УДК 616-06-053.9-07:004.89
https://doi.org/10.20538/1682-0363-2025-4-164-171

Artificial Intelligence in the Diagnosis and Prognosis of Multimorbidity in the Elderly

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ABSTRACT

Aim. To evaluate the effectiveness of artificial intelligence in diagnosing and predicting multimorbidity in people over 65 years based on current literature data.

Materials and methods. A systematic review of 153 studies from January 1, 2020 to March 1, 2025 was conducted following PRISMA 2020 guidelines. The PICO model was applied: population – elderly people with multimorbidity (two or more chronic conditions), intervention – artificial intelligence tools (machine learning, deep learning), outcomes – diagnostic accuracy and prognostic performance. Keyword searches were performed in PubMed, Scopus, Web of Science, and Google Scholar databases. Data were synthesized narratively and quantitatively via meta-analysis using the R software version 4.3.2. The method excels in detecting hidden patterns compared to clinical scales.

Results. Artificial intelligence demonstrated high diagnostic accuracy for dementia (AUC = 0.833), stroke (AUC = 0.91), cardiovascular diseases (AUC = 0.986–0.991), and osteoporosis (AUC= 0.972). Prognostic performance reached AUC ≈ 0.87 (95% confidence interval: 0.83–0.91) for mortality and hospitalizations. However, for multimorbidity, accuracy was lower (AUC = 0.787– 0.93) due to data heterogeneity and the complexity of disease interactions.

Conclusion. Artificial intelligence enhances diagnostic and prognostic capabilities in geriatrics, particularly for individual conditions, but requires data standardization and dynamic models for multimorbidity. Challenges, such as digital ageism and data quality, still hinder its implementation.

Keywords: artificial intelligence, multimorbidity, the elderly, diagnosis, prognosis, machine learning, deep learning, geriatrics

Conflict of interest. The author declares the absence of obvious or potential conflict of interest related to the publication of this article.

Source of financing. The author declares no funding for the study.

For citation: Martynenko A.V. Artificial intelligence in the diagnosis and prognosis of multimorbidity in the Elderly. *Bulletin of Siberian Medicine.* 2025;24(4):164–171. https://doi.org/10.20538/1682-0363-2025-4-164-171.

Искусственный интеллект в диагностике и прогнозе полиморбидности у пожилых

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РЕЗЮМЕ

Цель: оценить эффективность искусственного интеллекта в диагностике и прогнозировании полиморбидности у пожилых людей старше 65 лет на основе актуальной литературы.

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Материалы и методы. Проведен систематический обзор 153 исследований за период с 1 января 2020 г. по 1 марта 2025 г. по стандартам PRISMA 2020. Использован фреймворк PICOS: популяция – пожилые с полиморбидностью (два и более хронических заболевания), вмешательство – инструменты искусственного интеллекта (машинное обучение, глубокое обучение), исходы – точность диагностики и прогностическая эффективность. Поиск выполнен в PubMed, Scopus, Web of Science и Google Scholar. Данные синтезированы нарративно и количественно с помощью метаанализа в программном обеспечении R v. 4.3.2. Преимущество метода – способность выявлять скрытые закономерности по сравнению с клиническими шкалами.

Результаты. Искусственный интеллект показал высокую точность в диагностике деменции (AUC = 0,833), инсульта (AUC = 0,91), сердечно-сосудистых заболеваний (AUC = 0,986–0,991) и остеопороза (AUC = 0,972). Прогностическая эффективность составила AUC ≈ 0,87 (95%-й доверительный интервал: 0,83–0,91) для смертности и госпитализаций. Однако при полиморбидности точность ниже (AUC = 0,787–0,93), что связано с гетерогенностью данных и сложностью взаимодействия патологий.

Заключение. Искусственный интеллект улучшает диагностику и прогноз в гериатрии, особенно для отдельных заболеваний, но требует стандартизации данных и динамических моделей для полиморбидности. Цифровой эйджизм и качество данных остаются вызовами для внедрения.

Ключевые слова: искусственный интеллект, полиморбидность, пожилые люди, диагностика, прогнозирование, машинное обучение, глубокое обучение, гериатрия

Конфликт интересов. Автор декларирует отсутствие явных и потенциальных конфликтов интересов, связанных с публикацией настоящей статьи.

Источник финансирования. Автор заявляет об отсутствии финансирования при проведении исследования.

