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Artificial Intelligence in Multimorbidity Care: A Systematic Review of Opportunities, Challenges and Limitations

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Abstract

Aim: This study identified AI's role in supporting patients with multimorbidity in primary healthcare and explored associated opportunities, challenges, and limitations.

Methodology: A systematic literature search was conducted in Scopus, Web of Science, and PubMed using terms related to AI and multimorbidity in PHC. After screening, 53 articles met inclusion criteria and were analysed per PRISMA guidelines.

Results: AI can support multimorbidity patients through personalized treatment, clinical support, virtual assistance and coordinated care via monitoring and interventions. However, adoption remains limited by poor data quality, disease interactions, low model interpretability and underrepresentation of multimorbid populations in training data. Consequently, AI's role in supporting multimorbidity patients remains limited, with potential benefits unrealized.

Implications and recommendations: Realizing AI's potential for multimorbidity patients requires addressing technical, ethical, clinical and systemic challenges. Research must prioritize developing representative datasets and interpretable models that capture multimorbidity's complexity to help deliver coordinated, patient-centred care.

Originality/value: This analysis shows limited AI integration in multimorbidity care, highlighting the need for quality data and interpretable models. It identifies key challenges that must be overcome to transform AI from conceptual promise to practical support for individuals with multimorbidity.

Keywords: multimorbidity, artificial intelligence, systematic review, PRISMA

1. Introduction

Multimorbidity, characterised by the simultaneous presence of two or more chronic diseases in an individual (Ho et al., 2022; Lai et al., 2021), has emerged as a critical public health issue worldwide. This condition poses substantial challenges to healthcare systems because of its correlation with elevated mortality rates, increased healthcare utilisation, and significant economic impacts (Chowdhury et al., 2023). As the global population continues to age, the prevalence of multimorbidity is rising, further taxing healthcare resources and necessitating innovative patient management strategies. Patients with multimorbidity exhibit complex and distinct care requirements which differ from those of individuals with a single disease. A primary challenge in managing these patients is the fragmentation of care, as medical specialists often concentrate on treating individual conditions rather than addressing patients holistically (Chowdhury et al., 2023). This approach frequently leads to inefficiency, medical errors, and suboptimal patient outcomes. Effective care for multimorbidity necessitates coordination among diverse healthcare providers, continuity in treatment plans, and a patient-centred approach to disease management (Alowais et al., 2023; Majnarić et al., 2021). The use of artificial intelligence (AI) tools to support the care of patients with multimorbidity is increasingly seen as a promising strategy to address the challenges discussed above. This article focuses on narrow, data-driven machine-learning approaches − a subset of AI, defined by Akerkar (2019) as "the science and engineering of making intelligent machines, particularly intelligent computer programs" − that are designed to augment, not replace, clinical expertise. By analysing large, heterogeneous data sets, such AI systems can help clinicians detect hidden patterns, anticipate complications, and tailor therapies to complex multimorbid profiles, while virtual assistants and remote-monitoring tools relieve healthcare professionals of routine administrative tasks (Mikava & Mamulaidze, 2023). However, the literature on AI specifically designed to assist multimorbidity care remains sparse, with the existing evaluations concentrating on single-disease applications in diagnostics, chronic-disease management and predictive analytics (Gupta, 2023; Sarkar, 2023). Nonetheless, these studies primarily focused on single-disease models rather than on the complexities of multimorbidity (Zheng et al., 2021). Although some studies have examined digital health technologies and their role in improving patient outcomes (Farai et al., 2024), there is still a notable gap in understanding how AI can best support clinicians and patients facing multimorbidity. This gap underlines the need for further investigation of how AI can support healthcare providers in managing patients with multiple chronic conditions. The research question guiding this study is: How is AI used to support the management of patients with multimorbidity in primary healthcare, and what are its associated opportunities, challenges and limitations?

To answer this question, a systematic literature review was conducted using the PRISMA methodology. This approach provided a comprehensive analysis of existing research, identifying key areas where AI can support patients with multimorbidity and the limitations of this support. By synthesising current knowledge and identifying areas requiring further exploration, this study aimed to contribute to the ongoing discourse on the integration of AI into complex management strategies.

The article proceeds as follows: Section 2 provides the research background, outlining the conceptual foundations of multimorbidity and artificial intelligence, as well as the rationale for exploring their intersection; Section 3 describes the search strategy and inclusion criteria; Section 4 summarises the ways AI supports patients with multimorbidity, highlighting its practical applications and its current limitations in primary healthcare contexts; Section 5 presents a comprehensive discussion of the findings, including the study limitations, directions for future research, and implications for both theory and clinical practice.

2. Research Background

The global prevalence of multimorbidity is rising, particularly among ageing populations, placing increasing pressure on healthcare systems. Compared to individuals with single conditions, those with multimorbidity face poorer functional status, lower quality of life and greater healthcare dependency (Shi et al., 2021). Traditional disease-centric models are ill-suited for such complexity. Clinical guidelines often exclude multimorbid patients, complicating evidence-based care and leading to inconsistent treatment outcomes (Abuzour et al., 2024; Hoogendijk et al., 2023). Research shows these patients have higher utilisation of primary care, specialist services, and hospital admissions (Brummel & Carlson, 2016; Rafiq et al., 2024). Many systems lack the infrastructure to support their needs, with limited consultation time and shortages of trained professionals contributing to fragmented care (Hoogendijk et al., 2023; Lai et al., 2021; Majnarić et al., 2021). Mental health burdens are also common, including elevated risks of depression, anxiety, and cognitive decline (Ho et al., 2022; Majnarić et al., 2021). Patterns of multimorbidity vary across populations and are shaped by socioeconomic, lifestyle, and genetic factors (Lai et al., 2021). Chronic conditions like diabetes, hypertension, and cardiovascular diseases frequently co-occur (Álvarez-Gálvez et al., 2023). Traditional care models often overlook patient goals, necessitating a shift toward person-centred approaches and shared decision-making. Multidisciplinary strategies combining primary care, specialist input, and social support can improve outcomes and reduce resource use. This shift requires transitioning from disease-centred to holistic care that reflects the lived realities of multimorbid patients. AI, a branch of computer science simulating human intelligence, has shown great promise in this domain (Balyan et al., 2019; Kueper et al., 2020). It encompasses machine learning (ML), natural language processing (NLP), and expert systems that analyse large datasets to support clinical decisions (Majnarić et al., 2021). AI has advanced from theory to practice, improving diagnostics and treatment planning (Theng et al., 2023), ML can identify risks and optimise care based on patient data (Hoogendijk et al., 2023), whilst expert systems assist clinicians through predefined logic (Akyon et al., 2023). NLP processes medical texts to enhance access to information (Bousquet et al., 2024), and deep learning supports image analysis and pathology (Maleki Varnosfaderani & Forouzanfar, 2024). AI supports predictive analytics and care optimization. ML algorithms forecast emergency department visits in older adults by analysing medication and history (Bensken et al., 2023; Kellerer et al., 2021), and outperform traditional models in assessing mortality risk in cirrhosis (Kanwal et al., 2020). AI predicts fall risk from electronic health records (Chu et al., 2022), and reduces polypharmacy and adverse drug events (Molokhia & Majeed, 2017). It also identifies high-need patients and develops psychosocial phenotypes to guide coordinated care (Hewner et al., 2022). ML models integrate real-world and clinical data to personalise treatments for older adults (Hoogendijk et al., 2023). Unsupervised learning classifies patients into subgroups for targeted interventions (Ito et al., 2024). AI shows considerable potential in supporting patients with multimorbidity in primary healthcare (PHC), could also contribute across several areas for improving the quality, safety, and efficiency of care for patients with complex chronic conditions. Its integration into healthcare marks a paradigm shift – extending to hospital operations, research, and patient engagement (Theng et al., 2023) – it also improves workflow, reduces clinician burden (Edgoos et al., 2024), and expands care access via telemedicine (Rooper et al., 2025); AI supports evidence synthesis, automates literature reviews, and tailors clinical guidelines (Bousquet et al., 2024). Despite this transformative potential, the adoption of AI in supporting management multimorbidity remains constrained by multiple technical, clinical, ethical, and systemic barriers such as insufficient data quality, lack of model interpretability, privacy concerns, and integration challenges directly affect the reliability, acceptance, and sustainability of AI-based tools in PHC. Ensuring transparency in AI-driven decision-making is essential in building trust among clinicians and patients alike, while regulatory frameworks must be equipped to address cases of bias, protect sensitive health data, and support equitable access to AI solutions (Kanwal et al., 2020). Taken together, these opportunities and limitations reflect the dual reality of AI in healthcare: while the technology holds great promise for enhancing multimorbidity care, its real-world impact depends on deliberate, ethical, and context-sensitive implementation. This dual perspective forms the foundation for evaluating where and how AI can most effectively be used to support patients with complex health needs in primary care settings.

