Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Reporting of AI and ML Studies in Elderly Care Settings: A Rapid Systematic Scoping Review

Jonas Schropp

jonas.schropp@hs-kempten.de

Kempten University of Applied Sciences

Katja Bochtler

Kempten University of Applied Sciences

Research Article

Keywords: artificial intelligence, machine learning, elderly care, reporting quality, reporting guidelines, scoping review, health informatics

Posted Date: October 11th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9780627/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Background. Artificial intelligence (AI) and machine learning (ML) systems are increasingly proposed for elderly care settings such as nursing homes, assisted living, and home-based care. Existing reporting guidelines for AI studies have primarily been developed for medical and diagnostic applications, and their adequacy for elderly care contexts remains unclear. This rapid scoping review aimed to characterize current reporting and evaluation practices of AI and ML studies intended for elderly care settings.

Methods. PubMed and IEEE Xplore were searched on 2026-02-18 for peer-reviewed studies published from 2020 onwards reporting empirical AI or ML systems intended to support tasks in elderly care contexts. Purely diagnostic or prognostic medical AI studies were excluded. A random sample of 200 retrieved records was screened by two reviewers as part of a rapid scoping review approach. Data were extracted using a standardized form assessing reporting of contextual characteristics, data and population information, evaluation practices, bias, uncertainty, limitations, and deployment-related aspects. Results were synthesized descriptively.

Results. A total of 69 studies were included. Most focused on early-stage model development and internal technical validation, while external validation and evaluation in real-world care settings were uncommon. Use cases were dominated by monitoring and safety-oriented applications across home-based and institutional care settings. Reporting completeness varied substantially across domains. While intended system roles and data sources were commonly reported, reporting of missing data handling, external validation, uncertainty quantification, calibration, and subgroup analyses was limited. Intended users, decision-makers, and deployment contexts were frequently only partially specified.

Discussion.Current reporting practices for AI and ML systems in elderly care may focus more on technical model development rather than system-level considerations given the complexity of care environments. The identified gaps suggest that existing medical AI reporting guidelines may not fully address the contextual and operational requirements of elderly care applications.

Background

Artificial intelligence (AI) and machine learning (ML) systems are increasingly proposed for use in elderly care settings, including nursing homes, assisted living facilities, community- and home-based care. These systems often aim to support care planning, monitoring, safety management, or resource allocation rather than classical medical diagnosis or prognosis [1–3]. In these settings, ethical and socio-technical factors related to context, users, and deployment may be at least as relevant for the safe and effective use of AI systems as conventional performance metrics [4–5].

Existing reporting guidelines for AI-based studies have primarily been developed in the context of medical research and clinical decision-making [6–10]. While these guidelines provide robust standards for diagnostic and prognostic models, it remains unclear to what extent they adequately cover AI

systems deployed in elderly care contexts, where decision-makers, care pathways, accountability structures, and deployment environments differ substantially from traditional medical settings, as reflected in empirical analyses of community-based elderly care systems [1–3, 5].

When studies fail to report key information, use heterogeneous definitions of key concepts or lack standardized evaluation, readers struggle to judge the quality of published models and their applicability to their own use cases, reviews or validation studies and avoidable ‘reporting waste’ is generated [11]. A systematic mapping of current reporting and evaluation practices is therefore required to identify whether existing reporting standards sufficiently address these contexts, and where systematic gaps remain.

Methods

We conducted a rapid scoping review with a structured assessment of reporting practices to map the evolving landscape of AI and ML systems in elderly care settings. This approach is consistent with established principles for rapid reviews [12–14] and is appropriate for exploratory, policy- or funding-informed reviews.

Objectives

The objective of this rapid scoping review is to map how AI and ML studies intended for elderly care settings report key aspects related to transparency, evaluation, bias, uncertainty, and deployment context, and to identify systematic reporting gaps that may not be covered by existing medical AI reporting guidelines.

Specifically, the review aims to answer:

1. How are AI/ML systems intended for elderly care settings described with respect to care context, intended users, and decision-making role?

2. How are data sources, populations, and evaluation strategies reported?

3. To what extent do studies report considerations related to bias, subgroup performance, uncertainty, and contextual limitations?

4. Which observed reporting gaps appear insufficiently addressed by existing medical AI reporting guidelines?

Protocol and registration

Protocol and registration

This protocol has been developed a priori and is registered in an open-access repository hosted by the Open Science Framework (OSF) [15].

Eligibility criteria

The relevant inclusion and exclusion criteria for screening are listed in Table 1.

Table 1
Inclusion and Exclusion Criteria

Population	**Inclusion Criteria**	**Exclusion criteria**
	Older adults receiving care or individuals or institutions providing care to older adults	**Studies where "elderly" status is the *only* distinguishing feature and care context is standard hospital or outpatient medical care.**
Intervention	AI or ML–based systems intended to support use cases in elderly care, such as care planning, monitoring, safety or risk management, operational or organizational decision-making, escalation or allocation of care resources.	AI systems used exclusively for medical diagnosis, disease prognosis, prediction of clinical endpoints (e.g. mortality, disease progression), where existing medical AI reporting guidelines provide sufficient coverage.
Setting	nursing homes, assisted living facilities, home care, or mixed social–medical care settings.	Exclusive focus on hospital-based inpatient care, outpatient specialist clinics, acute medical care without care-setting–specific considerations.
Outcome	Any outcome related to care processes, safety monitoring, functional status, behavioral or contextual risk, care escalation or resource allocation.	Outcomes limited to diagnostic accuracy, prognostic discrimination, purely clinical endpoints traditionally evaluated in medical AI studies.
Study Type	Peer reviewed journal papers or full conference papers	Non-peer reviewed studies, reviews, surveys or meta-analyses
Year	Published between 2020-present	Published prior to 2020
Language	Papers published in English	Any language other than English

To ensure relevance to current reporting practice, only studies published from 2020 onwards were considered for inclusion. Earlier studies were excluded, as the aim of this review is to assess contemporary reporting standards rather than historical practices. Since the main focus of this review is the reporting of the AI system itself, studies where the primary object of development or evaluation was not the ML or AI model or system itself but a broader intervention in which AI was only one component (e.g., social robots used for companionship, where AI functionality was incidental to the evaluation) are excluded.

Information sources

The search was conducted in PubMed and IEEE Xplore on 2026-02-18. PubMed was selected to capture biomedical and health-focused research on AI systems in elderly care, while IEEE Xplore was included to ensure coverage of engineering- and computer-science–oriented research, particularly studies focusing on sensing, monitoring, and system-level AI applications in real-world care contexts.

Search

A deliberately broad search strategy was used, combining terms related to elderly care settings and AI/ML. Search strings were refined iteratively during screening to improve specificity. The final search strings are reported in the supplementary material.

Selection of sources of evidence

From all retrieved records, a random sample of 200 titles and abstracts (ca. 20%) was selected for screening by two reviewers. Both reviewers independently screened this sample using the predefined eligibility criteria. All records coded as “include” or “unsure” by at least one reviewer underwent full-text screening by one reviewer. We performed data extraction for every study determined relevant during full-text screening.

