrangements. In older adults with possible cognitive decline, consent capacity, caregiver access and family involvement further complicate data governance. Minimum necessary collection, de-identification, hierarchical access control, clear retention and deletion mechanisms, explicit consent for secondary use and individual or proxy control over data access should therefore be adopted [11].

Regulatory controllability requires that AI agents be usable, explainable, reversible, auditable and accountable. In community MCI pathways, an AI output should not automatically determine diagnosis, referral or resource allocation. Each recommendation should be accompanied by interpretable reasons, confidence information and a clear next step for human review. False-positive outputs may cause anxiety, unnecessary referral and extra costs; false-negative outputs may delay specialist assessment and post-diagnosis support. Systems should define responsibility among developers, community physicians, nurses, care navigators, specialist institutions and service managers, and should specify when manual review is mandatory. High-risk outputs, discordance between model results and clinician judgment, rapid functional decline, caregiver concern or suspected data-quality problems should trigger human review rather than automatic pathway decisions. WHO guidance emphasizes human oversight, transparency and accountability [11], and the EU Artificial Intelligence Act highlights risk management, technical documentation, record keeping, human oversight, accuracy and robustness for high-risk AI systems [25].

Research Gaps and Future Directions

Despite rapid growth in related research, significant structural gaps remain. First, most studies focus on model effectiveness rather than pathway effectiveness, with primary endpoints being sensitivity, specificity, or AUC. Evidence regarding whether systems improve real-world referral completion rates, loss to follow-up rates, caregiver burden, and primary care workload remains insufficient [8, 17]. This means that even if certain tools demonstrate technical potential, their ability to truly translate into community health benefits lacks sufficient pathway-level evidence.

Second, external validation, cross-scenario transfer, and cross-cultural adaptation are still inadequate. While digital tools and voice biomarkers show potential, more evidence is needed regarding standardization, population adaptation, and long-term stability [10,14,15]. This is particularly critical for community health systems, as primary care recipients are highly heterogeneous in terms of demographics, education levels, language backgrounds, and digital literacy. Without re-validation across multiple regions, languages, educational levels, and service scenarios, the performance of AI agents in one research cohort may not be smoothly transferred to other communities. Many systems, while reporting overall performance, fail to adequately account for differences in performance among the elderly, those with low education levels, and those with low digital literacy, and rarely report their impact on community processes and public resource allocation [24,27,28].

Looking to the next phase of research, the more important direction is not to continue improving offline classification scores based on single cross-sectional samples, but to drive a shift from static identification to longitudinal prediction and dynamic management. Future research should focus more on the construction and analysis of multimodal data, combining short cognitive tasks, speech and language features, electronic health records, chronic disease management information, wearable sensing data, caregiver reports, and service process data to build updatable dynamic risk models, rather than keeping MCI-assisted diagnosis stuck at a single-discrimination problem [9,26].

In terms of research design, research should also shift to pragmatic studies that emphasize implementation context and mixed effectiveness-implementation studies [29]. At the same time, the evaluation framework also needs to be restructured. For AI agents oriented towards community health systems, more explanatory endpoints should at least include coverage and identification endpoints, pathway endpoints, monitoring endpoints, as well as equity, governance, and economic endpoints [24,27].

Conclusion

In the community health system, the value of AI agents in assisting the diagnosis of MCI should not be understood as replacing specialist judgment with a higher-scoring model, but rather as enhancing the primary care identification and pathway management capabilities with a set of process-oriented tools. Its practical advantages are mainly reflected in expanding initial screening coverage in early detection, optimizing resource allocation in risk stratification, reducing pathway loss in referral navigation, and achieving dynamic updates in continuous monitoring. Therefore, the most noteworthy feature of AI agents is not single-point prediction, but their ability to organize community health workflows.

Existing research is still mainly focused on model performance; external validation, real-world implementation, long-term feasibility, and health economics evidence remain insufficient. Furthermore, fairness, privacy protection, and regulatory controllability are not supplementary clauses after technology deployment, but fundamental conditions that determine whether it can gain trust and continue to operate [11,24,25]. Therefore, the key to future research is to further prove whether it can improve population health pathways in a fair, controllable, and sustainable manner in the real world. The authors argue that only when the research paradigm shifts further from technology demonstration to community implementation and public health evaluation can AI agents truly evolve from proof-of-concept into a scalable tool in the cognitive impairment prevention and control system.