3. Methodology

To ensure the relevance and quality of the evidence included in this review, a set of inclusion and exclusion criteria was carefully established. Studies were considered eligible if they explored specific patterns of physical and/or mental multimorbidity, defined as the coexistence of two or more chronic conditions, in accordance with the World Health Organization's guidelines. This focus allowed for a comprehensive examination of multimorbidity as a clinically distinct phenomenon, rather than as a collection of unrelated health issues. Moreover, research had to examine the relationship between these multimorbidity patterns and the application of artificial intelligence (AI) in either clinical or research contexts. The review specifically targeted peer-reviewed articles published in English to ensure scientific rigour and accessibility.

Studies were excluded if they lacked peer review, such as conference abstracts, dissertations, editorials, commentaries, letters, books, or literature reviews, as these sources often do not provide sufficient methodological detail or undergo the same level of scrutiny. Research focusing solely on a single index disease or combining chronic and infectious diseases was also excluded as such approaches did not align with the review's aim of understanding complex, chronic multimorbidity patterns. Furthermore, studies that employed purely technical statistical models without clear clinical relevance or practical implications for multimorbidity management in primary healthcare (PHC) were excluded, as the emphasis of this review was on real-world, patient-centred applications.

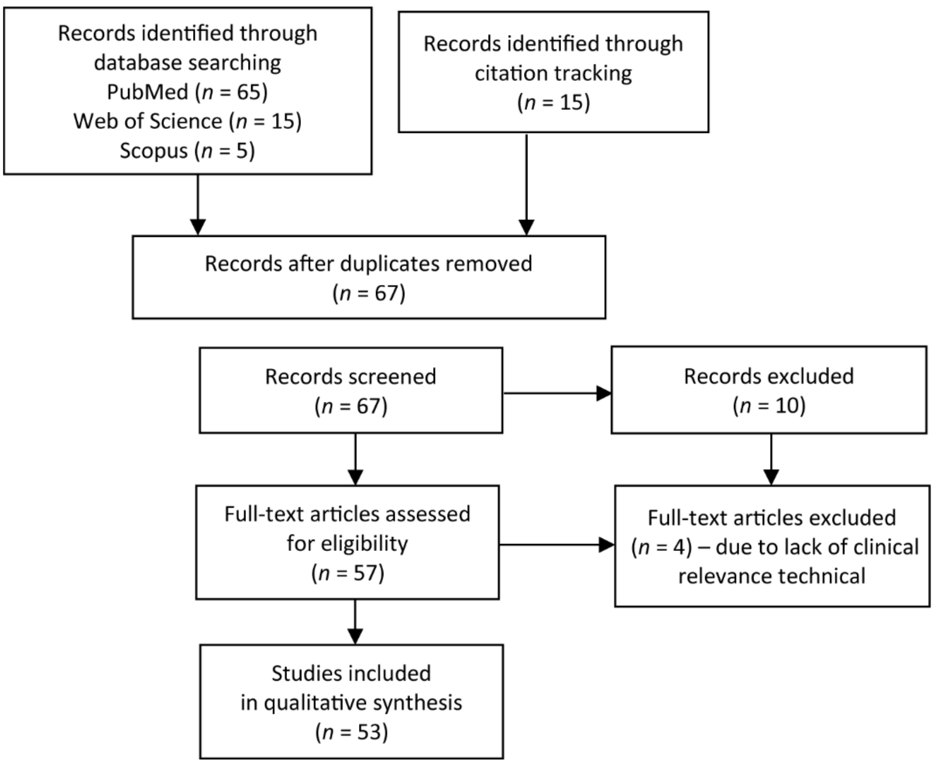

Fig. 1. PRISMA 2009 flow diagram illustrating the study selection process.

Source: adapted from (Moher et al., 2009).

This systematic review aimed to assess how AI technologies can support the management of patients with multimorbidity in PHC settings. Given the complexity of multimorbidity and the evolving nature of AI, this analysis also critically examined the key challenges and limitations that had to be addressed to ensure effective, ethical, and sustainable implementation. A comprehensive search was conducted across three major databases − Scopus, Web of Science (WoS), and PubMed − using a Boolean search strategy designed to capture the intersection of AI, primary healthcare, and multimorbidity. The search terms included: “artificial intelligence” OR “AI” OR “machine learning” AND “primary healthcare” OR “family medicine” OR “general practice” AND “multiple diseases” OR “multimorbidity” OR “comorbidities” OR “chronic conditions.” The initial search yielded five records from Scopus, 15 from WoS, and 65 from PubMed, whilst an additional 15 were identified through snowballing techniques, such as screening references and citations of key papers, resulting in a total of 100 records. After removing 33 duplicates, 67 articles were screened based on their titles, abstracts, and keywords. Ten of these were excluded for not meeting the eligibility criteria, leaving 53 studies for full-text assessment and qualitative synthesis. The entire selection process adhered to PRISMA guidelines and is shown in Figure 1.

4. Results

4.1. How AI Can Support Patients with Multimorbidity

AI shows considerable potential in supporting patients with multimorbidity in PHC. Based on the reviewed literature, four key thematic areas of AI application were identified: (1) personalised treatment recommendations, (2) clinical decision support systems, (3) virtual health assistance and patient self-management, and (4) care coordination and system-level integration. Each area demonstrates a distinct mode of AI contribution toward improving care quality, safety, and efficiency for patients with complex chronic conditions.

These categories are summarised below and further detailed in the following subsections. A visual summary is presented in Table 1 which maps the main AI functionalities to their clinical applications in multimorbidity care.