Data charting process

Data were extracted using a standardized charting form developed for this review. The form was pilot-tested on a small number of studies and the answer format was standardized for better comparability, but no items were added or removed. Data extraction was performed by one reviewer.

Data items

Following established methodological reviews of ML prediction models, we focused on whether key information is reported, not on its correctness or quality [16]. Extracted items and general topics were developed to characterize reporting practices and extract general recurring topics in reporting based on similar reviews in the space of AI or ML for medical applications [16–18]. The extracted items are reported in Supplementary Table 1. Items A to P were coded as “yes” (fully reported), “partial” (partially reported) and “no” (not reported).

In addition to predefined extraction items, reviewers recorded recurring reporting issues or gaps not captured by the initial categories using free-text notes. These inductively identified themes are summarized narratively.

Critical appraisal of individual sources of evidence

Consistent with rapid scoping review methodology, no formal critical appraisal or risk-of-bias assessment was conducted. The review focuses on mapping reporting practices rather than evaluating methodological quality.

Synthesis of results

Results are summarized using descriptive statistics and structured narrative synthesis. Reporting gaps are mapped across thematic domains (e.g. context, evaluation, bias, uncertainty). Findings are discussed in relation to the scope of existing medical AI reporting guidelines to identify areas of redundancy and areas of insufficient coverage. Findings are mapped at a conceptual level against TRIPOD + AI [8] to illustrate overlaps and gaps.

Results

Screening

Abstract screening was intentionally permissive to ensure high sensitivity. Every abstract was given a decision code (*include*, *unsure*, *exclude*). If the decision was "*exclude*", we additionally recorded the key criterion that led to the exclusion (one of *population*, *intervention*, *setting*, *outcome*, *study type*).

200 abstracts were screened by two reviewers, followed by full-text screening and extraction by one reviewer. All studies marked by at least one reviewer as "*include*" or "*unsure*" were extracted. During full-text review, inclusion criteria were applied strictly to ensure alignment with AI systems that influence care processes (e.g., care planning, monitoring, safety management, or resource allocation). Studies were excluded when the primary object of development or evaluation was not the ML or AI model or system itself but a broader intervention in which AI was only one component (e.g., social robots used for companionship, where AI functionality was incidental to the evaluation). Figure 1 shows a flowchart of the systematic screening process.

For agreement analyses, 'unsure' decisions were treated as inclusion decisions, reflecting the permissive screening strategy used for full-text selection. Interrater agreement was 83.5% with substantial agreement (Cohen's $\kappa \approx 0.64$; 95% CI=[0.53–0.75]).

Characteristics of Included Studies

A total of 69 studies were included. Most studies focused on early-stage model development combined with internal technical evaluation. Typical study designs involved the development of classification or monitoring models followed by evaluation on retrospective datasets, laboratory-generated data, or held-out subsets of the same dataset. External validation using independent datasets or evaluation across multiple care environments was comparatively uncommon. Only a minority of studies reported implementation-oriented evaluations involving real-world deployment, longitudinal use, or interaction with routine care workflows. Several studies combined multiple stages, such as prototype development followed by pilot testing in simulated or semi-realistic care environments.

The dominant output types were alerts, classifications, and monitoring signals intended to identify falls, abnormal behavior, mobility impairment, health deterioration, or other safety-related events. Some studies generated risk scores or predictive estimates intended to support care planning or escalation decisions, while fewer studies produced explicit recommendations or autonomous system actions. Most applications functioned as assistive or decision-support tools rather than fully autonomous systems.

Use cases were dominated by monitoring and safety-oriented applications. Fall detection, activity recognition, gait or mobility monitoring, abnormal-behavior detection, bed-exit detection, and alert generation appeared frequently across studies. Additional use cases included health-status monitoring, prediction of care needs or adverse outcomes, caregiver burden prediction, assistive prompting, social engagement systems, robotic or virtual companion systems, and organizational tasks such as service-quality monitoring or inspection prioritization.

Intended settings included home-based care, smart-home or ambient-assisted-living environments, nursing homes, long-term care facilities, assisted living, rehabilitation settings, and community-care contexts. Some use cases appeared across multiple settings, particularly fall detection and activity monitoring, while organizational applications were more commonly described in institutional care settings.

The intended users and decision-makers of AI systems were heterogeneous and often only partially specified. Systems were variously described as supporting older adults, professional caregivers, nurses, physicians, therapists, family members, or institutional staff. In several studies, the distinction between the primary system user and the individual expected to act on model outputs was not clearly defined. Some systems intended to support professional care decisions were evaluated without involvement of the corresponding professional user groups, and several studies used datasets derived from healthy volunteers, convenience samples, or simulated environments rather than the target populations described in the intended use case.

Reporting completeness

Figure 2 shows the extracted reporting items for each included study. Intended role of the AI system was consistently described across all studies (100%), key contextual aspects such as the intended decision-maker were frequently only partially specified (52%) or not reported at all (19%), indicating limited clarity regarding how systems are embedded in real-world care processes.

Reporting of data and population characteristics was generally adequate for data sources but limited for population detail and missing data handling. While most studies clearly described their data sources (91%), descriptions of the target population beyond age were often incomplete (55% partial), and reporting of missing data handling was largely absent (74%).

Reporting of evaluation practices was heterogeneous and often incomplete. While internal validation was reported in the majority of studies (64%), external validation was rare (16% present or partially present), and only a minority of studies reported complete evaluation in real-world care contexts (20%).

Description of the separation between training and evaluation data was also inconsistent, with a substantial proportion of studies providing only implicit or insufficient information for replication, or did not separate training and evaluation data at all.

Reporting of bias, uncertainty, and limitations was limited and heterogeneous. Subgroup analyses were infrequently reported (23%), and discussions of bias or fairness were present in a minority of studies (19%). Uncertainty quantification (9%) and calibration (9%) were rarely addressed, while contextual or deployment-related limitations were more commonly discussed (65%), though often without systematic treatment and at strongly varying levels of detail. Existing reporting standards were only mentioned and applied in one study (TRIPOD + AI). A descriptive summary for each reporting item is available in Table 2.

Table 2
Summary of reporting items.

Label	Number and proportion reported			
	Context and framing	**yes**	**partial**	**no**
A	Care setting	57 (83%)	12 (17%)	0 (0%)
B	Intended decision-maker	20 (29%)	36 (52%)	13 (19%)
C	Intended role of the AI system	69 (100%)	0 (0%)	0 (0%)
	Data and population			
D	Description of study population (beyond age)	31 (45%)	38 (55%)	0 (0%)
E	Data source	63 (91%)	6 (9%)	0 (0%)
F	Reporting of missing data handling	10 (14%)	8 (12%)	51 (74%)
	Evaluation			
G	Internal validation reported	44 (64%)	15 (22%)	10 (14%)
H	External validation reported	4 (6%)	7 (10%)	58 (84%)
I	Evaluation in real-world care context reported	14 (20%)	37 (54%)	18 (26%)
J	Separation of training and evaluation data described	42 (61%)	11 (16%)	16 (23%)
	Bias, uncertainty, and limitations			
K	Subgroup analyses reported	16 (23%)	15 (22%)	38 (55%)
L	Any discussion of bias or fairness	13 (19%)	33 (48%)	23 (33%)
M	Any uncertainty quantification reported	6 (9%)	15 (22%)	48 (70%)
N	Any calibration reported	6 (9%)	5 (7%)	58 (84%)
O	Contextual or deployment-related limitations discussed	45 (65%)	22 (32%)	2 (3%)

Label	Number and proportion reported			
	Context and framing	yes	partial	no
P	Any reporting guideline mentioned	1 (1%)	0 (0%)	68 (99%)

Additional emerging reporting issues

Across studies, several additional reporting issues emerged that point to systemic limitations in how predictive models are currently described. While most studies clearly stated the intended prediction task, they often lacked sufficient detail on the clinical or operational context in which the model is expected to be used, including the decision threshold, timing of predictions, and how outputs would translate into concrete actions. This creates a gap between model development and its potential role in real-world workflows.