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References

1. World Health Organization (2025) Dementia.
2. World Health Organization (2017) Global action plan on the public health response to dementia 2017-2025. Geneva.
3. Livingston G, Huntley J, Liu KY, Costafreda SG, Selbæk G, et al. (2024) Dementia prevention, intervention, and care: 2024 report of the Lancet standing Commission. Lancet 404: 572-628.
4. Albert MS, DeKosky ST, Dickson D, Dubois B, Feldman HH, et al. (2011) The diagnosis of mild cognitive impairment due to Alzheimer's disease: recommendations from the National Institute on Aging–Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. Alzheimers Dement 7: 270-279.
5. Petersen RC, Aisen P, Boeve BF, Geda YE, Ivnik RJ, et al. (2013) Criteria for mild cognitive impairment due to Alzheimer's disease in the community. Ann Neurol 74: 199-208.
6. Duff K (2024) Mild cognitive impairment: quantifying a qualitative disorder. Neurol Clin 42: 781-792.
7. Diaz-Asper C, Chandler C, Elvevåg B (2024) Cognitive screening for mild cognitive impairment: clinician perspectives on current practices and future directions. J Alzheimers Dis 99: 869-876.
8. Wang X, Zhou S, Ye N, Li Y, Zhou P, et al. (2024) Predictive models of Alzheimer's disease dementia risk in older adults with mild cognitive impairment: a systematic review and critical appraisal. BMC Geriatr 24: 531.
9. Milner T, Brown MRG, Jones C, Leung AWS, Brémault-Phillips S (2024) Multidimensional digital biomarker phenotypes for mild cognitive impairment: considerations for early identification, diagnosis and monitoring. Front Digit Health 6: 1265846.
10. Jafari Z, Andrew MK, Rockwood K (2025) Diagnostic utility of speech-based biomarkers in mild cognitive impairment: a systematic review and meta-analysis. Age Ageing 54: afaf316.
11. World Health Organization (2021) Ethics and governance of artificial intelligence for health. Geneva.
12. World Health Organization (2024) Preferred product characteristics of blood-based biomarker diagnostics for Alzheimer disease. Geneva.
13. Tideman P, Karlsson L, Strandberg O, Calling S, Smith R, et al. (2025) Primary care detection of Alzheimer's disease using a self-administered digital cognitive test and blood biomarkers. Nat Med 31: 4131-4139.
14. Bonvino A, Cornacchia E, Scaramuzzi GF, Gasparre D, Manippa V, et al. (2025) Digital tools for mild cognitive impairment: a systematic review and meta-analysis of diagnostic accuracy and methodological challenges. Neuropsychol Rev.
15. Wen S, Cheng D, Zhao N, Chen X, Lu X, et al. (2025) Psychometric properties of screening tools for mild cognitive impairment in older adults based on COSMIN guidelines: a systematic review. BMC Geriatr 25: 401.
16. Kallmyer BA, Bass D, Baumgart M, Callahan CM, Dulaney S, et al. (2023) Dementia care navigation: building toward a common definition, key principles, and outcomes. Alzheimers Dement (N Y) 9: e12408.
17. Saragosa M, MacEachern E, Chiu M, Weylie S, Schneider K, et al. (2024) Mapping the evidence on dementia care pathways: a scoping review. BMC Geriatr 24: 690.
18. Cox CG, Brush BL, Kobayashi LC, Roberts JS (2025) Determinants of dementia diagnosis in U.S. primary care in the past decade: a scoping review. J Prev Alzheimers Dis 12: 100035.
19. Sorrentino M, Fiorilla C, Mercogliano M, Stilo I, Esposito F, et al. (2025) Barriers for access and utilization of dementia care services in Europe: a systematic review. BMC Geriatr 25: 162.
20. World Health Organization (2019) iSupport for Dementia: Training and Support Manual for Carers of People with Dementia. Geneva.
21. Lee KW, Hong YJ, Yang EJ, Lee SB, Kim SH, et al. (2024) Feasibility and usefulness of cognitive monitoring using a new home-based cognitive test in mild cognitive impairment: a prospective single arm study. BMC Geriatr 24: 241.
22. Rykov YG, Patterson MD, Gangwar BA, Jabar SB, Leonardo J, et al. (2024) Predicting cognitive scores from wearable-based digital physiological features using machine learning: data from a clinical trial in mild cognitive impairment. BMC Med 22: 36.
23. Rocha IC, Arantes M, Moreira A, Vilaca JL, Morais P, et al. (2024) Monitoring wearable devices for elderly people with dementia: a review. Designs 8: 75.
24. Liu M, Ning Y, Teixayavong S, Liu X, Mertens M, et al. (2025) A scoping review and evidence gap analysis of clinical AI fairness. NPJ Digit Med 8: 360.

25. European Union. Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, 2024, 07-12.

26. Butler PM, Yang J, Brown R, Hobbs M, Becker A, et al. (2025) Smartwatch- and smartphone-based remote assessment of brain health and detection of mild cognitive impairment. Nat Med 31: 829-839.

27. Vargas-Martínez AM (2024) Economic evaluations of technology-based interventions used to provide care support for people with mild dementia or mild cognitive impairment and their caregivers: A systematic review. J Alzheimers Dis 102: 597-616.

28. Gläser E, Kilimann I, Platen M, Hoffmann W, Brosseron F, et al. (2025) The economic burden of subjective cognitive decline, mild cognitive impairment and Alzheimer's dementia: excess costs and associated clinical and risk factors. Alzheimers Res Ther 17: 142.

29. Bian D, Zhang J, Yu C, Han X, Lu P, et al. (2026) Adaptive community care for mild cognitive impair ment: a SMARTrandomized trial with cognitive and implementation outcomes. Dementia 2: 7.