Table 1. Key areas of AI potential in supporting patients with multimorbidity

AI application area	Key functions	Clinical relevance
Personalised treatment	Data-driven treatment optimisation, real-time adjustments, adverse interaction prediction	Supports individual care plans, medication safety, outcome prediction
Clinical decision support systems (CDSS)	Aggregation and interpretation of EHRs, forecasting, risk stratification, treatment simulation	Supports clinicians in diagnostics, therapy selection, and early intervention
Virtual health assistance	Patient education, symptom monitoring, reminders, behavioural nudges	Supports adherence, autonomy, and chronic condition self-management
Care coordination & integration	Data sharing across systems, care team collaboration, real-time dashboards	Supports continuity and personalised interdisciplinary care, reduces fragmentation

Source: author’s own work.

4.2. Personalised Treatment Recommendations

AI can support personalized treatment by analysing large volumes of patient data, including medical history, medications, and treatment responses. By integrating electronic health records (EHRs), AI provides a comprehensive view of complex disease interactions, enabling individualised clinical recommendations that improve outcomes (Majnarić et al., 2021; Prabhakaran et al., 2019; Young et al., 2024). Predictive models anticipate complications and support early, proactive interventions. AI also simulates treatment outcomes to guide clinicians in selecting optimal strategies (Majnarić et al., 2021) and suggests personalised regimens based on patient-specific factors while minimising adverse drug interactions (Macfarlane, 2020; Majnarić et al., 2021). It enhances chronic disease management by adjusting treatments in real time based on metrics such as blood pressure and glucose levels (Burnazovic et al., 2024; Laymouna et al., 2024). Chatbots and virtual assistants’ support adherence by offering reminders, lifestyle guidance, and follow-up prompts (Burnazovic et al., 2024; Majnarić et al., 2021; Rafiq et al., 2024; Rooper et al., 2025). AI also assesses drug interactions and side effects to help design safer, more effective therapies (Alowais et al., 2023; Laymouna et al., 2024; Majnarić et al., 2021). In precision medicine, AI analyses genomic data to create highly individualised treatments (Moser & Narayan, 2020). By leveraging complex datasets, AI delivers real-time insights that refine care strategies (Rafiq et al., 2024), identifies at-risk patients and proposes targeted interventions (Hewner et al., 2022).

4.3. Decision Support

AI-powered Clinical Decision Support Systems (CDSS) complement clinical expertise while maintaining healthcare professionals at the centre of decision-making (Majnarić et al., 2021; Prabhakaran et al., 2019). Integrating AI into clinical workflows enhances diagnostic accuracy and treatment effectiveness (Alowais et al., 2023; Laymouna et al., 2024). AI aggregates data from sources such as EHRs, lab results, imaging and patient-reported outcomes, offering a comprehensive view of disease interactions. Advanced analytics can reveal patterns often missed by traditional methods (Alowais et al., 2023; Majnarić et al., 2021). AI also supports dose optimisation and therapeutic drug monitoring, enhancing safety and efficacy through predictive models that identify adverse drug events (Brummel & Carlson, 2016; Majnarić et al., 2021). AI-enabled forecasting highlights the value of both prospective and retrospective studies in refining prediction accuracy. Predictive analytics identify patients at risk for chronic illness or hospital readmission, supporting timely, targeted interventions. ML models such as random forests, have proven effective in predicting in-hospital mortality among older adults (Alowais et al., 2023; Martínez-García et al., 2013), improving outcomes and enabling patient-centred care. Additionally, AI can simulate treatment scenarios in multimorbid patients, helping clinicians anticipate outcomes and select optimal strategies (Kueper et al., 2020; Šabanović et al., 2018). These simulations encompass drug interactions, disease progression, and therapy response forecasting − essential for decision support (Martínez-García et al., 2013). Analysing large-scale datasets allows AI to uncover insights and trends overlooked by traditional research, creating evidence-based guidelines and targeted therapies (Abuzour et al., 2024; Alowais et al., 2023).

4.4. Virtual Health Assistants

AI-powered virtual assistants support self-management and patient empowerment while alleviating administrative burdens for healthcare staff (Alowais et al., 2023; Brummel & Carlson, 2016; Lin et al., 2019; Maleki Varnosfaderani & Forouzanfar, 2024; Rafiq et al., 2024). Their capacity to simulate human interaction and provide tailored support highlights their transformative potential in healthcare delivery (Bajwa et al., 2021; Laymouna et al., 2024; Lin et al., 2019). When integrated with wearable devices or mobile apps, AI can monitor vital signs and symptoms, alerting clinicians when intervention is needed – thus supporting proactive chronic disease management (Majnarić et al., 2021). Additionally, AI enhances patient education by offering individualized information about conditions and treatments. Chatbots and virtual assistants help answer questions, promote medication adherence, and guide lifestyle changes, ultimately improving patient autonomy and adherence to care plans (Bajwa et al., 2021; Majnarić et al., 2021).

4.5. Streamlining Care Coordination

Managing patients with multimorbidity presents considerable challenges, often leading to fragmented care due to the involvement of multiple providers and systems. AI offers promising solutions by integrating patient data from diverse national and international sources into unified infrastructures that promote coordinated care (Abuzour et al., 2024; Alowais et al., 2023; Hewner et al., 2022). Studies emphasise the importance of incorporating EHRs into shared frameworks to support research and clinical decisions. AI and big data analytics enable this integration, improving care continuity and quality for patients with complex chronic conditions (Alowais et al., 2023; Maleki Varnosfaderani & Forouzanfar, 2024). By consolidating data from disparate systems, AI helps generate personalised care plans adapted to the complexity of multimorbidity (Majnarić et al., 2021; Moser & Narayan, 2020). AI tools also provide real-time insights, support interdisciplinary collaboration, and ensure that care teams stay updated on evolving treatment strategies (Alghalyini, 2023; Alowais et al., 2023; Moser & Narayan, 2020). This coordinated approach is vital for delivering high-quality, patient-centred care. Furthermore, AI's capacity to interpret complex health data enhances communication among providers, improving both outcomes and the care experience for patients with multiple conditions (Amisha et al., 2019).

4.6. Limitations and Challenges of AI in Supporting Patients with Multimorbidity

Despite its transformative potential, the application of artificial intelligence in the care of patients with multimorbidity remains limited by several technical, ethical, clinical, and systemic challenges. These barriers not only constrain the effectiveness of AI-based tools but also impact their acceptance, integration, and long-term sustainability in primary healthcare settings.

This section provides synthesis of the main limitations and risks identified in the literature, organizing them into key thematic areas. These include issues related to data quality, model complexity, transparency, patient trust, training requirements, system integration, and broader ethical, regulatory, and organizational dynamics. Understanding these challenges is crucial for evaluating the potential as well as the limitations of AI in supporting the management of multimorbidity in primary healthcare, and for guiding its responsible and impactful use. Table 2 provides a structured summary of the identified limitations and their potential consequences for multimorbidity care.