Another notable pattern was the implicit rather than explicit specification of key assumptions. Many studies appeared to rely on unstated assumptions regarding the stability of data distributions, the consistency of care processes, or the transferability of model performance across settings. These assumptions were rarely articulated or justified, limiting the ability to critically assess the conditions under which reported results are expected to hold.

In addition, studies often lacked a clear delineation between technical model performance and system-level validity. While performance metrics were reported, they were not consistently contextualized in terms of how they relate to decision-making, workflow integration, or potential consequences in practice. This made it difficult to determine whether reported results reflect meaningful improvements in real-world settings or only performance under constrained study conditions.

Finally, reporting frequently did not support a clear assessment of model readiness for deployment. Although limitations were sometimes mentioned, they were rarely linked to specific risks, failure modes, or requirements for further validation. As a result, it remained unclear what additional evidence would be needed to move from development to safe and effective use in practice.

Discussion

This rapid scoping review identified consistent and systematic limitations in the reporting of AI and ML studies in elderly care settings. While most studies provided basic descriptions of model purpose and data sources, reporting was frequently incomplete with respect to contextual embedding, evaluation strategies, and aspects related to model reliability and real-world applicability. These findings suggest that current reporting practices are primarily oriented toward technical model development rather than comprehensive evaluation of AI systems within the complex socio-technical environments of elderly care.

A key observation across domains was a progressive decline in reporting completeness from technical description to real-world relevance. Core elements such as the intended role of the AI system and data sources were generally described with acceptable detail, whereas information required to understand how systems operate in practice, such as the intended decision-maker, population characteristics, or deployment context, was often incomplete or rudimentary. In elderly care applications, inadequate population reporting may be particularly problematic because behavioral, physiological, and functional characteristics often differ substantially between healthy convenience samples and real-world care populations. As a result, incomplete population characterization may obscure major limitations in applicability and external validity.

This pattern became more pronounced in the evaluation domain, where internal validation was commonly reported, but external validation and evaluation in real-world care settings were rarely described in sufficient detail for replication. Similarly, reporting of uncertainty, calibration, and subgroup performance was largely absent. Taken together, these findings indicate that many studies do not provide sufficient information to assess whether reported performance is robust, generalizable, or meaningful in real-world use.

Beyond individual reporting items, the review identified broader structural issues in how AI systems are described. In particular, studies often lacked a coherent linkage between data, model development, and evaluation, making it difficult to assess whether reported results are consistent with the underlying data-generating process or intended use. In addition, key assumptions, especially the stability of data distributions or transferability across care settings, were frequently implicit rather than explicitly stated or justified. This limits the ability to critically appraise the conditions under which model performance can be expected to hold and contributes to uncertainty regarding real-world applicability.

Current reporting guidelines such as TRIPOD and TRIPOD + AI overlap with several of the reporting domains identified in this review, particularly in relation to the description of data sources, study populations, model development, validation procedures, and model performance evaluation. Many of the reporting deficiencies observed in the included studies therefore concern areas that are already addressed within existing guidance. Supplementary Table 2 provides a conceptual comparison between the reporting gaps identified in this review and the extent to which these issues are addressed within TRIPOD + AI. For example, the limited reporting of missing data handling (14%), incomplete description of the separation between training and evaluation data (61% fully reported), and the rarity of external validation (6% fully reported) directly correspond to established TRIPOD domains related to participant selection, predictor and outcome handling, model development procedures, and model validation. Similarly, the infrequent reporting of calibration (9%), subgroup analyses (23%), and uncertainty quantification (9%) reflects persistent gaps in the reporting of model performance and reliability that are explicitly emphasized in recent AI-focused extensions such as TRIPOD + AI. The finding that only one study mentioned any reporting guideline further suggests that incomplete adherence to existing standards remains a major issue in this literature.

At the same time, several recurring themes identified in this review appear only partially captured by current reporting frameworks. Many studies insufficiently specified the intended decision-maker, the operational role of the system within care workflows, or how model outputs were expected to translate into concrete actions in practice. In addition, studies frequently relied on implicit assumptions regarding transferability across care settings, stability of data distributions, or integration into existing organizational processes without explicitly discussing these assumptions or their implications. While TRIPOD + AI substantially extends traditional prediction-model reporting toward AI-specific methodological issues, its primary focus remains the transparent reporting of prediction model development and validation within clinical contexts. By contrast, many AI applications in elderly care function as socio-technical systems embedded in heterogeneous care environments involving caregivers, institutional staff, family members, and older adults themselves. The observed gaps related to workflow integration, deployment assumptions, accountability structures, and system-level evaluation therefore suggest potential areas where current medical AI reporting guidelines may only partially address the requirements of real-world elderly care applications.

Importantly, the results highlight that the challenge is not limited to missing individual reporting items, but rather reflects the absence of a coherent evaluative framework that links model development, validation, and real-world use. Many studies report technical performance metrics without clearly situating them within the broader system in which the model is intended to operate. As a result, it remains unclear whether these models are ready for deployment, what risks they may entail, and what additional evidence would be required to support safe and effective use. This gap between technical evaluation and real-world applicability represents a key translational challenge for AI in elderly care.

Taken together, these findings suggest that further systematic work is needed to determine which aspects of elderly-care AI are already adequately addressed by existing reporting frameworks and which may require additional methodological guidance. In particular, future work should more systematically evaluate how existing frameworks address context, system-level evaluation, epistemic uncertainty, and structured assessment of whether AI systems are fit for purpose in specific care settings. The results of this review provide an empirical basis for such developments and highlight priority areas for future methodological work.

Limitations

This rapid scoping review has several limitations. Screening was conducted by a single reviewer, and the search was restricted to two databases (PubMed and IEEE) as well as English-language publications. These choices were made to enable timely completion but may have reduced the comprehensiveness of the evidence base. The results should therefore be interpreted as indicative rather than exhaustive.

During screening, we applied strict inclusion criteria, excluding studies in which elderly care contexts were only one of multiple potential application domains, as well as studies in which the AI or ML component was not the primary object of investigation. While this approach may have reduced the

breadth of included studies, it increased the specificity of the sample with respect to the research objective. Including such studies may have introduced additional heterogeneity in reporting practices, potentially complicating interpretation.

