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REVIEW PAPER

Enhancing healthcare for patients with multiple chronic conditions using machine learning and medical specialist data: a scoping review

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Abstract

Purpose The aging population is leading to a rise in the number of patients with multiple chronic conditions (MCC), which is putting pressure on healthcare systems. Artificial Intelligence, including Machine Learning (ML) offers potential to enhance care for patients with MCC. This scoping review summarizes current ML applications, discusses shortcomings and identifies opportunities. Additionally, it aims to identify applications explored in practice.

Methods We searched PubMed, Embase, and Web of Science for studies published between 2015 and January 2025 that used ML techniques and specialist care data, focusing on adults with MCC. Screening was assisted by ASReview.

Results The search identified 13381 articles, of which 454 were reviewed full text, resulting in 21 included articles. ML was mainly used for clustering (n = 14), primarily focusing on cardiovasculair diseases, with eight studies focusing on chronic diseases and six studies on clinical features, like medical specialties involved and symptoms. Stated potential clinical use of the clusters varied, but primarily aimed to promote integrated, personalized care. Predictive modelling was employed to support clinical decision-making and enhance research (n = 7). No applications were clinically evaluated.

Conclusion Current research on ML for patients with MCC primarily focuses on cluster analysis and predictive modelling, mainly aiming to enable holistic care. Future efforts should explore clinical evaluation and implementation, Natural Language Processing and Large Language Models. These technologies could significantly enhance care by extracting valuable insights from the data-rich electronic patient records of MCC patients, potentially leading to more effective decision-making and tailored interventions.

Keywords Multimorbidity · Artificial intelligence · Machine learning · Cluster analysis · Integrated care · Natural language processing

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1 Introduction

The number of persons aged 65 years and older will double worldwide from 0.73 billion in 2019 to 1.5 billion in 2050 [1].Due to this aging population, the number of patients with multiple chronic conditions (MCC) is expected to increase [1]. Patients with MCC often face complex healthcare needs, with issues on multiple health domains requiring attention. Further, current healthcare systems are not designed to meet their healthcare needs [2], as hospital care is still focused on managing single diseases. Consequently, care for patients with MCC is provided by multiple healthcare providers simultaneously, and when there is no effective collaboration and access to health information, these patients are likely to experience care fragmentation [3]. Care fragmentation itself lowers care quality and leads to poor patient outcomes, including under- and overtreatment, emergency department visits and costs [4–6]. As a result, the rising number of patients with MCC is putting pressure on current healthcare systems [7, 8].

New strategies are therefore necessary to combat these rising costs and pressure in healthcare. A transition into more patient-centred, value-driven care that prioritizes health over illness might offer opportunities for the sustainability of care [9]. This transition can be aided by technological innovation, particularly artificial intelligence (AI), and its subfield, Machine Learning (ML) [10]. To unlock the potential of ML, the results should be understandable and applicable for practicing healthcare professionals,—i.e. the "black box" idea for ML needs to be eliminated [11]. In essence, ML uses modern mathematical algorithms for analysing multiple predictors in complex patterns while improving its performance with self-learning properties[12]. ML has a range of potential computer applications that help apply the results in medical practice such as 1) clinical ML-derived probability calculators (for example for personalized risk estimation of postoperative development of a delirium in older patients [13]), 2) natural language processing which makes use of textual (unstructured) data (NLP, for example for identifying ageing related syndromes such as falling and sarcopenia [14]) and 3) deep learning (DL, for example computer vision for fracture recognition on X-rays with Convolutional Neural Networks [15]).

Particularly for MCC patients, who generate vast amounts of clinical data due to their higher care consumption, ML could provide actionable insights by untangling the complexity of multimorbidity care [16]. Data-driven insights could facilitate the holistic care approach and make it more efficient [17–20]. For example, early personalized comorbidity prediction enables setting up integrated treatment and preventive strategies [19]. Ultimately, an integrated care approach for MCC, supported by AI/ML, could result in a reduction in healthcare costs and lower pressure on healthcare systems.

To our knowledge, no systematic search has been conducted providing an overview of ML applications for patients with MCC. We therefore chose to conduct a scoping review, which aims to rapidly map the key concepts underpinning a research area and the main sources and types of evidence available [21]. The purpose of this scoping review was to 1) summarize current applications and implications of ML in MCC patients using data from care provided by the medical specialist and to assess how many are clinically implemented, 2) to present and discuss opportunities for research and clinical applications.

2 Materials & methods

To explore, map and synthesize the applications of ML in patients with MCC based on data from medical specialist care, a scoping review was conducted following the 5-stage-approach of Arksey and O'Malley's. This method is in accordance with the PRISMA Extension for Scoping Reviews [21, 22]. This scoping review was pre-registered in Open Science Framework [23].