Table 2. Limitations of AI and their potential consequences for multimorbidity care

Limitation area	Description	Implication for practice
Data quality and availability	Incomplete, inconsistent, or biased patient records undermine model training and predictive reliability	Reduced AI performance; risk of harmful or inappropriate recommendations
Complexity of interactions	Multimorbidity involves nonlinear disease interactions and treatment effects that are difficult to model	Risk of oversimplification, misdiagnosis, or inadequate treatment strategies
Interpretability and transparency	Many AI models lack explainability ("black-box" systems), limiting clinician understanding and trust	Hinders clinical decision-making and impedes adoption in routine care
Trust and acceptance	Patients and providers may question AI's reliability, ethical intent, or empathy	Decreased willingness to use AI; increased demand for human-centred safeguards
Training and data representation	Effective models require large, diverse, well-annotated datasets reflecting real-world multimorbidity patterns	Time- and resource-intensive data collection; limited model generalisability
Workflow integration	Implementing AI in daily practice poses logistical, institutional, and technical challenges	Workflow disruption, clinician frustration, and inconsistent use of AI tools
Ethical and equity concerns	Data privacy, algorithmic bias, and digital divides may deepen health disparities if unaddressed	Risk of unequal access or harm to vulnerable populations; need for transparent AI governance
Regulatory challenges	AI requires compliance with evolving legal, ethical, and clinical standards	Delays in implementation and uncertainty in approval pathways
Team dynamics and professional roles	Risk of overreliance on AI or erosion of clinical judgment, especially among junior staff	Disruption in clinician–patient relationships and potential deskilling
Disease-centric bias	Most AI tools are developed based on single-disease models, neglecting multimorbidity complexity	Reduced effectiveness for patients with overlapping or interacting conditions

Source: author's own work.

4.6.1. Data Quality and Availability

AI systems depend on high-quality, comprehensive datasets for accurate training, reliable predictions, and effective clinical decision support. However, in healthcare – particularly for multimorbid patients – data quality remains a major challenge. Patient records are often incomplete, inconsistent, and/or biased, especially in individuals with multiple chronic conditions. These limitations can compromise AI performance, reduce predictive accuracy, and lead to suboptimal or even harmful clinical recommendations. (Alowais et al., 2023; Burnazovic et al., 2024; Chu et al., 2022; Hewner et al., 2022; Kellerer et al., 2021; Park et al., 2023; Young et al., 2024; Zafari et al., 2022).

4.6.2. Complexity of Interactions

Patients with multimorbidity often experience complex, evolving interactions between coexisting conditions and their treatments. These interdependencies can lead to unpredictable disease courses and heightened risks from polypharmacy or conflicting therapies. Modelling this complexity is a significant challenge for AI algorithms, which may struggle to capture the nonlinear and nuanced relationships typical of multimorbid populations. Consequently, predictive models may produce inaccurate forecasts or clinically inappropriate, even contradictory, recommendations (Akyon et al., 2023; Alghalyini, 2023; Bensken et al., 2023; Bousquet et al., 2024; Farai et al., 2024; Laymouna et al., 2024; Majnarić et al., 2021; Moser & Narayan, 2020; Šabanović et al., 2018; Theng et al., 2023; Young et al., 2024; Zafari et al., 2022).

4.6.3. Interpretability and Transparency

Many AI algorithms, particularly those using deep learning, are often viewed as “black boxes” due to the limited interpretability of their internal processes. This lack of transparency poses a major challenge in clinical settings where explainability is crucial for informed decision-making. When clinicians cannot fully evaluate the reasoning behind AI recommendations, trust may be eroded, hindering their adoption. Moreover, limited interpretability can reduce patient confidence and obstruct shared decision-making, ultimately slowing the integration of AI into routine practice. (Abuzour et al., 2024; Kellerer et al., 2021; Majnarić et al., 2021; Šabanović et al., 2018; Sarkar, 2023).

4.6.4. Trust and Acceptance

Individuals often express ambivalence toward AI in healthcare, with some showing scepticism and preferring human involvement in clinical decisions. This hesitation arises from concerns about transparency, reliability, and the ethical intent of AI. A perceived lack of empathy, accountability, and explainability in AI systems further undermines trust. These concerns highlight the need to promote transparency, build trust, and ensure AI supports – rather than replaces – human-centred care in clinical practice (Edgoos et al., 2024; Gupta, 2023; Laymouna et al., 2024; Mikava & Mamulaidze, 2023; Moser & Narayan, 2020; Rooper et al., 2025).

4.6.5. Training Requirements

Developing effective and reliable AI systems requires broad access to high-quality datasets for training and validation. In multimorbidity, this need is even more pressing as data must reflect the heterogeneity of patient populations – across age, gender, socioeconomic status and the complex interplay of chronic conditions. Creating representative, detailed datasets that mirror real-world clinical scenarios is both time and resource-intensive. The added need for longitudinal data and thorough clinical annotations further complicates data collection and curation, posing significant challenges to building robust AI tools for multimorbid care (Ahmad & Azeez, 2023; Alowais et al., 2023; Kanwal et al., 2020; Kasthurirathne et al., 2019; Majnarić et al., 2021; Maleki Varnosfaderani & Forouzanfar, 2024).

4.6.6. Integration into Clinical Workflows

Integrating AI into healthcare systems and clinical workflows presents various practical and organizational challenges. Providers may face institutional resistance, limited infrastructure and insufficient technical support. Successful adoption also depends on comprehensive training to help clinicians interpret and use AI outputs effectively. Without adequate preparation and continued support, implementation can disrupt workflows, frustrate users, and limit AI's potential to enhance patient care and clinical efficiency. (Abuzour et al., 2024; Alowais et al., 2023; Burnazovic et al., 2024; Davies et al., 2024; Farai et al., 2024; Khan et al., 2022; Kueper et al., 2020; Lai et al., 2021; Rafiq et al., 2024).

4.6.7. Ethical Concerns

Integrating AI into healthcare demands careful ethical oversight to ensure its responsible and fair use. Major concerns include data privacy and protecting sensitive patient information, especially given the large volumes required to train AI systems. Algorithmic bias – arising from unrepresentative data or systemic inequities – can lead to unequal treatment outcomes for certain populations, making transparency in algorithm design and validation essential. Additionally, disparities in infrastructure and digital literacy challenge equitable access to AI, potentially deepening existing health inequalities if not properly addressed (Amisha et al., 2019; Baxter et al., 2024; Gupta, 2023; Moser & Narayan, 2020; Nothnagel et al., 2024; Prabhakaran et al., 2019; Rafiq et al., 2024; Sarkar, 2023).

4.6.8. Regulatory Challenges

AI technologies in healthcare are subject to strict regulatory oversight to ensure safety, efficacy and adherence to ethical and legal standards. Authorities mandate thorough evaluations, including clinical validity, reliability, and patient safety. Navigating this evolving regulatory landscape is complex for developers and healthcare institutions. Compliance with national and international frameworks − such as medical device regulations, data protection laws, and clinical trial protocols − can significantly extend approval timelines. Consequently, regulatory hurdles may delay AI integration into clinical settings, slowing the translation of innovation into improved patient care (Alowais et al., 2023; Bajwa et al., 2021; Farai et al., 2024; Gupta, 2023; Maleki Varnosfaderani & Forouzanfar, 2024).

4.6.9. Healthcare Team Dynamics

The integration of AI into healthcare may unintentionally affect team dynamics and clinical relationships. A major concern is that overreliance on AI could reduce the use of clinical judgment, especially among less-experienced professionals, potentially hindering the development of key decision-making skills. AI's role in patient care may also disrupt the clinician-patient relationship if patients perceive technology as replacing human empathy and personalised attention, leading to reduced trust, satisfaction, and adherence. To avoid this, AI should be implemented to support − not replace − human expertise and connection (Majnarić et al., 2021; Nothnagel et al., 2024).