In addition, this review focused on the completeness of reporting rather than the methodological quality or risk of bias of included studies. The presence of complete reporting does not imply the absence of systematic bias, and conversely, incomplete reporting does not necessarily indicate poor methodological quality. As such, the findings should be understood as reflecting reporting practices rather than the validity of the underlying models. Likewise, this review was not designed to determine whether the identified reporting issues are specific to AI in elderly care or instead reflect broader reporting practices across AI literature.

Conclusion

This rapid scoping review identified consistent gaps in the reporting of AI and ML studies in elderly care settings, particularly with respect to contextual embedding, evaluation beyond internal validation, and the assessment of uncertainty, bias, and real-world applicability. While core elements of model description are typically reported, the information required to assess whether systems are reliable, generalizable, and fit for use in practice is often incomplete. Although these reporting deficiencies may not be unique to elderly-care AI, their implications may be particularly consequential in elderly-care settings due to the strong dependence of system validity on contextual, demographic, and workflow-related factors.

These findings suggest that current reporting practices may focus more on technical model development rather than system-level considerations given the complexity of care environments. Existing reporting guidelines for AI and ML in medicine appear to have had limited uptake in the elderly care literature, and several recurring reporting issues identified in this review may not be fully captured by their current scope. Addressing this gap will require systematic evaluation of how frameworks can explicitly integrate context, evaluation, and epistemic considerations, and how they can support a structured assessment of model readiness for deployment.

Future work should focus on systematic framework mapping, taxonomy development, stakeholder-informed guideline refinement, and empirical evaluation in real-world care settings.

Abbreviations

AI Artificial Intelligence

ML Machine Learning

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Data associated with this rapid systematic scoping review are available on the project's OSF page at https://osf.io/73v2y. These materials include the search histories for PubMed and IEEE Xplore, as well as the results of title and abstract screening. Full-text articles are not included due to copyright restrictions.

Competing interests

The authors declare that they have no competing interests.

Funding

No specific funding has been obtained for this scoping review.

Authors' contributions

JS: conceptualization; methodology; data curation (reference screening; data extraction); writing – original draft; visualization; KB: conceptualization; data curation (reference screening); writing – review & editing; supervision.

Acknowledgements

Not applicable.

Protocol Deviations

The present review deviated from the registered protocol by including all 69 studies identified during full-text screening rather than stopping at a predefined subset of up to 30 studies. This decision was made prior to final data extraction and analysis and was driven by the observed heterogeneity of use cases and the emergence of additional reporting issues. Expanding the sample allowed for a more comprehensive characterization of reporting practices across different application contexts.

References

1. Zhao Y, Li J. Opportunities and challenges of integrating artificial intelligence in China's elderly care services. Sci Rep 22 April. 2024;14(1):9254. 10.1038/s41598-024-60067-w.
2. Lee CH, Wang C, Fan X, Li F, Chen CH. Artificial intelligence-enabled digital transformation in elderly healthcare field: Scoping review. Adv Eng Inf Januar. 2023;55:101874. 10.1016/j.aei.2023.101874.

3. Band S, Biyari M, Hsu CC, Ruga T, Zumpano E, Caroprese L, et al. A Review on AI Approaches in Elderly fall Monitoring Systems: Taxonomies, Challenges, and Open Issues. Cogn Comput Dezember. 2025;17(6):176. 10.1007/s12559-025-10532-z.
4. Mhlanga D. Artificial Intelligence in Elderly Care: Navigating Ethical and Responsible AI Adoption for Seniors. In: Mhlanga D, Dzingirai M, editors. Fostering Long-Term Sustainable Development in Africa. Cham: Springer Nature Switzerland; 2024. pp. 411–40. 10.1007/978-3-031-61321-0_18.
5. Zhu J, Shi K, Yang C, Niu Y, Zeng Y, Zhang N, et al. Ethical issues of smart home-based elderly care: A scoping review. J Nurs Manage. 2022;30(8):3686–99. 10.1111/jonm.13521.
6. Altman DG, Simera I, Hoey J, Moher D, Schulz K. EQUATOR: reporting guidelines for health research. Lancet. 2008;371(9619):1149–50. 10.1016/S0140-6736(08)60505-X.
7. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): The TRIPOD Statement. Ann Intern Med. 2015;162(1):55–63. 10.7326/M14-0697.
8. Cohen JF, Bossuyt PMM. TRIPOD + AI: an updated reporting guideline for clinical prediction models. BMJ. 2024;q824. 10.1136/bmj.q824.
9. Wolff RF, Moons KGM, Riley RD, Whiting PF, Westwood M, Collins GS, et al. PROBAST: A Tool to Assess the Risk of Bias and Applicability of Prediction Model Studies. Ann Intern Med. 2019;170(1):51–8. 10.7326/M18-1376.
10. Moons KGM, Damen JAA, Kaul T, Hooft L, Andaur Navarro C, Dhiman P, et al. PROBAST + AI: an updated quality, risk of bias, and applicability assessment tool for prediction models using regression or artificial intelligence methods. BMJ. 2025;388:e082505. 10.1136/bmj-2024-082505.
11. Chalmers I, Glasziou P. Avoidable waste in the production and reporting of research evidence. Lancet. 2009;374(9683):86–9. 10.1016/S0140-6736(09)60329-9.
12. Garritty C, Hamel C, Trivella M, Gartlehner G, Nussbaumer-Streit B, Devane D, et al. Updated recommendations for the Cochrane rapid review methods guidance for rapid reviews of effectiveness. BMJ. 2024;384:e076335. 10.1136/bmj-2023-076335.
13. Tricco AC, Langlois EV, Straus SE. Rapid reviews to strengthen health policy and systems: a practical guide. Geneva: World Health Organization; 2017. pp. 1–116.
14. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Ann Intern Med. 2018;169(7):467–73. 10.7326/M18-0850.
15. Schropp J. Developing Standards for the Transparent Reporting of AI Systems in Elderly Care. 2026. 10.17605/OSF.IO/73V2Y
16. Andaur Navarro CL, Damen JAA, Van Smeden M, Takada T, Nijman SWJ, Dhiman P, et al. Systematic review identifies the design and methodological conduct of studies on machine learning-based prediction models. J Clin Epidemiol. 2023;154:8–22. 10.1016/j.jclinepi.2022.11.015.
17. Yusuf M, Atal I, Li J, Smith P, Ravaud P, Fergie M, et al. Reporting quality of studies using machine learning models for medical diagnosis: a systematic review. BMJ Open. 2020;10(3):e034568.

10.1136/bmjopen-2019-034568.