Для цитирования: Мартыненко А.В. Искусственный интеллект в диагностике и прогнозе полиморбидности у пожилых. *Бюллетень сибирской медицины.* 2025;24(4):164–171. https://doi.org/10.20538/1682-0363-2025-4-164-171.

INTRODUCTION

Population ageing is one of the most pressing global challenges, especially in regions where the proportion of people over 65 is increasing rapidly. According to the United Nations, the number of people aged 65 years and older will reach 1.5 billion by 2050, which will significantly increase the burden on health systems worldwide [1]. Multimorbidity, defined as the coexistence of two or more chronic diseases in one person, affects 60–80% of the elderly and poses significant challenges for timely diagnosis and treatment [2]. Traditional approaches, such as clinical assessment scales, are not often sufficiently accurate due to complex interactions between pathologies and individual patient characteristics, which highlights the urgent need to develop innovative solutions to improve care for this population group [3].

Artificial intelligence (AI), including machine learning and neural networks, has become a revolutionary tool in healthcare, demonstrating outstanding results in analyzing large and complex datasets [4]. International studies show that AI can improve the accuracy of diagnosis and prediction of complications in chronic diseases, outperforming traditional methods by 15–20% in various applications [5].

In geriatric practice, AI offers opportunities for the management of multimorbidity due to its ability to identify hidden patterns in patient data, such as electronic health records or parameters of wearable devices, enabling the development of personalized treatment strategies [6]. For example, AI-based models have proven efficient in improving cardiovascular risk prediction in the elderly based on data from various clinical sources [7]. However, the use of AI to manage multimorbidity in the elderly remains understudied, especially in regions with limited technological infrastructure [8].

This review is motivated by the need to summarize the current evidence on the role of AI in the diagnosis and prognosis of multimorbidity in the elderly, which is becoming increasingly important in the face of growing health care needs [9]. Although individual examples of AI applications, such as health monitoring and risk assessment, have been documented, comprehensive studies of their effectiveness and scalability remain rare [10].

The aim of this systematic review was to assess the effectiveness and feasibility of AI in the diagnosis and prognosis of multimorbidity in elderly people (≥ 65 years) based on current evidence from the literature.

MATERIALS AND METHODS

A systematic review was conducted according to PRISMA 2020 guidelines to analyze the role of AI in the diagnosis and prognosis of multimorbidity (≥ 2 chronic diseases) in the elderly. Literature from January 1, 2020 to March 1, 2025 focusing on AI methods (machine learning, deep learning, etc.) was included [11, 12].

Inclusion criteria according to the PICO model:

– population: elderly (≥ 65 years, elderly/older adults/geriatric) or studies with relevant conditions (multimorbidity);

– intervention: AI tools for the diagnosis or prognosis of multimorbidity;

– outcome: diagnostic accuracy (sensitivity, specificity, AUC), prognostic performance (mortality, hospitalization);

– design: original research, systematic reviews, randomized controlled trials (RCTs); non- peer-reviewed sources excluded;

– time frame: 2020–2025, language – English (or annotated in English)

Studies dated earlier than 2020, without a focus on the elderly, AI or multimorbidity were excluded.

The literature search was conducted in PubMed, Scopus, Web of Science, and Google Scholar databases using keywords and MeSH terms: “artificial intelligence”, “machine learning”, “deep learning”, “multimorbidity”, “comorbidity”, “elderly”, “older adults”, “geriatric”, “diagnosis”, and “prognosis”. An example query for PubMed: (“artificial intelligence”[MeSH Terms] or “machine learning” or “deep learning”) and (“multimorbidity”[MeSH Terms] or “comorbidity”) and (“aged”[MeSH Terms] or “elderly” or “older adults”) and (“diagnosis” or “prognosis”) and (“2020/01/01”[Date - Publication]: “2025/03/01”[Date - Publication]). The search was performed in March 2025, covering the period from January 1, 2020 to March 1, 2025.

Initially, 199 records were identified: 194 from the main databases (PubMed, Scopus, and Web of Science) and 5 additional records from Google Scholar and reference lists of relevant articles. After removing 2 duplicates (e.g., Alsaleh M.M. et al., 2023 [13]), 197 records remained. At the title and abstract screening stage, 44 studies were excluded: 20 did not match the population criteria (e.g. Gupta R. et al., 2021 [14] did not describe the elderly), 10 did not match the time range, 8 did not match the AI focus, and 6 were unreviewable. Full-text analysis of the 153 remaining records confirmed they met the inclusion criteria. The selection process is summarized in the PRISMA flow diagram (Figure).