4.6.10. Emphasising Singular Disease Models

Traditional healthcare research and clinical practice have largely followed a disease-centric, reductionist model, focusing on individual conditions rather than the complexity of multimorbidity (Zheng et al., 2021). While this has advanced the treatment of specific diseases, it overlooks the interactions and overlapping trajectories of multiple chronic conditions, thus AI tools developed within this framework may be less effective for complex, multimorbid patients. This highlights the need for more holistic, integrative research approaches that reflect the real-world experiences of patients managing multiple health challenges (Alowais et al., 2023; Kurowski et al., 2021; Majnarić et al., 2021; Maleki Varnosfaderani & Forouzanfar, 2024; Young et al., 2024).

5. Discussion and Conclusions

AI has the potential to transform the management of patients with multimorbidity by enabling personalised, coordinated, and efficient care. As highlighted in recent literature, AI technologies − particularly in personalised treatment recommendations, decision support systems, virtual assistance and care coordination − can meaningfully enhance traditional care models (Majnarić et al., 2021; Prabhakaran et al., 2019; Rafiq et al., 2024). However, its use in routine clinical practice remains limited due to critical barriers such as poor data quality and the inherent complexity of multimorbid conditions (Alowais et al., 2023; Hewner et al., 2022; Young et al., 2024). AI is particularly valuable for generating individualised care plans that consider interactions between coexisting diseases and the risks of polypharmacy. By leveraging large datasets from EHRs, AI can predict adverse drug interactions, monitor therapeutic efficacy in real time, and tailor treatment strategies (Macfarlane, 2020; Majnarić et al., 2021). AI-powered decision support systems also enhance diagnostic accuracy and risk stratification, enabling timely intervention (Majnarić et al., 2021; Martínez-García et al., 2013). Virtual assistants support continuity of care by promoting treatment adherence and self-management through personalised interaction and real-time monitoring (Bajwa et al., 2021; Rafiq et al., 2024). AI can also improve care coordination by aggregating and analysing data across sources and systems, supporting interdisciplinary collaboration (Abuzour et al., 2024; Alowais et al., 2023; Moser & Narayan, 2020). Despite this promise, technical, ethical, clinical, and systemic challenges remain. Data quality is a major concern as clinical records for multimorbid patients are often incomplete, fragmented or inconsistently coded, compromising predictive accuracy and clinical utility (Chu et al., 2022; Kellerer et al., 2021; Majnarić et al., 2021). The complexity of disease interactions, treatment responses, and care needs in multimorbidity challenges the development of reliable AI models, which may result in inaccurate or conflicting recommendations (Bensken et al., 2023; Farai et al., 2024; Martínez-García et al., 2013). Additional issues include poor model interpretability, clinician scepticism, training demands, ethical concerns, and a mismatch between current AI design − often built around single-disease paradigms − and the real-world complexity of multimorbid care (Majnarić et al., 2021; Zheng et al., 2021). As a result, AI's clinical role remains limited, with most applications focused on supportive tools such as virtual assistants, which, while useful for promoting adherence and education, do not yet address the core challenges of personalised decision-making and integrated care planning (Alowais et al., 2023; Hewner et al., 2022; Young et al., 2024). Unlocking AI's full potential requires high-quality, representative datasets and models that capture the clinical complexity of multimorbidity. Current research often relies on theoretical models or retrospective data that lack real-world clinical context. Variability in study populations, data sources, and outcome measures further limits generalisability (Alowais et al., 2023). Many AI systems underrepresent older adults, clinically complex cases, and marginalised populations, namely those most affected by multimorbidity (Gupta, 2023; Kueper et al., 2020). Future research must prioritise the development of high-quality representative datasets that accurately reflect the complex longitudinal trajectories of patients with multimorbidity, as this gap may worsen health disparities and reduce clinical relevance. Future efforts should prioritise integrated, interoperable data infrastructures and real-world prospective studies that assess not only predictive performance but also clinical relevance, usability, and patient impact (Hewner et al., 2022; Moser & Narayan, 2020). Interdisciplinary collaboration among clinicians, data scientists, ethicists, and patients, is essential to co-design AI tools that are interpretable, transparent, and aligned with person-centred care principles (Majnarić et al., 2021; Sarkar, 2023). A shift from disease-specific models to holistic, systems-based approaches that account for condition interdependencies and social determinants of health are critical for developing AI solutions that are both technically sound and clinically meaningful in the context of multimorbidity.

This systematic review offers a structured synthesis of current evidence on how artificial intelligence (AI) can support the management of patients with multimorbidity in primary healthcare (PHC). However, several methodological limitations must be acknowledged. First, the review was limited to peer-reviewed articles published in English, which may have excluded relevant studies in other languages or non-indexed regional journals. Furthermore, the exclusion of grey literature, such as conference papers or technical reports, while enhancing methodological rigour, may have omitted emerging insights or practical innovations not yet captured in peer-reviewed publications. Second, although the inclusion criteria focused on clinically meaningful definitions of multimorbidity, the diversity of study designs, outcome measures, and AI approaches made direct comparison between studies challenging. This heterogeneity may have limited the ability to draw generalisable conclusions or quantify the overall impact of AI across care settings. Third, the review excluded studies using purely technical AI models with no clear clinical relevance. While this approach ensured a focus on patient-centred applications, it may have unintentionally excluded innovative tools that are still in early development but hold future potential for PHC settings. Finally, while the search strategy was comprehensive, covering Scopus, Web of Science, and PubMed, and enhanced by snowballing, it remains possible that some relevant studies were missed due to variability in terminology and indexing.

Given these limitations and the evolving landscape of AI in healthcare, future research should focus on several key areas which include the development and validation of interpretable AI models trained on high-quality, representative datasets that accurately reflect the complexity and diversity of multimorbid populations. There is also a need for greater emphasis on prospective, real-world studies in primary healthcare settings that evaluate not only predictive performance but also clinical utility, integration into existing workflows, and patient-centred outcomes. Furthermore, research should strive to include underrepresented populations (e.g. older adults and individuals facing socioeconomic disadvantages), and promote equity in the development and implementation of AI technologies. Interdisciplinary and participatory approaches to the design of AI tools should be explored, engaging clinicians, patients, data scientists and ethicists to ensure that the solutions are in line with the principles of person-centred care. It is equally important to conduct studies that explicitly examine the feasibility, scalability and sustainability of AI applications within the real-world PHC infrastructure. Finally, addressing ethical, clinical and systemic challenges is essential, as these may otherwise hinder adoption despite technological readiness. By confronting these methodological and contextual gaps, future studies can advance the scientific as well as practical understanding of AI's supportive role in improving care for patients with multimorbidity.

References

Abuzour, A. S., Wilson, S. A., Woodall, A. A., Mair, F. S., Clegg, A., Shantsila, E., Gabbay, M., Abaho, M., Aslam, A., Bollegala, D., Cant, H., Griffiths, A., Hama, L., Leeming, G., Lo, E., Maskell, S., O'Connell, M., Popoola, O., Relton, S., & Walker, L. E. (2024). A Qualitative Exploration of Barriers to Efficient and Effective Structured Medication Reviews in Primary Care: Findings from the DynAIRx study. *PLoS ONE*, *19*(8), 1-18. https://doi.org/10.1371/journal.pone.0299770

Ahmad, S., & Azeez, N. P. A. (2023). The Digitalization of India's Healthcare System: A Paradigm Shift amidst the COVID-19 Pandemic. *South Asian Journal of Social Studies and Economics*, *19*(4), 1-12. https://doi.org/10.9734/sajsse/2023/v19i4681

Akerkar, R. (2019). *Artificial Intelligence for Business*. Springer.