18. Nagendran M, Chen Y, Lovejoy CA, Gordon AC, Komorowski M, Harvey H, et al. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ. 2020. m689.
19. Zhou F, Wan X, Du X, Lu Z, Wu J. Design and Implementation of An Intelligent Health Management System for Nursing Homes. In: 2022 IEEE 7th International Conference on Smart Cloud (SmartCloud). Shanghai, China: IEEE; 2022. pp. 145–50. 10.1109/SmartCloud55982.2022.00029
20. Zhang H, Xing ZZ, Hao J. Recognition of Painful Expressions in Elderly People Based on Deep Learning. In: 2024 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC). Dalian, China: IEEE; 2024. pp. 234–8. 10.1109/IPEC61310.2024.00047
21. Yuh AH, Kang SJ. Real-Time Sound Event Classification for Human Activity of Daily Living using Deep Neural Network. In: 2021 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics). Melbourne, Australia: IEEE; 2021. pp. 83–8. 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics53846.2021.00027
22. Yang SY, Qiu YW, Hung LH, Tasi CH. Automated Generation of Health Care Dynamic Recommendation Reports Through GPT-Powered Interoperability in Health Care IoT Environment. In: 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE). Las Vegas, NV, USA: IEEE; 2023. pp. 261–5. doi:10.1109/CSCE60160.2023.00046.
23. Xu FY, Lee JC, Pan YJ. YOLOv10-C2f-FENG: Efficient Anomaly Detection for Smart Care Monitoring. In: 2025 IEEE International Conference on Computation, Big-Data and Engineering (ICCBE). Penang, Malaysia: IEEE; 2025. pp. 1004–8. 10.1109/ICCBE65177.2025.11256033
24. Xie L, Sun Y, Chambers JA, Naqvi SM. Privacy Preserving Multi-class Fall Classification Based on Cascaded Learning And Noisy Labels Handling. In: 2022 25th International Conference on Information Fusion (FUSION). Linköping, Sweden: IEEE; 2022. pp. 1–6. 10.23919/FUSION49751.2022.9841327
25. Wu D, Pu L, Jo J, Hexel R, Moyle W. Deploying Robot-Led Activities for People with Dementia at Aged Care Facilities: A Feasibility Study. J Am Med Dir Assoc. 2024;25(7):105028. 10.1016/j.jamda.2024.105028.
26. Warunsin K, Phairoh T. Wristband Fall Detection System Using Deep Learning. In:, Systems C, ICCCS). (. Wuhan, China: IEEE; 2022. pp. 223–7. 10.1109/ICCCS55155.2022.9846023
27. Wang L, Kong C. Wireless Sensor Network Based Home Elderly Care Medical Detection System using Deep Learning Model. In: 2024 Second International Conference on Data Science and Information System (ICDSIS). Hassan, India: IEEE; 2024. pp. 1–4. 10.1109/ICDSIS61070.2024.10594638
28. Wang Z, Ren A, Zhang Q, Zahid A, Abbasi QH. Recognition of Approximate Motions of Human Based on Micro-Doppler Features. IEEE Sens J. 2023;23(11):12388–97. 10.1109/JSEN.2023.3267820.

29. Vargas G, Cunanan VA, Villaverde J. IoT-Based Wrist-Worn Ambient Assisted Living Device with Attention-Enhanced CNN-GRU for Human Activity Recognition. In: 2025 11th International Conference on Control, Automation and Robotics (ICCAR). Kyoto, Japan: IEEE; 2025. pp. 542–7. 10.1109/ICCAR64901.2025.11073037
30. Valli C, Amutha R. Exploring Classifier Selection for Human Activity Recognition Using Machine Learning Approach. 2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS). Chennai, India: IEEE; 2023. pp. 1–5. 10.1109/ICCEBS58601.2023.10448982.
31. Torabi SM, Narimani M, Park EJ. Enhanced In-Home Human Activity Recognition Using Multimodal Sensing and Spatiotemporal Machine Learning Architecture. In: 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Orlando, FL, USA: IEEE; 2024. pp. 1–5. 10.1109/EMBC53108.2024.10782799
32. Syed AS, Sierra-Sosa D, Kumar A, Elmaghraby A. A Deep Convolutional Neural Network-XGB for Direction and Severity Aware Fall Detection and Activity Recognition. Sensors. 2022;22(7):2547. 10.3390/s22072547.
33. Susilo R, Sudarsono A, Budi T, Secure. and Real-Time Behavior Prediction of Elderly Data Using RSA-AES Hybrid Encryption and ANN with Backpropagation Method. In: 2025 International Electronics Symposium (IES). Surabaya, Indonesia: IEEE; 2025. pp. 869–74. 10.1109/IES67184.2025.11161758
34. Suponenkovs A, Lacis M, Markovics Z, Kovalovs M, Platkajis A, Kalnins A. Application of Image Processing and Machine Learning Technologies for Home Care Bed. In: 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME). Maldives, Maldives: IEEE; 2022. pp. 1–7. 10.1109/ICECCME55909.2022.9988273
35. Sun H, Qu Q, Dorje L, Chen Y, Li X. Senior Safety Monitoring in Microverse using Fuzzy Neural Network Enhanced Action Recognition. In: 2026 IEEE 23rd Consumer Communications & Networking Conference (CCNC). Las Vegas, NV, USA: IEEE; 2026. pp. 1–2. doi:10.1109/CCNC65079.2026.11366515.
36. Spournias A, Faliagka E, Skandamis T, Antonopoulos C, Voros NS, Keramidas G. Gestures detection and device control in AAL environments using machine learning and BLEs. In: 2023 12th Mediterranean Conference on Embedded Computing (MECO). Budva, Montenegro: IEEE; 2023. pp. 1–5. 10.1109/MECO58584.2023.10154987
37. Son CS, Kang WS, Lee JH, Moon KJ. Machine Learning to Identify Psychomotor Behaviors of Delirium for Patients in Long-Term Care Facility. IEEE J Biomed Health Inf. 2022;26(4):1802–14. 10.1109/JBHI.2021.3116967.
38. Shu Q, Tu Z, Xu X, Wang Z. A Social Sensing Approach for Quality Changes of Real-World Services. In: 2020 IEEE International Conference on Service Oriented Systems Engineering (SOSE). Oxford, United Kingdom: IEEE; 2020. pp. 82–91. 10.1109/SOSE49046.2020.00017
39. Sheehy L, Bouchard S, Kakkar A, El Hakim R, Lhoest J, Frank A. Development and Initial Testing of an Artificial Intelligence-Based Virtual Reality Companion for People Living with Dementia in Long-Term Care. JCM. 2024;13(18):5574. 10.3390/jcm13185574.