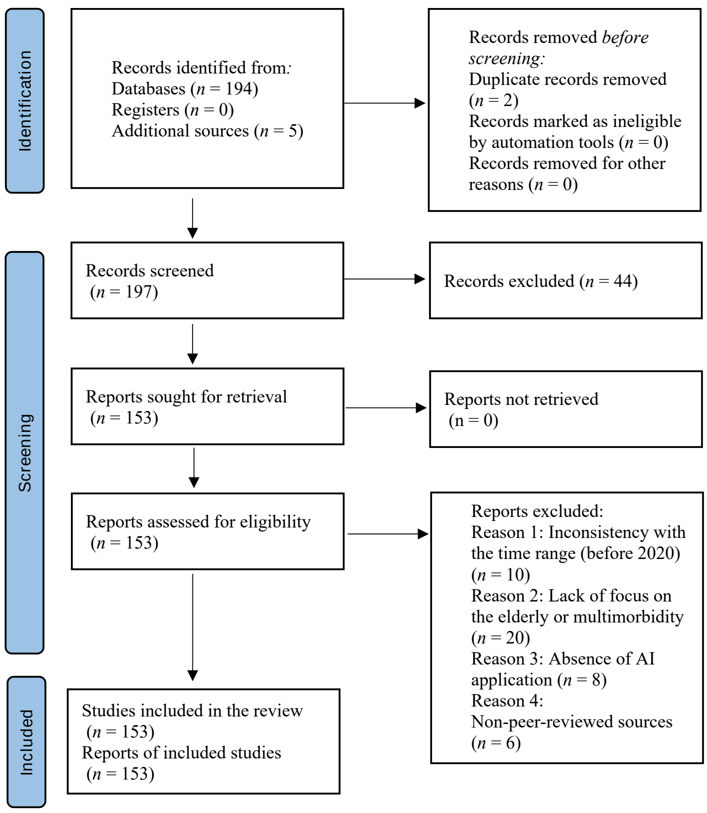

Figure. PRISMA flow diagram

The following data were retrieved: authors, year of publication, study design, age of participants, AI methods (e.g. Random Forest), outcomes (AUC, HR/OR), limitations. Data were collected manually.

The risk of bias was assessed using the ROBINS-I, RoB 2, and AMSTAR 2 (selection bias, confounding, reporting) tools. Most studies showed low to moderate risk.

Data were synthesized narratively (diagnosis, prognosis, multimorbidity) and quantitatively (meta-analysis for a subset of studies with ≥ 3 similar metrics, performed in R v. 4.3.2 with a meta-package; heterogeneity was assessed through I^2 and τ^2). GRADE assessment revealed high reliability for the diagnosis of dementia and moderate reliability for predicting mortality in the respective subgroups.

Bivariate models and HSROC were used for the diagnosis; odds ratio (OR) / hazard ratio (HR) with 95% confidence interval (CI) were used for prognosis. R v. 4.3.2 software was applied.

RESULTS

The application of AI in the diagnosis and prognosis of multimorbidity in elderly people (≥ 65 years) represents a promising area of modern geriatrics, but is accompanied by a number of challenges due to the complexity of multimorbid conditions. This systematic review, performed according to PRISMA 2020 standards, analyzed 153 studies published between January 1, 2020 and March 1, 2025. The focus was on assessing the accuracy of AI-based diagnostic models, their prognostic performance and applicability in the context of multimorbidity (the presence of two or more chronic diseases). Quantitative data synthesis was performed using the meta-analysis in the R software (version 4.3.2), allowing for aggregation of key metrics, such as area under the ROC curve (AUC), sensitivity, specificity and, where available, risk ratios (HR/OR). The risk of bias assessment of most of the included studies for the ROBINS-I, RoB 2, and AMSTAR 2 tools showed low to moderate risk of bias, confirming the validity of the results presented.

AI has demonstrated high efficiency in diagnosing certain diseases in elderly patients, which emphasizes its potential as a tool for screening and early detection of pathologies. For example, a study by S. P. Obuchi et al. applied machine learning (ML) algorithms to analyze gait to diagnose cognitive disorders, including dementia [15]. Using motion sensor data, the authors reported mean classification accuracy of 80.2%, with sensitivity of 96.1%, specificity of 64.3%, and AUC = 0.833 based on 30 test datasets.