Akyon, S. H., Akyon, F. C., & Yılmaz, T. E. (2023). Artificial Intelligence-Supported Web Application Design and Development for Reducing Polypharmacy Side Effects and Supporting Rational Drug Use in Geriatric Patients. *Frontiers in Medicine*, *10*(March), 1-16. https://doi.org/10.3389/fmed.2023.1029198

Alghalyini, B. (2023). Applications of Artificial Intelligence in the Management of Childhood Obesity. *Journal of Family Medicine and Primary Care*, *12*, 2558-2564.

Alowais, S., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Saleh, K. B., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing Healthcare: The Role of Artificial Intelligence in Clinical Practice. *BMC Medical Education*, *23*, 689. https://doi.org/10.1186/s12909-023-04698-z

Álvarez-Gálvez, J., Ortega-Martín, E., Carretero-Bravo, J., Pérez-Muñoz, C., Suárez-Lledó, V., & Ramos-Fiol, B. (2023). Social Determinants of Multimorbidity Patterns: A Systematic Review. *Frontiers in Public Health*, *11*.

Amisha, Malik, P., Pathania, M., & Rathaur, V. (2019). Overview of Artificial Intelligence in Medicine. *Journal of Family Medicine and Primary Care*, *8*, 2328-2331.

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial Intelligence in Healthcare: Transforming the Practice of Medicine. *Future Healthcare Journal*, *8*(2), e188-e194. https://doi.org/10.7861/fhj.2021-0095

Balyan, R., Crossley, S. A., Brown, W., Karter, A. J., McNamara, D. S., Liu, J. Y., Lyles, C. R., & Schillinger, D. (2019). Using Natural Language Processing and Machine Learning to Classify Health Literacy from Secure Messages: The ECLIPPSE Study. *PLoS ONE*, *14*(2), 1-17. https://doi.org/10.1371/journal.pone.0212488

Baxter, R., Nind, T., Sutherland, J., McAllister, G., Hardy, D., Hume, A., Macleod, R., Caldwell, J., Krueger, S., Tramma, L., Teviotdale, R., Gillen, K., Scobbie, D., Baillie, I., Brooks, A., Prodan, B., Kerr, W., Sloan-Murphy, D., Herrera, J. F. R., & Jefferson, E. (2024). The Scottish Medical Imaging Archive: 57.3 Million Radiology Studies Linked to Their Medical Records. *Radiology: Artificial Intelligence*, *6*(1), 1-6. https://doi.org/10.1148/ryai.220266

Bensken, W. P., Vaca, G. F. B., Williams, S. M., Khan, O. I., Jobst, B. C., Stange, K. C., Sajatovic, M., & Koroukian, S. M. (2023). Disparities in Adherence and Emergency Department Utilization among People with Epilepsy: A Machine Learning Approach. *Seizure*, *110*, 169-176. https://doi.org/10.1016/j.seizure.2023.06.021

Bousquet, J., Schünemann, H. J., Sousa-Pinto, B., Zuberbier, T., Togias, A., Samolinski, B., Bedbrook, A., Czarlewski, W., Hofmann-Apitius, M., Litynska, J., Vieira, R. J., Anto, J. M., Fonseca, J. A., Brozek, J., Bognanni, A., Brussino, L., Canonica, G. W., Cherrez-Ojeda, I., Cruz, A. A., & Zidarn, M. (2024). Concepts for the Development of Person-Centered, Digitally Enabled, Artificial Intelligence-Assisted ARIA Care Pathways (ARIA 2024). *Journal of Allergy and Clinical Immunology: In Practice*, *Aria*. https://doi.org/10.1016/j.jaip.2024.06.040

Brummel, A., & Carlson, A. M. (2016). Comprehensive Medication Management and Medication Adherence for Chronic Conditions. *Journal of Managed Care and Specialty Pharmacy*, *22*(1), 56-62. https://doi.org/10.18553/jmcp.2016.22.1.56

Burnazovic, E., Yee, A., Levy, J., Gore, G., & Abbasgholizadeh Rahimi, S. (2024). Application of Artificial Intelligence in COVID-19-Related Geriatric Care: A Scoping Review. *Archives of Gerontology and Geriatrics*, *116*(December 2022), 105129. https://doi.org/10.1016/j.archger.2023.105129

Cassell, A., Edwards, D., Harshfield, A., Rhodes, K., Brimicombe, J., Payne, R., & Griffin, S. (2018). The Epidemiology of Multimorbidity in Primary Care. *British Journal of General Practice*, *68*(669), 1-7. http://bjgp.org/content/early/2018/03/12/bjgp18X695465

Chowdhury, S. R., Chandra Das, D., Sunna, T. C., Beyene, J., & Hossain, A. (2023). Global and Regional Prevalence of Multimorbidity in the Adult Population in Community Settings: A Systematic Review and Meta-Analysis. *EClinicalMedicine*, *57*, 101860. https://doi.org/10.1016/j.eclinm.2023.101860

Chu, W. M., Kristiani, E., Wang, Y. C., Lin, Y. R., Lin, S. Y., Chan, W. C., Yang, C. T., & Tsan, Y. T. (2022). A Model for Predicting Fall Risks of Hospitalized Elderly in Taiwan – A Machine Learning Approach Based on Both Electronic Health Records and Comprehensive Geriatric Assessment. *Frontiers in Medicine*, *9*(c). https://doi.org/10.3389/fmed.2022.937216

Davies, A. H., Ahmed, H., Thomas-Wood, T., & Wood, F. (2024). Primary Care Health Professionals' Approach to Clinical Coding: A Qualitative Interview Study. *British Journal of General Practice*, *75*(750), BJGP.2024.0036. https://doi.org/10.3399/bjgp.2024.0036

Edgoos, J. Y. C., Anaya, Y. B., & Rakel, D. (2024). Face-to-Face Relationships Still Matter in a Digital Age: A Call for a 5th C in the Core Tenets of Primary Care. *The Annals of Family Medicine*, *22*(5), 453-455.