40. Shao L, Wang Z, Xie X, Xiao L, Shi Y, Wang Z et al. an,. Development and External Validation of a Machine Learning–based Fall Prediction Model for Nursing Home Residents: A Prospective Cohort Study. Journal of the American Medical Directors Association. 2024;25(9):105169. 10.1016/j.jamda.2024.105169
41. Şerbetci NO, Blüher S, Gellert P, Leser U. Explaining care need assessment surveys: qualitative and quantitative evaluation of state-of-the-art local and global explainable artificial intelligence methods. JAMIA Open. 2025;8(4):ooaf064. 10.1093/jamiaopen/ooaf064.
42. Santhanamari G, Choudhary S, Mohan Ps SM, Gurusharan LVA. Smart Wearable-Based Fall Detection and Health Monitoring System for Elderly Care Using IoT and Machine Learning. In: 2025 International Conference on Next Generation Computing Systems (ICNGCS). Coimbatore, India: IEEE; 2025. pp. 1–6. 10.1109/ICNGCS64900.2025.11183514
43. Sangeetha S, Anitha K, Natarajan C, Sarkar S, Karthika SS. Enhancing Fall Detection in Assisted Living Using Deep Learning Approach. In: 2025 Second International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS). Coimbatore, India: IEEE; 2025. pp. 1–5. 10.1109/ICC-ROBINS64345.2025.11086168
44. Sang D, Miao L, Wu Q. A smart community interactive art therapy platform based on multimodal computer graphics and resilient artificial intelligence for home-based elderly care. Sci Rep. 2025;15(1):43057. 10.1038/s41598-025-27129-z.
45. Sadreazami H, Bolic M, Rajan S. Contactless Fall Detection Using Time-Frequency Analysis and Convolutional Neural Networks. IEEE Trans Ind Inf. 2021;17(10):6842–51. 10.1109/TII.2021.3049342.
46. Rothmeier T, Kunze S. Comparison of Machine Learning and Rule-based Approaches for an Optical Fall Detection System. In: 2022 IEEE 9th International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA). Chemnitz, Germany: IEEE; 2022. pp. 1–6. 10.1109/CIVEMSA53371.2022.9853711
47. Peimankar A, Winther TS, Ebrahimi A, Wiil UK. A Machine Learning Approach for Walking Classification in Elderly People with Gait Disorders. Sensors. 2023;23(2):679. 10.3390/s23020679.
48. Payandeh S, Park J. Passive Observer of Activities for Aging in Place Using a Network of RGB-D Sensors. Hu F, editor. International Journal of Telemedicine and Applications. 2020;2020:1–15. 10.1155/2020/8867926
49. Onim MSH, Humble TS, Thapliyal H. Emotion Recognition in Older Adults with Quantum Machine Learning and Wearable Sensors. In: 2025 IEEE Computer Society Annual Symposium on VLSI (ISVLSI). Kalamata, Greece: IEEE; 2025. pp. 1–6. 10.1109/ISVLSI65124.2025.11130356
50. Naser A, Lotfi A, Mwanje MD, Zhong J, Privacy-Preserving. Thermal Vision With Human in the Loop Fall Detection Alert System. IEEE Trans Human-Mach Syst. 2023;53(1):164–75. 10.1109/THMS.2022.3203021.
51. Moazam SM, Machado P, Bird JJ, Wada YS, Inoue S, Lotfi A, et al. Position-Aware Indoor Human Activity Recognition and Fall Detection. IEEE Sens J. 2026;26(4):6173–87.

10.1109/JSEN.2026.3651213.

52. Mishra PK, Taati B, Ye B, Newman K, Mihailidis A, Iaboni A, et al. Large Language Models Improve Scene-Invariant Detection of Behavior of Risk in Dementia Residential Care Across Multiple Surveillance Camera Views. IEEE Trans Neural Syst Rehabil Eng. 2026;34:788–97. 10.1109/TNSRE.2026.3656747.
53. Mekruksavanich S, Phaphan W, Jitpattanakul A. Harnessing Deep Learning for Activity Recognition in Seniors' Daily Routines with Wearable Sensors. In: 2024 47th International Conference on Telecommunications and Signal Processing (TSP). Prague, Czech Republic: IEEE; 2024. pp. 164–7. 10.1109/TSP63128.2024.10605946
54. Mashouri P, Taati B, Quirt H, Iaboni A. Quality Indicators as Predictors of Future Inspection Performance in Ontario Nursing Homes. J Am Med Dir Assoc. 2020;21(6):793–e7981. 10.1016/j.jamda.2019.09.007.
55. Manni A, Rescio G, Caroppo A, Leone A. Muscle Fatigue Assessment in Healthcare Application by Using Surface Electromyography: A Transfer Learning Approach. Sensors. 2026;26(2):654. 10.3390/s26020654.
56. Luo Y, Kubo M, Kobayashi Y, Fukunishi H. Long-Term Care Risk Prediction by Claims Data Analysis. In: 2020 IEEE International Conference on Healthcare Informatics (ICHI). Oldenburg, Germany: IEEE; 2020. pp. 1–2. 10.1109/ICHI48887.2020.9374356
57. Liu Y, Luo J, Wu JA, Real-Time. Fall Detection System Based on Vision. In: 2025 International Conference on Electrical, Communication and Computer Engineering (ICECCE). Istanbul, Turkiye: IEEE; 2025. pp. 1–6. 10.1109/ICECCE67514.2025.11257964
58. Liu S. Enhancing Elderly Safety: A Machine Learning-Driven Acoustic System for In-Home Fall Detection and Alerting. In: 2024 International Conference on Computers, Information Processing and Advanced Education (CIPAE). Ottawa, ON, Canada: IEEE; 2024. pp. 220–4. 10.1109/CIPAE64326.2024.00045
59. Lin WC, Chu ETH, Lee CR, EgoFall:. A First-Person View Fall Detection System. In: 2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Copenhagen, Denmark: IEEE; 2025. pp. 1–4. 10.1109/EMBC58623.2025.11254084
60. Lin CL, Lee PT, Ho YH, Lin FY, Hsieh PH, Chen YZ. Pseudo-Siamese Neural Network for Bed-Exit Detection With Low-Resolution Sensors. IEEE Sens J. 2025;25(14):27577–86. 10.1109/JSEN.2025.3576801.
61. Lin YC, Fan J, Tate JA, Sarkar N, Mion LC. Use of robots to encourage social engagement between older adults. Geriatr Nurs. 2022;43:97–103. 10.1016/j.gerinurse.2021.11.008.
62. Li H, Li Y, Li Z, Shen Y, Li J, Wen Z. Deep Learning-Based Human Fall Detection and Application of Cameras. In: 2025 6th International Conference on Computer Vision and Data Mining (ICCVDM). London, United Kingdom: IEEE; 2025. pp. 342–6. 10.1109/ICCVDM66874.2025.11290540
63. Lee SY, Huang TY, Yen CY, Lee IP, Chen JY, Huang CR. A Deep Learning-Based Cloud-Edge Healthcare System With Time-of-Flight Cameras. IEEE Sens J. 2024;24(5):7064–74.

10.1109/JSEN.2023.3347718.