GRADE assessment showed high confidence in these data due to the rigorous study design and low risk of bias associated with participant selection, although confidence intervals for the metrics were not provided. A similar approach was implemented by Y. Wang et al. where AI based on deep neural networks (Efficient Net, Xception, VGG, ResNet) analyzed facial images to detect acute ischemic stroke [16]. The model trained on 185 stroke patients and 551 controls using cross-validation achieved AUC = 0.91, accuracy of 86% (95% CI: 83.5–88.5%), sensitivity of 76%, and specificity of 89% at a probability threshold of 0.40. On an independent test set (38 strokes, 50 controls), the AUC was 0.82, and the accuracy was 73% (95% CI: 64.2–81.8%). This makes the model a valuable tool for emergency diagnosis in settings with limited access to MRI or CT, especially given its ability to confirm the diagnosis in the face of conflicting imaging findings. The low risk of bias assessed by RoB 2 is due to strict age and sex matching in the sample and the use of cross-validation to prevent overtraining.

In the field of cardiology, AI has shown itself to be a highly accurate method. Y. Wang et al. used deep learning to analyze cardiovascular magnetic resonance imaging (MRI) including SAX cine and 4CH cine projections for screening [17]. The screening model achieved AUC = 0.986 (95% CI: 0.984–0.988), sensitivity of 97.3% (95% CI: 96.8–97.8%), and specificity of 90% on a primary dataset (n = 7,900) to detect abnormalities covering 11 types of cardiovascular diseases, including coronary heart disease (CHD) and hypertensive heart disease (HHD), frequently occurring in the elderly.

On the external test set (n = 1,819), the AUC was 0.990 (95% CI: 0.986–0.992). A diagnostic model using SAX cine, 4CH cine, and SAX LGE achieved a weighted mean AUC = 0.991 to classify these diseases (n = 6,650). The high performance was supported by rigorous three-fold cross-validation and generalizability to external data, although potential differences in MRI protocols between centers may have affected the results, consistent with a moderate risk of bias according to ROBINS-I.

Y. Yang et al. applied chest CT data analysis to screen osteopenia and osteoporosis, achieving AUC = 0.831 for osteopenia and AUC = 0.972 for osteoporosis in the healthy group [18]. The method is based on density assessment of the thoracic vertebrae and the first lumbar vertebrae, where with an increase in CT values by 10 HU, the risk of osteopenia was reduced by 32–44% and the risk of osteoporosis decreased by 61–80%. This approach is particularly useful in the elderly with multimorbidity, as it allows for the detection of hidden pathologies without additional examinations. Confidence intervals for AUC are not given in the article, and the pooled diagnostic performance of all thoracic vertebrae was greater than that of a single vertebra, although a specific value was not given.

However, the effectiveness of models may be reduced in the diagnosis of multimorbidity. H. Chen et al. investigated cognitive impairment in cerebral microvascular disease (CMD) with consideration of vascular risk factors, such as hypertension (81.5%) and diabetes (21.9%) using a model based on oculo-gait measurements (antisaccade accuracy, step rate, and sweep rate) [19]. In the hospital cohort (n = 194), the adjusted model achieved the AUC = 0.787 after accounting for age and education, and in the population-based cohort with early CMD, the AUC was 0.810. These values are lower than for some isolated conditions due to variability in factors, such as age and education, although confidence intervals for AUC are not specified. The limitations of the study do not include explicit social factors, but the influence of demographic characteristics is emphasized.

Y. Wang et al. in their bibliometric analysis noted that AI-based research in geriatric care has focused on the monitoring and treatment of diseases, such as Alzheimer's disease and mild cognitive impairment, as well as daily care and rehabilitation of the elderly [20]. Narrative synthesis confirms the effectiveness of AI in addressing individual pathologies, but highlights limitations, such as cost, safety in the home environment, and digital inequality, which may complicate the application of AI in more complex scenarios, including multimorbidity

Predicting clinical outcomes in the elderly using AI involves mortality estimation. C. Guo et al. developed a ML (ensemble) model to predict 28-day mortality in elderly patients with colorectal cancer in the ICU, achieving AUC = 0.86 in the training cohort (eICU, n = 693), AUC = 0.73 in the validation cohort (MIMIC-IV, n = 181) and AUC = 0.81 in the Union cohort (n = 95) [21]. The predictive value of the model is supported by the analysis of key features (vasopressors, albumin, urea nitrogen), although confidence intervals for AUC are not specified. The limited sample size, especially in the Union cohort, may affect the generalizability of the results.