Farai, O. A., Ogundairo, O., Maduka, C. P., Okongwu, C. C., Babarinde, A. O., & Sodamade, O. T. (2024). Digital Health Technologies in Chronic Disease Management: A Global Perspective. *International Journal of Research and Scientific Innovation*, *X*(XII). https://doi.org/10.51244/ijrsi.2023.1012041

Gupta, P. (2023). The Potential of AI in Healthcare. *International Journal of Advanced Research*, *11*(09), 1112-1115. https://doi.org/10.21474/ijar01/17624

Hewner, S., Smith, E., & Sullivan, S. S. (2022). Identifying High-Need Primary Care Patients Using Nursing Knowledge and Machine Learning Methods. *Applied Clinical Informatics*, *14*(3), 408-417. https://doi.org/10.1055/a-2048-7343

Ho, I. S. S., Azcoaga-Lorenzo, A., Akbari, A., Davies, J., Khunti, K., Kadam, U. T., Lyons, R. A., McCowan, C., Mercer, S. W., Nirantharakumar, K., Staniszewska, S., & Guthrie, B. (2022). Measuring Multimorbidity in Research: Delphi Consensus Study. *BMJ Medicine*, *1*(1), e000247. https://doi.org/10.1136/bmjmed-2022-000247

Hoogendijk, E. O., Onder, G., Smalbil, L., Vetrano, D. L., Hirdes, J. P., Howard, E. P., Morris, J. N., Fialová, D., Szczerbińska, K., Kooijmans, E. C. M., Hoogendoorn, M., Declercq, A., De Almeida Mello, J., Leskelä, R. L., Häsä, J., Edgren, J., Ruppe, G., Liperoti, R., Joling, K. J., & Van Hout, H. P. J. (2023). Optimising the Care for Older Persons with Complex Chronic Conditions in Home Care and Nursing Homes: Design and Protocol of I-CARE4OLD, an Observational Study Using Real-World Data. *BMJ Open*, *13*(6), 1-8. https://doi.org/10.1136/bmjopen-2023-072399

Ito, Y., Iwagami, M., Komiyama, J., Hamasaki, Y., Kuroda, N., Suzuki, A., Ito, T., Goto, T., Wan, E. Y. F., Lai, F. T. T., & Tamiya, N. (2024). Clinical Subtypes of Older Adults Starting Long-Term Care in Japan and Their Association with Prognoses: A Data-Driven Cluster Analysis. *Scientific Reports*, *14*(1), 1-10. https://doi.org/10.1038/s41598-024-65699-6

Kanwal, F., Taylor, T. J., Kramer, J. R., Cao, Y., Smith, D., Gifford, A. L., El-Serag, H. B., Naik, A. D., & Asch, S. M. (2020). Development, Validation, and Evaluation of a Simple Machine Learning Model to Predict Cirrhosis Mortality. *JAMA Network Open*, *3*(11), E2023780. https://doi.org/10.1001/jamanetworkopen.2020.23780

Kasthurirathne, S. N., Biondich, P. G., Grannis, S. J., Purkayastha, S., Vest, J. R., & Jones, J. F. (2019). Identification of Patients in Need of Advanced Care for Depression Using Data Extracted from a Statewide Health Information Exchange: A Machine Learning Approach. *Journal of Medical Internet Research*, *21*(7), 1-12. https://doi.org/10.2196/13809

Kellerer, C., Jörres, R. A., Schneider, A., Alter, P., Kauczor, H. U., Jobst, B., Biederer, J., Bals, R., Watz, H., Behr, J., Kauffmann-Guerrero, D., Lutter, J., Hapfelmeier, A., Magnussen, H., Trudzinski, F. C., Welte, T., Vogelmeier, C. F., & Kahnert, K. (2021). Prediction of Lung Emphysema in COPD by Spirometry and Clinical Symptoms: Results from COSYCONET. *Respiratory Research*, *22*(1), 1-11. https://doi.org/10.1186/s12931-021-01837-2

Khan, A. I., Harris, J. K., Barnsley, J., & Wodchis, W. (2022). Exploring Intra and Interorganizational Integration Efforts Involving the Primary Care Sector – A Case Study from Ontario. *International Journal of Integrated Care*, *22*(3), 1-17. https://doi.org/10.5334/ijic.5541

Kueper, J. K., Terry, A. L., Zwarenstein, M., & Lizotte, D. J. (2020). Artificial Intelligence and Primary Care Research: A Scoping Review. *Annals of Family Medicine*, *18*(3), 250-258. https://doi.org/10.1370/afm.2518

Kurowski, B. G., Greve, K., Bailes, A. F., Zahner, J., Vargus-Adams, J., Mcmahon, M. A., Aronow, B. J., & Mitelpunkt, A. (2021). Electronic Health Record and Patterns of Care for Children with Cerebral Palsy. *Developmental Medicine and Child Neurology*, *63*(11), 1337-1343. https://doi.org/10.1111/dmcn.14867

Lai, F. T. T., Beeler, P. E., Yip, B. H. K., Cheetham, M., Chau, P. Y. K., Chung, R. Y., Wong, E. L. Y., Yeoh, E. K., Battegay, E., & Wong, S. Y. S. (2021). Comparing Multimorbidity Patterns Among Discharged Middle-Aged and Older Inpatients Between Hong Kong and Zurich: A Hierarchical Agglomerative Clustering Analysis of Routine Hospital Records. *Frontiers in Medicine*, *8*(July), 1-13. https://doi.org/10.3389/fmed.2021.651925

Laymouna, M., Ma, Y., Lessard, D., Schuster, T., Engler, K., & Lebouché, B. (2024). Roles, Users, Benefits, and Limitations of Chatbots in Health Care: Rapid Review. *Journal of Medical Internet Research*, *26*, 1-28. https://doi.org/10.2196/56930

Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019). Ten Ways Artificial Intelligence Will Transform Primary Care. *Journal of General Internal Medicine*, *34*(8), 1626-1630. https://doi.org/10.1007/s11606-019-05035-1

Lund, J. L., Kuo, T. M., Brookhart, M. A., Meyer, A. M., Dalton, A. F., Kistler, C. E., Wheeler, S. B., & Lewis, C. L. (2019). Development and Validation of a 5-Year Mortality Prediction Model Using Regularized Regression and Medicare Data. *Pharmacoepidemiology and Drug Safety*, *28*(5), 584-592. https://doi.org/10.1002/pds.4769

Macfarlane, A. (2020). General Practice and the Community: Research on Health Service, Quality Improvements and Training. Selected Abstracts from the EGPRN Meeting in Vigo, Spain, 17–20 October 2019. *European Journal of General Practice*, *26*(1), 42-50. https://doi.org/10.1080/13814788.2020.1719994

Majnarić, L. T., Babič, F., O'Sullivan, S., & Holzinger, A. (2021). AI and Big Data in Healthcare: Towards a More Comprehensive Research Framework for Multimorbidity. *Journal of Clinical Medicine*, *10*(4), 1-23. https://doi.org/10.3390/jcm10040766

Maleki Varnosfaderani, S., & Forouzanfar, M. (2024). The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. *Bioengineering*, *11*(4), 1-38. https://doi.org/10.3390/bioengineering11040337

Martínez-García, A., Moreno-Conde, A., Jódar-Sánchez, F., Leal, S., & Parra, C. (2013). Sharing Clinical Decisions for Multimorbidity Case Management Using Social Network and Open-Source Tools. *Journal of Biomedical Informatics*, *46*(6), 977-984. https://doi.org/10.1016/j.jbi.2013.06.007

Mikava, N., & Mamulaidze, T. (2023). Implications of Artificial Intelligence in Healthcare in Developing Countries: Perspectives and Challenges. *Agora International Journal of Economical Sciences*, *17*(2), 110-120. https://doi.org/10.15837/aijes.v17i2.6448

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., Antes, G., Atkins, D., Barbour, V., Barrowman, N., Berlin, J. A., Clark, J., Clarke, M., Cook, D., D'Amico, R., Deeks, J. J., Devereaux, P. J., Dickersin, K., Egger, M., Ernst, E., Gøtzsche, P. C., & Tugwell, P. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, *6*(7). https://doi.org/10.1371/journal.pmed.1000097

Molokhia, M., & Majeed, A. (2017). Current and Future Perspectives on the Management of Polypharmacy. *BMC Family Practice*, *18*(1), 1-9. https://doi.org/10.1186/s12875-017-0642-0