64. Lee SK, Shin JH, Ahn J, Lee JY, Jang DE. Identifying the Risk Factors Associated with Nursing Home Residents' Pressure Ulcers Using Machine Learning Methods. IJERPH. 2021;18(6):2954. 10.3390/ijerph18062954.
65. Kingkaew K, Thaenthong J, Suwanapong T. A Comparative Analysis of Lightweight CNN Architectures for Wi-Fi CSI-Based Fall Detection. In: 2025 20th International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP). Phuket, Thailand: IEEE; 2025. pp. 1–6. 10.1109/iSAI-NLP66160.2025.11320519
66. Khodke A, Kulkarni G, Junghare S, Deshpande AM. A Transfer Learning Framework for Elderly Action Monitoring and Stillness Detection. In: 2024 4th International Conference on Computer, Communication, Control & Information Technology (C3IT). Hooghly, India: IEEE; 2024. pp. 1–6. doi:10.1109/C3IT60531.2024.10829437.
67. Khan SS, Mishra PK, Javed N, Ye B, Newman K, Mihailidis A et al. Unsupervised Deep Learning to Detect Agitation From Videos in People With Dementia. IEEE Access; 2022. 2022;10:10349–58. 10.1109/ACCESS.2022.3143990
68. Hutabarat JP, Ahmadi N, Adiono T. Human Activity Recognition Based on Wearable Devices and Feedforward Neural Networks. In: 2023 International Conference on Electrical Engineering and Informatics (ICEEI). Bandung, Indonesia: IEEE; 2023. pp. 1–4. 10.1109/ICEEI59426.2023.10346836
69. Haque MM, Maruf AA, Obeid AJ, Judi HK, Bhuiyan MH, Aung Z. Exploring Elderly Activity Recognition Using Deep Learning Through Sensor-Enabled Android App Data Collection. In: 2024 Third International Conference on Power, Control and Computing Technologies (ICPC2T). Raipur, India: IEEE; 2024. pp. 582–7. 10.1109/ICPC2T60072.2024.10474756
70. Han H, Hatano M. Prediction of BPSD Onset Using Multimodal Sensors: A Study on Dementia Patients in Long-Term Care. In: Househ MS, Tariq ZUA, Al-Zubaidi M, Shah U, Huesing E, editors. Studies in Health Technology and Informatics. IOS; 2025. 10.3233/SHTI251236.
71. Gasmi A, Augusto V, Faucheu J, Hilaire M, Moulin R, Morin C et al. Frailty Onset Predictions Using Sleep Analysis. In: 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME). Maldives, Maldives: IEEE; 2022. pp. 1–4. 10.1109/ICECCME55909.2022.9988255
72. Gaddam A, Nair S, Khan MZ, Thiruvady D. Enhancing Elderly Care: Indoor Detection of ADL and Gait Disorders with IoT and LiDAR. In: 2024 17th International Conference on Sensing Technology (ICST). Sydney, Australia: IEEE; 2024. pp. 1–7. 10.1109/ICST62759.2024.10992193
73. Francis L, Ghafurian M. Preserving the self with artificial intelligence using VIPCare—a virtual interaction program for dementia caregivers. Front Sociol. 2024;9:1331315. 10.3389/fsoc.2024.1331315.
74. Farmer MS, Popescu M, Powell K. Development and evaluation of a 4M taxonomy from nursing home staff text messages using a fine-tuned generative language model. J Am Med Inform Assoc. 2025;32(3):535–44. 10.1093/jamia/ocaf006.

75. Elbadrawy A, Abedi H, Ramahi O, Shaker G. Severity of Fall Detection using Digital Twin for Radar Systems. In: 2023 IEEE Microwaves, Antennas, and Propagation Conference (MAPCON). Ahmedabad, India: IEEE; 2023. pp. 1–3. 10.1109/MAPCON58678.2023.10506223
76. Cui C, Wang C, Dong X, An Z. Intelligent Mobile Body Temperature Monitoring & Management System For Nursing Home. In: 2021 IEEE 6th International Conference on Computer and Communication Systems (ICCCS). Chengdu, China: IEEE; 2021. pp. 812–8. 10.1109/ICCCS52626.2021.9449137
77. Chien SC, Yen CM, Chang YH, Chen YE, Liu CC, Hsiao YP, et al. Using large language model (LLM) to identify high-burden informal caregivers in long-term care. Comput Methods Programs Biomed. 2024;255:108329. 10.1016/j.cmpb.2024.108329.
78. Cheung JCW, Tam EWC, Mak AHY, Chan TTC, Zheng YP. A Night-Time Monitoring System (eNightLog) to Prevent Elderly Wandering in Hostels: A Three-Month Field Study. IJERPH. 2022;19(4):2103. 10.3390/ijerph19042103.
79. Chapron K, Lapointe P, Bouchard K, Gaboury S. Highly Accurate Bathroom Activity Recognition Using Infrared Proximity Sensors. IEEE J Biomed Health Inf. 2020;24(8):2368–77. 10.1109/JBHI.2019.2963388.
80. Calderita LV, Vega A, Barroso-Ramírez S, Bustos P, Núñez P. Designing a Cyber-Physical System for Ambient Assisted Living: A Use-Case Analysis for Social Robot Navigation in Caregiving Centers. Sensors. 2020;20(14):4005. 10.3390/s20144005.
81. Blasco-García JD, García-López G, Jiménez-Muñoz M, López-Riquelme JA, Feliu-Batlle JJ, Pavón-Pulido N, et al. A Computer Vision-Based System to Help Health Professionals to Apply Tests for Fall Risk Assessment. Sensors. 2024;24(6):2015. 10.3390/s24062015.
82. Beristain Iraola A, Álvarez Sánchez R, Hors-Fraile S, Petsani D, Timoleon M, Díaz-Orueta U, et al. User Centered Virtual Coaching for Older Adults at Home Using SMART Goal Plans and I-Change Model. IJERPH. 2021;18(13):6868. 10.3390/ijerph18136868.
83. Banushri S, Jagadeesha R. Human Activity Recognition-Based Fall Detection with GCRNN via Ninja Optimizer. In:, Computing 3, Informatics. (ICICI). Bangalore, India: IEEE; 2025. pp. 649–55. 10.1109/ICICI65870.2025.11069616
84. Bacic B, Zhang J. Towards Real-Time Drowsiness Detection for Elderly Care. In: 2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA). Sydney, Australia: IEEE; 2020. pp. 1–6. 10.1109/CITISIA50690.2020.9371810
85. Alqasama A, Assaf T, Martinez-Hernandez U. Towards an AI-Driven Elderly Assistance Framework with Multi-Sensor Data for Real-Time Fall Detection. In: 2025 34th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN). Eindhoven, Netherlands: IEEE; 2025. pp. 1342–7. 10.1109/RO-MAN63969.2025.11217848
86. Alberternst S, Anisimov A, Antakli A, Duppe B, Hoffmann H, Meiser M, et al. Orchestrating Heterogeneous Devices and AI Services as Virtual Sensors for Secure Cloud-Based IoT Applications. Sensors. 2021;21(22):7509. 10.3390/s21227509.

87. Abedi A, Khan SS, Iaboni A, Bronskill SE, Bethell J. Prediction of Social Engagement in Long-Term Care Homes by Sex: A Population-Based Analysis Using Machine Learning. J Appl Gerontol. 2025;44(6):902–15. 10.1177/07334648241290589.