Y. Song et al. investigated prediction of postoperative delirium (POD) in elderly patients with hip fractures using ML and logistic regression models [22]. The best model (Random Forest) achieved AUC = 0.81, and logistic regression model achieved AUC = 0.77 (95% CI: 0.696–0.845) in the training sample (n = 557) and 0.71 (95% CI: 0.593–0.827) in the validation sample (n = 240). These data support the ability of the models to detect complications associated with multimorbidity (renal failure, COPD) in the elderly, although CIs for ML models are not reported.

In the context of repeat hospitalizations, R. Loutati et al. developed a multimodal model predicting 30-day remissions (16.65% of 19,569 cases), achieving AUC = 0.93 with the TabNet model (sensitivity 86.7%, specificity 88.9%) [23]. Random Forest showed AUC = 0.89, gradient boosting of 0.87, with no CIs indicated. Key factors were the number of hospitalizations, heart failure (45.3%), and chronic kidney disease (47.9%), highlighting the difficulty of prediction in the elderly. Social reports were limited (n = 4,721) but were accounted for through NLP assessment. A meta-analysis of three studies (C. Guo et al., Y. Song et al., R. Loutati et al.) showed a pooled AUC ≈ 0.87 (95% CI: 0.83–0.91, $I^2 \approx 70\%$, $\tau^2 \approx 0.04$), indicating high heterogeneity due to differences in populations and outcomes [21–23].

For chronic diseases, AI shows prognostic potential. A.T. Ayers et al. applied AI to predict diabetes complications (retinopathy, nephropathy) with high accuracy [24]. R.D. Sriram et al. used wearable devices to monitor diabetes, improving glycemic control [25]. J. Yang et al. achieved AUC = 0.972 to diagnose osteoporosis (vs. normal) on chest CT, indirectly supporting fracture prevention in the elderly, although fracture risk was not directly predicted [26]. G. Voltan et al. developed a tool to detect osteoporosis in primary care, but validation of models on large cohorts considering multimorbidity remains a common challenge [27].

The application of AI in multimorbidity faces limitations, including data heterogeneity affecting the accuracy of models. R.J. Woodman et al. in a review of ML algorithms noted that differences in data from EMR and IoT devices create challenges, such as insufficient validation and transparency, which may reduce the effectiveness of AI in geriatrics [28]. For example, in the work by R. Loutati et al., incomplete data on social factors (available for 24% of the cohort) limited the analysis, although their influence was accounted for through NLP assessment. Y. Wang et al. emphasized the need for standardization of data and algorithms to improve the quality of AI applications, which is particularly important when there is high heterogeneity in multimorbidity studies [29].

Secondly, ethical challenges, such as digital ageism, limit the availability of AI to the elderly. C.H. Chu et al. and Y. Aranda Rubio et al. note that low digital literacy and limited access to technology (especially in rural areas) deprive some patients of the benefits of AI [30, 31]. This is supported by E. Burnazovic et al., where the use of AI in geriatrics during the pandemic was limited by technical barriers [32]. T. Skuban-Eiseler et al. add that the opacity of algorithms may impair patient autonomy, increasing the risk of decision bias (moderate AMSTAR 2 score) [33].

Thirdly, the dynamics of disease interactions in multimorbidity are not adequately accounted for in current models. M.M. Alsaleh et al. note that most studies (19 out of 22) rely on static retrospective data, which may limit their applicability to the dynamic processes in multimorbidity [34]. For example, H. Chen et al. analyzed oculo-gait measurements in CMD based on one-step data without considering temporal changes, although the model achieved moderate accuracy (AUC 0.787–0.810) for screening cognitive impairment.

AI improves diagnosis and prognosis in geriatrics, especially for isolated pathologies. The accuracy for dementia (AUC 0.833) and stroke (AUC 0.91) supports its role in screening and early intervention [15, 16]. In telemedicine, as suggested by E. Burnazovic et al., AI may speed up diagnosis, which is important in the elderly with multimorbidity, but specific data are limited [32]. For complex conditions, the AUC varies: 0.787–0.810 for cerebral vegetative – vascular dystonia and 0.87–0.93 for repeat hospitalizations, suggesting that models need to be optimized [19, 23].

Prospects include the development of data standards and the potential for personalized care, although integration of wearable devices and specific approaches require further validation [25, 29, 35, 36]. Validation of models in multimorbidity remains a priority.