2.1 Stage 1: identifying the research question

What is the current application and implementation of ML using data from care provided by the medical specialist in patients with MCC?

2.2 Stage 2: identifying relevant studies

We searched Pubmed, Embase, Web of Science up to January 1 st, 2025 (Supplementary Table 1). A clinical librarian was consulted to help build the search. The search consisted of two main domains, the first domain included the population with MCC, the second concerned ML. We focused on original studies published from 2015 onwards to base our overview on recent studies.

2.3 Stage 3: selecting studies

Screening of titles and abstracts was performed with the assistance of the ML algorithm from ASReview [24]. This program ranks articles based on their textual similarities to previously selected articles, reducing time expenditure in the early screening phase. After identifying 100 consecutive irrelevant articles in the initial screening, the program has enough input to complete the remaining title abstract screening automatically with a near 100% accuracy [25]. The initial title/abstract screening with ASReview was independently performed by two authors (HD & MSM), with interim discussions on article interpretations. Articles selected by both authors were immediately included. Instances where only one author had selected an article for inclusion were re-evaluated by consensus. Disagreements were discussed and resolved by a third person (MV or JO) where necessary. Studies were included if they met the following criteria:

- Studies evaluated ML methods of any kind (including ML for prediction models, DL and NLP studies). We considered advanced logistic regression models as ML methods, e.g. penalized logistic regression (LASSO, ridge or elastic-net), boosted logistic regression and bagged logistic regression [26].
- All patients included had MCC, which is defined as having more than one chronic condition. This should clearly be described in the inclusion criteria or as patient characteristic of the study population. We considered conditions as chronic based on a list of diagnosis groups designed by the Dutch Hospital Data—Clinical Classifications Software (DHD-CCS). In this list, diagnoses were classified according to the International Classification of Diseases 10th Revision Procedure Coding System (ICD-10-PCS), which was developed by the Agency for Healthcare Research and Quality (AHRQ) (Supplementary Appendix Excel sheet). We considered oncologic conditions as chronic conditions. When the diagnosis was not listed, identification of the disease as chronic was based on consensus.
- The study used data from care provided by a medical specialist (e.g. not solely from data from care provided by the general practitioner).
- All patients included were 18 years of age or older.

We excluded the following studies:

- Non-English and non-Dutch studies.
- Studies solely reporting non-ML techniques, such as logistic or linear regression used for association or prediction studies.
- Non-relevant study design types, such as case reports.
- Studies for which we were unable to obtain full text.
- Studies concerning the biomedical pathogenesis of multiple conditions, such as bioinformatical studies or genetics.

2.4 Stage 4 and stage 5: charting, collating, summarizing the data

We extracted the following data: year of publication, study population, algorithms used, methods for variable selection, reported outcome, reported performance measures, such as Area Under the Curve of the Receiver Operating Curve (if reported), summary of most important findings and the potential clinical use. We categorized the information after discussing the findings in a team of experts in this field of research in an iterative process.

3 Results

3.1 Description of search results and included articles

The search resulted in 13,381 articles, of which 454 were assessed in full-text for eligibility. A total of 21 articles met the inclusion criteria (Fig. 1) [27–47] which are summarised in Table 1. Most included studies were published in 2024 (n = 7)[27, 28, 39, 41–44] reflecting a recent acceleration in ML exploration. The first authors were mostly affiliated with the United States of America (n = 5) [31, 35, 37, 38, 43], followed by China (n = 3) [30, 39, 42]. The use of ML could be divided into two main methods, clustering (n = 14) [27–30, 30–34, 36–38, 40, 46–48] and predictive modelling (n = 7) [35, 39, 41–45]. Temporal distribution of employed ML type is shown in Fig. 2. K-means clustering and hierarchical supervised clustering were the most employed clustering methods while Random Forest was most frequently the best performing predictive model. Other information on the studies included is shown in Table 1 and Supplementary Table 1.

3.2 Clustering by presence chronic diseases

Clustering based on the presences of certain chronic diseases was performed in eight studies [27, 29, 30, 32, 34, 40, 46, 47]. The described clinical use mainly focused on primary prevention of MCC or the development of additional diseases (Fig. 3). For clarity purposes, we focused on the five most prevalent clusters in each study and the three most common diseases in these clusters (see Supplementary Table 2). Cardiovascular diseases, predominantly hypertension, were the most prevalent diseases in these clusters (Fig. 3). Other articles also contextualized their identified clusters to alternative information such as location, follow-up duration and frailty status (n = 3, Supplementary Table 2) [30, 40, 47].