Moser, E. C., & Narayan, G. (2020). Improving Breast Cancer Care Coordination and Symptom Management by Using AI Driven Predictive Toolkits. *Breast*, *50*, 25-29. https://doi.org/10.1016/j.breast.2019.12.006

Nothnagel, K., Hay, A., Watson, J., & Banks, J. (2024). AI-Guided Deep Vein Thrombosis Diagnosis in Primary Care: Protocol for Cohort with Qualitative Assessment. *BJGP Open*, BJGPO.2024.0165. https://doi.org/10.3399/bjgpo.2024.0165

Park, S., Lee, C., Lee, S. B., & Lee, J. Y. (2023). Machine Learning-Based Prediction Model for Emergency Department Visits Using Prescription Information in Community-Dwelling Non-Cancer Older Adults. *Scientific Reports*, *13*(1), 1-10. https://doi.org/10.1038/s41598-023-46094-z

Prabhakaran, D., Ajay, V. S., & Tandon, N. (2019). Strategic Opportunities for Leveraging Low-Cost, High-Impact Technological Innovations to Promote Cardiovascular Health in India. *Ethnicity and Disease*, *29*(47), 145-152. https://doi.org/10.18865/ed.29.S1.145

Rafiq, M., Mazzocato, P., Guttmann, C., Spaak, J., & Savage, C. (2024). Predictive Analytics Support for Complex Chronic Medical Conditions: An Experience-Based Co-Design Study of Physician Managers' Needs and Preferences. *International Journal of Medical Informatics*, *187*(May 2023), 105447. https://doi.org/10.1016/j.ijmedinf.2024.105447

Rooper, I. R., Liem, W. W., Burla, M., Gordon, J., Baez, L. M., Kornfield, R., & Berry, A. B. L. (2025). Designing Values Elicitation Technologies for Mental Health and Chronic Care Integration: User-Centered Design Approach. *JMIR Formative Research*, *9*. https://doi.org/10.2196/68419

Šabanović, Š., Ljiljana, M. T., Babič, F., Vadovský, M., Paralič, J., Včev, A., & Holzinger, A. (2018). Metabolic Syndrome in Hypertensive Women in the Age of Menopause: A Case Study on Data from General Practice Electronic Health Records. *BMC Medical Informatics and Decision Making*, *18*(1), 1-18. https://doi.org/10.1186/s12911-018-0601-2

Sarkar, A. (2023). The Impact and Potential of Artificial Intelligence in Healthcare: A Critical Review of Current Applications and Future Directions. *International Journal for Research in Applied Science and Engineering Technology*, *11*(8). https://doi.org/10.22214/ijraset.2023.55537

Shi, X., Nikolic, G., Van Pottelbergh, G., van den Akker, M., Vos, R., & De Moor, B. (2021). Development of Multimorbidity Over Time: An Analysis of Belgium Primary Care Data Using Markov Chains and Weighted Association Rule Mining. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences*, *76*(7), 1234-1241. https://doi.org/10.1093/gerona/glaa278

Stasevych, M., & Zvarych, V. (2023). Innovative Robotic Technologies and Artificial Intelligence in Pharmacy and Medicine: Paving the Way for the Future of Health Care – A Review. *Big Data and Cognitive Computing*, *7*(3). https://doi.org/10.3390/bdcc7030147

Theng, B., Tran, J. T., Serag, H., Raji, M., Tzeng, H.-M., Shih, M., & Lee, W.-C. (Miso). (2023). Understanding Caregiver Challenges: A Comprehensive Exploration of Available Resources to Alleviate Caregiving Burdens. *Cureus*, *15*(8). https://doi.org/10.7759/cureus.43052

Young, R. A., Martin, C. M., Sturmberg, J. P., Hall, S., Bazemore, A., Kakadiaris, I. A., & Lin, S. (2024). What Complexity Science Predicts about the Potential of Artificial Intelligence/Machine Learning to Improve Primary Care. *Journal of the American Board of Family Medicine*, *37*(2), 332-345. https://doi.org/10.3122/jabfm.2023.230219R1

Zafari, H., Langlois, S., Zulkernine, F., Kosowan, L., & Singer, A. (2022). AI in predicting COPD in the Canadian Population. *BioSystems*, *211*(December 2021), 104585. https://doi.org/10.1016/j.biosystems.2021.104585

Zheng, H., Ryzhov, I. O., Xie, W., & Zhong, J. (2021). Personalized Multimorbidity Management for Patients with Type 2 Diabetes Using Reinforcement Learning of Electronic Health Records. *Drugs*, *81*(4), 471-482. https://doi.org/10.1007/s40265-020-01435-4

Sztuczna inteligencja w opiece nad pacjentami wielochorobowymi: przegląd systematyczny możliwości, wyzwań i ograniczeń

Streszczenie

Cel: W niniejszym badaniu określono rolę sztucznej inteligencji we wspieraniu pacjentów z wielochorobowością w podstawowej opiece zdrowotnej oraz zbadano związane z tym możliwości, wyzwania i ograniczenia.

Metodyka: Przeprowadzono systematyczne wyszukiwanie literatury w bazach Scopus, Web of Science i PubMed, używając terminów związanych ze sztuczną inteligencją i wielochorobowością w podstawowej opiece zdrowotnej. Po wstępnej selekcji 53 artykuły spełniły kryteria włączenia i zostały przeanalizowane zgodnie z wytycznymi PRISMA.

Wyniki: AI ma potencjał, aby usprawnić opiekę nad pacjentami z wielochorobowością poprzez wspieranie personalizacji leczenia, pomoc w podejmowaniu decyzji klinicznych, wykorzystanie wirtualnych asystentów zdrowotnych oraz ułatwianie skoordynowanej opieki dzięki monitorowaniu, analizie danych i ukierunkowanym interwencjom. Jednak jej zastosowanie pozostaje ograniczone ze względu na niską jakość danych, interakcje między chorobami, niską interpretowalność modeli i niedostateczną reprezentację populacji wielochorobowych w danych szkoleniowych. W rezultacie rola sztucznej inteligencji we wspieraniu pacjentów z wielochorobowością pozostaje ograniczona, a potencjalne korzyści nie są w pełni wykorzystywane.

Implikacje i rekomendacje: Wykorzystanie potencjału sztucznej inteligencji w leczeniu pacjentów z wielochorobowością wymaga rozwiązania problemów technicznych, etycznych, klinicznych i systemowych. Badania muszą priorytetowo traktować opracowywanie reprezentatywnych zbiorów danych i interpretowalnych modeli, które odzwierciedlają złożoność chorób wielonarządowych, aby pomóc w zapewnieniu skoordynowanej opieki skoncentrowanej na pacjencie.

Oryginalność/wartość: Niniejsza analiza pokazuje ograniczoną integrację sztucznej inteligencji w opiece nad osobami cierpiącymi na wiele schorzeń, podkreślając potrzebę posiadania wysokiej jakości danych i modeli umożliwiających interpretację. Wskazuje ona kluczowe wyzwania, które należy pokonać, aby przekształcić sztuczną inteligencję z koncepcyjnej obietnicy w praktyczne wsparcie dla osób z wieloma chorobami przewlekłymi.

Słowa kluczowe: wielochorobowość, sztuczna inteligencja, przegląd systematyczny, PRISMA