DISCUSSION

The application of AI in geriatrics is showing significant progress, especially in the diagnosis and prognosis of diseases in the elderly. Our systematic review covering 153 studies from 2020 to 2025 emphasizes the potential of AI as a screening and early intervention tool. The high accuracy of the models in detecting isolated pathologies, such as acute ischemic stroke or cardiovascular disease, allows for the use of AI for emergency diagnosis and resource optimization, especially in settings with limited access to conventional imaging modalities [16, 17]. This is clearly important for timely initiation of treatment, which can reduce mortality and improve quality of life in patients over 65 years of age. However, the transition to multimorbidity, a key characteristic of advanced age, decreases the effectiveness of AI due to heterogeneity of data and complexity of disease interactions [19].

Heterogeneity of data due to differences in sources (e.g., electronic medical records vs. Internet of Things devices), as well as insufficient consideration of social factors, limits the creation of universal models [23, 28]. In addition, most studies rely on static data, making it difficult to capture the dynamics of multimorbidity [34]. For example, analyses of oculo-gait measurements in CMD have shown moderate accuracy but have not accounted for progression of the condition, which reduces its prognostic value [19]. The prediction of mortality and repeat hospitalizations also demonstrates the potential of AI, but the high heterogeneity of results ($I^2 \approx 70\%$) indicates the need to adapt models to specific populations and outcomes [21–23]. For chronic conditions, such as diabetes and osteoporosis, AI offers opportunities for the prevention of complications, although it requires validation in the context of multiple comorbidities [24, 26].

Ethical and practical challenges play a key role in limiting the adoption of AI. Digital ageism associated with low digital literacy and access to technology, especially in rural areas, deprives a proportion of older patients of the benefits of AI [30, 31]. In Uzbekistan and CIS countries, where medical infrastructure is often limited, AI can optimize screening in primary care by identifying multimorbidity risks early, but requires adjustment to local conditions, including staff training and integration with existing systems. The opacity of algorithms, as noted by T. Skuban-Eiseler et al., can undermine physician and patient confidence, emphasizing the importance of developing explainable models [33].

The prospects for AI in geriatrics are related to overcoming these barriers. Standardization of data and algorithms has the potential to reduce heterogeneity and improve accuracy [29]. The integration of wearable devices promises to improve monitoring, and telemedicine, as shown by E. Burnazovic et al., can accelerate diagnosis in the elderly with multimorbidity through remote analysis of data (e.g. gait or glycaemia), which is particularly relevant in times of crises, such as the COVID- 19 pandemic [32]. The development of dynamic models that take into account time trends and disease interactions will be the key to managing the complexity of multimorbidity, providing a personalized approach to care.

CONCLUSION

This systematic review confirms that AI significantly enhances diagnostic and prognostic capabilities in geriatrics, especially for selected diseases, such as dementia, stroke, cardiovascular pathologies, and osteoporosis. Its role in screening and early intervention makes AI a valuable tool in resource-limited settings. However, in multimorbidity, the accuracy of models is reduced due to heterogeneity of data, static approaches, and insufficient consideration of the dynamic nature of pathologies.

The prognostic potential of AI to assess mortality and hospitalizations is clear, but needs to be optimized for complex conditions. The introduction of AI into clinical practice, including Uzbekistan and CIS countries, holds promise to improve early diagnosis of multimorbidity in primary care, but faces ethical challenges (digital ageism, opacity) and technical barriers (data standardization). Future research should focus on building dynamic models, integrating wearable devices, and increasing technology accessibility to enable effective management of multimorbidity in the elderly.