3.3 Disease unrelated clustering

Clustering based on other factors than the presence of chronic diseases was performed in six articles [28, 31, 33, 36–38]. In two studies, clustering was based on symptom

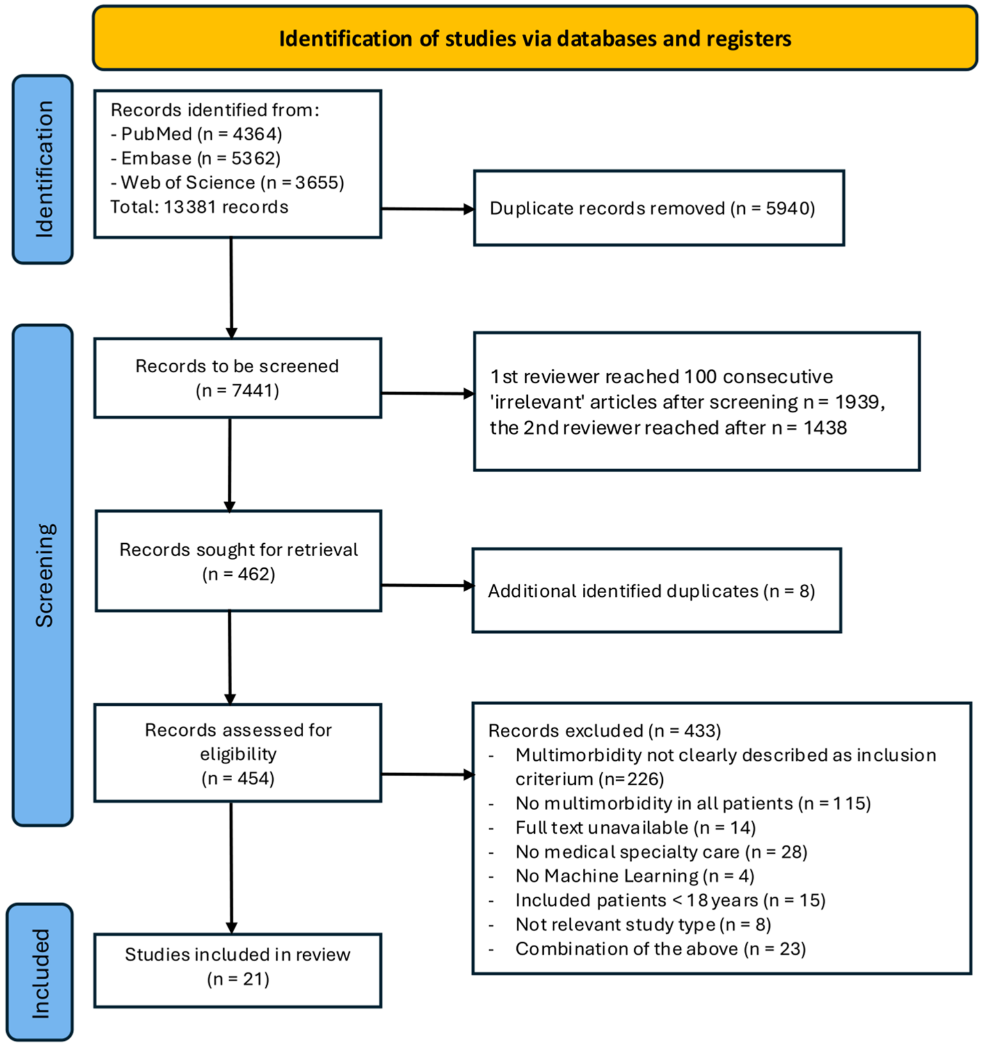

Fig. 1 Flowchart of results from systemic search strategy

presence, with cohorts characterized by both diabetes and another condition, such as cancer [38] and Human Immunodeficiency Virus (see Supplementary Table 3) [37]. The most frequent theme identified in the described clinical implications was contributing to integrative care (n = 3) and fostering future research and exploration (n = 3, Fig. 3).

3.4 Predictive modelling

Machine Learning based predictive modelling was reported in seven articles [35, 39, 41–45], with the most prominent clinical implications being advancing research and supporting clinical decision-making (Fig. 3). Mortality prediction was explored in two studies [35, 39]. One study examined patients with sarcoidosis and heart failure [35], and the other, coronary heart disease and hypertension [39] (see Supplementary Table 4). In both studies, a Random Forest model delivered the best performance, with an AUC of 0.71 and 0.81 respectively. Additionally, healthcare utilization was predicted in two studies (see Supplementary Table 4). Le Lay et al. [45] developed ML models to predict 30-day and 365-day rehospitalization and length of stay, where the Random Forest model performed the best with an AUC of 0.63. Similarly, Weil et al. [41] aimed to predict a high number of future outpatient visits, emergency admissions and acute hospitalizations in patients with MCC, with eXtreme Gradient Boosting achieving the highest AUCs ranging from 0.73–0.82.