Figures

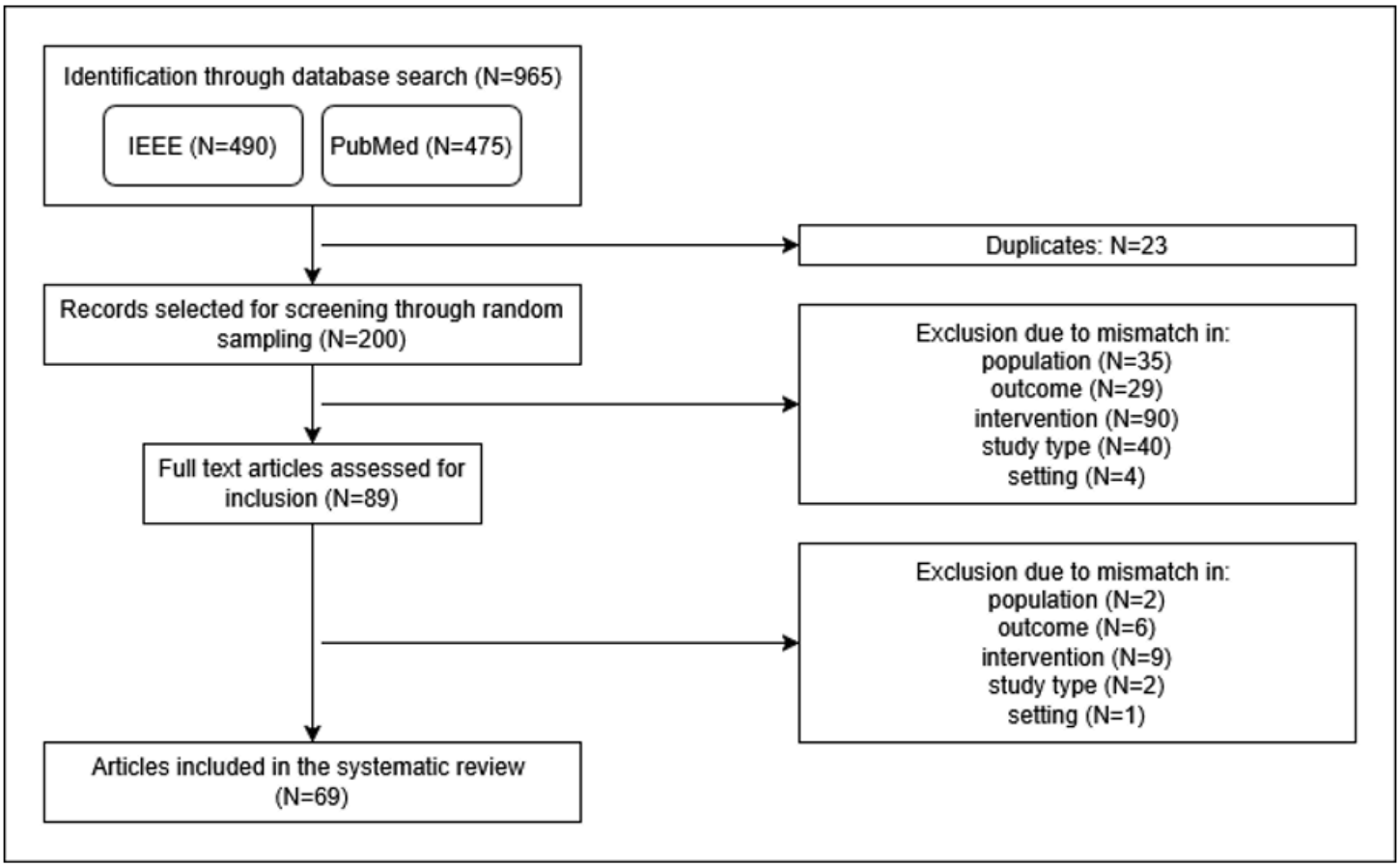


Figure 1

Flowchart of the screening process.

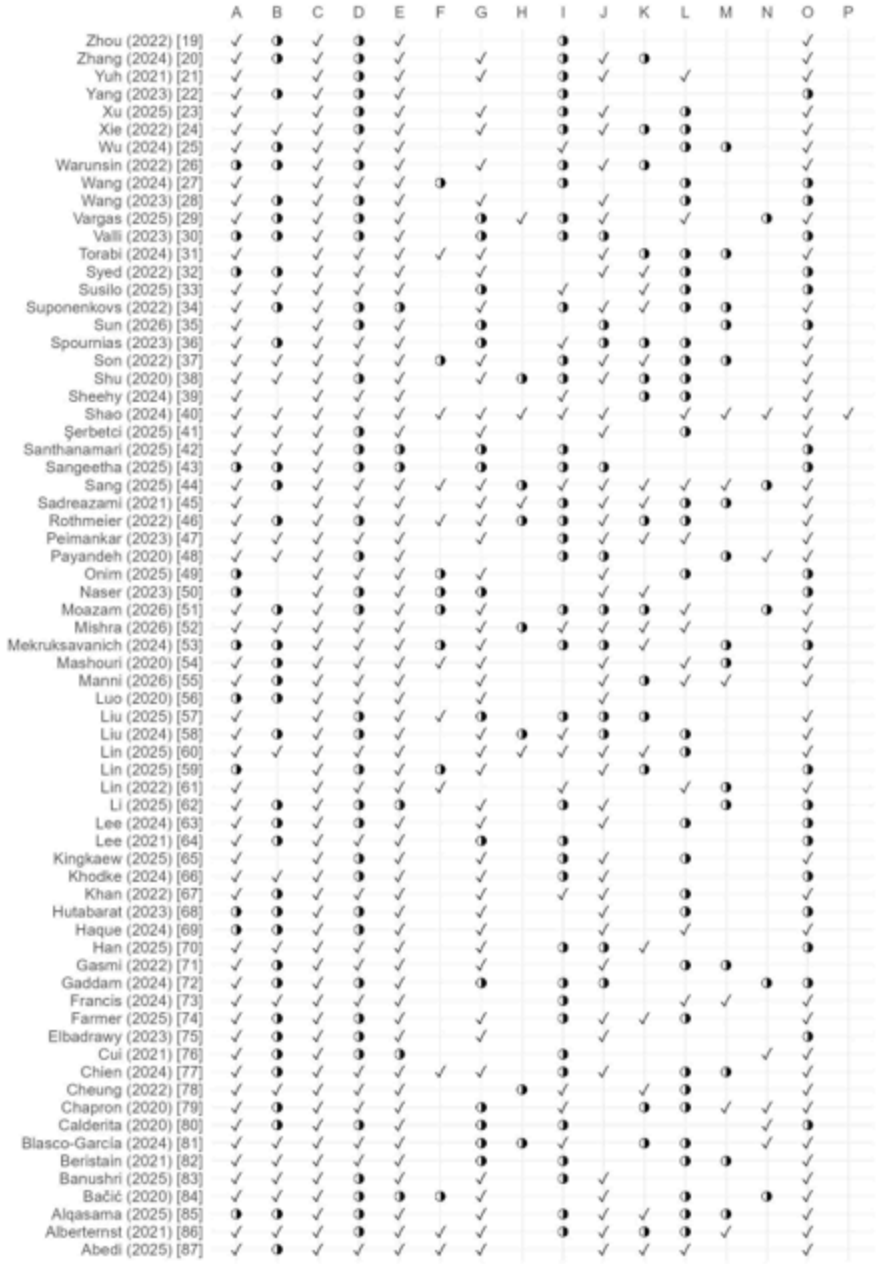


Figure 2

Extracted reporting items for the primary studies. Legend: ✓ = yes; ◑ = partial; blank = no. Reporting items: A=Care setting; B=Intended decision-maker; C=Intended role of the AI system; D=Description of study population (beyond age); E=Data source; F=Reporting of missing data handling; G=Internal validation reported; H=External validation reported; I=Evaluation in real-world care context reported; J=Separation of training and evaluation data described; K=Subgroup analyses reported; L=Any discussion of bias or fairness; M=Any uncertainty quantification reported; N=Any calibration reported; O=Contextual or deployment-related limitations discussed; P=Any reporting guideline mentioned.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SchroppBochtlerSupplementaryMaterialReportingofAIandMLStudiesinElderlyCareSettings.docx