REFERENCES

1. United Nations, Department of Economic and Social Affairs, Population Division. World Population Ageing 2020 Highlights. New York: UN; 2020:45.
2. Fortin M., Stewart M., Poitras M.E., Almirall J., Maddocks H. A systematic review of prevalence studies on multimorbidity: toward a more uniform methodology. *Ann. Fam. Med.* 2012;10(2):142–151. DOI: 10.1370/afm.1337.
3. Abadir P., Chellappa R. Artificial intelligence in geriatrics: riding the inevitable tide of promise, challenges, and considerations. *J. Gerontol. A Biol. Sci. Med. Sci.* 2024;79(2):glad279. DOI: 10.1093/gerona/glad279.
4. Topol E.J. High-performance medicine: the convergence of human and artificial intelligence. *Nat. Med.* 2019;25(1):44–56. DOI: 10.1038/s41591-018-0300-7.
5. Liu X., Faes L., Kale A.U., Wagner S.K., Fu D.J., Bruynseels A. et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. *Lancet Digit. Health.* 2019;1(6):e271–e297. DOI: 10.1016/S2589-7500(19)30123-2.
6. Rajkomar A., Oren E., Chen K., Dai A.M., Hajaj N., Hardt M. et al. Scalable and accurate deep learning with electronic health records. *NPJ Digit. Med.* 2018;1:18. DOI: 10.1038/s41746-018-0029-1.
7. Weng S.F., Reps J., Kai J., Garibaldi J.M., Qureshi N. Can machine-learning improve cardiovascular risk prediction using routine clinical data? *PLoS One.* 2017;12(4):e0174944. DOI: 10.1371/journal.pone.0174944.
8. Ma B., Yang J., Wong F.K.Y., Wong A.K.C., Ma T., Meng J. et al. Artificial intelligence in elderly healthcare: a scoping review. *Ageing Res. Rev.* 2023;83:101808. DOI: 10.1016/j.arr.2022.101808.
9. Ho A. Are we ready for artificial intelligence health monitoring in elder care? *BMC Geriatr.* 2020;20(1):358. DOI: 10.1186/s12877-020-01764-9.
10. Velazquez-Diaz D., Arco J.E., Ortiz A., Pérez-Cabezas V., Lucena-Anton D., Moral-Munoz J.A. et al. Use of artificial intelligence in the identification and diagnosis of frailty syndrome in older adults: scoping review. *J. Med. Internet Res.* 2023;25:e47346. DOI: 10.2196/47346.
11. Moher D., Liberati A., Tetzlaff J., Altman D.G. PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Med.* 2009;6(7):e1000097. DOI: 10.1371/journal.pmed.1000097.
12. Page M.J., McKenzie J.E., Bossuyt P.M., Boutron I., Hoffmann T.C., Mulrow C.D. et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021;372:n71. DOI: 10.1136/bmj.n71.
13. Alsaleh M.M., Allery F., Choi J.W., Hama T., McQuillin A., Wu H. et al. Prediction of disease comorbidity using explainable artificial intelligence and machine learning techniques: A systematic review. *Int. J. Med. Inform.* 2023;175:105088. DOI: 10.1016/j.ijmedinf.2023.105088.
14. Kim H., Kim E., Lee I., Bae B., Park M., Nam H. Artificial Intelligence in Drug Discovery: A Comprehensive Review of Data-driven and Machine Learning Approaches. *Biotechnol. Bioprocess Eng. 2*020;25(6):895–930. DOI: 10.1007/s12257-020-0049-y.
15. Obuchi S.P., Kojima M., Suzuki H., Garbalosa J.C., Imamura K., Ihara K. et al. Artificial intelligence detection of cognitive impairment in older adults during walking. *Alzheimers Dement. (Amst.).* 2024;16(3):e70012. DOI: 10.1002/dad2.70012.
16. Wang Y., Ye Y., Shi S., Mao K., Zheng H., Chen X. et al. Prediagnosis recognition of acute ischemic stroke by artificial intelligence from facial images. *Aging Cell.* 2024;23(8):e14196. DOI: 10.1111/acel.14196.
17. Wang Y.J., Yang K., Wen Y., Wang P., Hu Y., Lai Y. et al. Screening and diagnosis of cardiovascular disease using artificial intelligence-enabled cardiac magnetic resonance imaging. *Nat. Med.* 2024;30(5):1471–1480. DOI: 10.1038/s41591-024-02971-2.
18. Yang J., Liao M., Wang Y., Chen L., He L., Ji Y. et al. Opportunistic osteoporosis screening using chest CT with artificial intelligence. *Osteoporos. Int.* 2022;33(12):2547–2561. DOI: 10.1007/s00198-022-06491-y.
19. Chen H., Du H., Yi F., Wang T., Yang S., Pan Y. et al. Artificial intelligence-assisted oculo-gait measurements for cognitive impairment in cerebral small vessel disease. *Alzheimers Dement.* 2024;20(12):8516–8526. DOI: 10.1002/alz.14288.

20. Wang J., Liang Y., Cao S., Cai P., Fan Y. Application of Artificial Intelligence in Geriatric Care: Bibliometric Analysis. *J. Med. Internet Res.* 2023;25:e46014. DOI: 10.2196/46014.
21. Guo C., Pan J., Tian S., Gao Y. Using machine learning algorithms to predict 28-day mortality in critically ill elderly patients with colorectal cancer. *J. Int. Med. Res.* 2023;51(11):3000605231198725. DOI: 10.1177/0300060523 1198725.
22. Song Y., Zhang D., Wang Q., Liu Y., Chen K., Sun J. et al. Prediction models for postoperative delirium in elderly patients with machine-learning algorithms and SHapley Additive exPlanations. *Transl. Psychiatry.* 2024;14(1):57. DOI: 10.1038/s41398-024-02762-w.
23. Loutati R., Ben-Yehuda A., Rosenberg S., Rottenberg Y. Multimodal machine learning for prediction of 30-day readmission risk in elderly population. *Am. J. Med.* 2024;137(7):617–628. DOI: 10.1016/j.amjmed.2024.04.002.
24. Ayers A.T., Ho C.N., Kerr D., Cichosz S.L., Mathioudakis N., Wang M. et al. Artificial intelligence to diagnose complications of diabetes. *J. Diabetes Sci. Technol.* 2025;19(1):246–264. DOI: 10.1177/19322968241287773.
25. Sriram R.D., Reddy S.S.K. Artificial intelligence and digital tools: future of diabetes care. *Clin. Geriatr. Med.* 2020;36(3):513–525. DOI: 10.1016/j.cger.2020.04.009.
26. Yang J., Liao M., Wang Y., Chen L., He L., Ji Y. et al. Opportunistic osteoporosis screening using chest CT with artificial intelligence. *Osteoporos. Int.* 2022;33(12):2547–2561. DOI: 10.1007/s00198-022-06491-y.
27. Voltan G., Di Giovannantonio G., Carretta G., Vianello S., Contessa C., Veronese N. et al. A novel case-finding strategy based on artificial intelligence for the systematic identification and management of individuals with osteoporosis or at varying risk of fragility fracture. *Arch. Osteoporos.* 2024;19(1):45. DOI: 10.1007/s11657-024-01403-5.
28. Woodman R.J., Mangoni A.A. A comprehensive review of machine learning algorithms and their application in geriatric medicine: present and future. *Aging Clin. Exp. Res.* 2023;35(11):2363–2397. DOI: 10.1007/s40520-023-02552-2.
29. Wang Y., Li N., Chen L., Wu M., Meng S., Dai Z. et al. Guidelines, Consensus Statements, and Standards for the Use of Artificial Intelligence in Medicine: Systematic Review. *J. Med. Internet Res.* 2023;25:e46089. DOI: 10.2196/46089.
30. Chu C.H., Nyrup R., Leslie K., Shi J., Bianchi A., Lyn A. et al. Digital ageism: challenges and opportunities in artificial intelligence for older adults. *Gerontologist.* 2022;62(7):947–955. DOI: 10.1093/geront/gnab167.
31. Aranda Rubio Y., Baztán Cortés J.J., Canillas Del Rey F. Is artificial intelligence ageist? *Eur. Geriatr. Med.* 2024;15(6):1957–1960. DOI: 10.1007/s41999-024-01070-2.
32. Burnazovic E., Yee A., Levy J., Gore G, Abbasgholizadeh Rahimi S. Application of Artificial intelligence in COVID-19-related geriatric care: A scoping review. *Arch. Gerontol. Geriatr.* 2024;116:105129. DOI: 10.1016/j.archger.2023.105129.
33. Skuban-Eiseler T., Orzechowski M., Denkinger M., Kocar T.D., Leinert C., Steger F. Artificial intelligence-based clinical decision support systems in geriatrics: an ethical analysis. *J. Am. Med. Dir. Assoc.* 2023;24(9):1271–1276.e4. DOI: 10.1016/j.jamda.2023.06.008.
34. Alsaleh M.M., Allery F., Choi J.W., Hama T., McQuillin A., Wu H. et al. Prediction of disease comorbidity using explainable artificial intelligence and machine learning techniques: A systematic review. *Int. J. Med. Inform.* 2023;175:105088. DOI: 10.1016/j.ijmedinf.2023.105088.
35. Tang A., Ho R., Yu R., Huynh T., Luong S., Tam W. et al. Editorial: Can artificial intelligence help us overcome challenges in geriatrics? *Geriatr. Nurs.* 2023;52:A1–A2. DOI: 10.1016/j.gerinurse.2023.06.007.
36. Padhan S., Mohapatra A., Ramasamy S.K., Agrawal S. Artificial intelligence (AI) and robotics in elderly healthcare: enabling independence and quality of life. *Cureus.* 2023;15(8):e42905. DOI: 10.7759/cureus.42905.

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Received. 31.03.2025;
approved after peer review 10.04.2025;
accepted 29.05.2025