4 Discussion

As the older population increases and the pressure on healthcare systems to manage patients with MCC grows, novel technologies like ML may be essential to address this challenge. This scoping review, the first one of its kind to our knowledge, identified 21 studies employing ML for

Table 1 Overview of the key characteristics of all included papers of the scoping review

Study characteristics	
Sample size (median [IQR])	3338 [776–15,865]
Sample size	
< 1000	7(33.3%)
> 1000 < 10,000	7(33.3%)
> 10,000 < 100,000	4(19.0%)
> 100,000	3(14.3%)
Year of publication	
2024	7(33.3%)
2023	3(14.3%)
2022	3(14.3%)
2021	2(9.5%)
2020	2(9.5%)
2015–2019	4(19.0%)
Country of first author	
United States of America	5(23.8%)
China	3(14.3%)
Netherlands	2(9.5%)
Spain	2(9.5%)
Sweden	2(9.5%)
United Kingdom	2(9.5%)
Other	5(23.8%)
Study design	
Retrospective cohort	14(66.7%)
Longitudinal cohort	3(14.3%)
Cross-sectional	2(9.5%)
Prospective cohort	2(9.5%)
Scope data source	
Multicenter	5(23.8%)
Population	7(33.3%)
Single center	8(38.1%)
Single center and population*	1(4.8%)
Type of multimorbidity	
Two or more chronic conditions	12(57.1%)
Combination of two specific chronic conditions	9(42.9%)
Studies divided by type of machine learning	
Cluster analysis	14(66.7%)
Predictive modelling**	8(38.1%)
Type of algorithm used for cluster modelling (n = 28)***	
K-means	5(19.2%)
Hierarchical	5(19.2%)
Fuzzy c-means	3(11.5%)
Other	15(57.7%)
Clustering characterized by: (n = 14)	
Presence of chronic disease	8(57.1%)
Symptoms and outcomes	3(21.4%)
Medical specialty involved	1(7.1%)
Clinical history	1(7.1%)
Engagement with digital platform	1(7.1%)
Type of algorithm used for predictive modelling (no. of algorithms =)***	
Random Forest	5(20.8%)
Extreme Gradient Boosting	4(16.7%)
Logistic Regression	4(16.7%)
Decision Tree	3(12.5%)
Other	8(33.3%)

Scope: Lai et al.[38] *was a comparative study using both a population-based study and a single center study, therefore counted as multicenter and population*

** *Prasad* et al.[35] *performed both cluster analysis and predictive modelling and was therefore counted in both*

****Total number of algorithms exceed the number of articles in both clustering and prediction articles. Machon* et al. *Martins* et al.[27] *and Sheng* et al.[28] *compared multiple clustering algorithms while all articles except for Hillman* et al.[33] *explored multiple prediction algorithms*

MCC patients. Overall, these findings show that, over the last 10 years, ML applications for MCC in specialist care have mainly used cluster analysis to phenotype this heterogeneous patient population hoping to enhance early detection, prevention, and overcome the consequences of fragmented care. More recently, there has been a focus on developing prediction models that could support clinical decision-making. No studies were identified that clinically implemented ML applications or utilized NLP or DL techniques.

4.1 Machine Learning for patients with MCC compared to other healthcare settings and clinical evaluation

Our findings regarding articles clustering by type of chronic disease were largely consistent with a systematic review on multimorbidity patterns in primary care [49]. These patterns were identified using heterogeneous clustering methods. In this study, a mental health pattern was commonly observed across studies, followed by a cardiovascular pattern, with hypertension being the most prevalent condition [49]. The lack of a dominant mental health pattern in our study may be accounted for by the fact that mental health is primarily managed by general practitioners or psychiatrists who often work outside hospital settings. Nonetheless, cardiovascular diseases seem to be a key factor in multimorbidity in different healthcare settings.

Comparing ML methods applied for specialist care of patients with MCC versus those applied for general patients in primary care suggests that MCC-focused approaches may be less advanced. To explain, a scoping review of AI methods in community-based primary care showed partial alignment with our findings. Notably, NLP, a rapidly advancing technology, was present in the reviewed primary care studies but absent from those in our analysis [50]. Additionally, while that review identified neural networks as the most

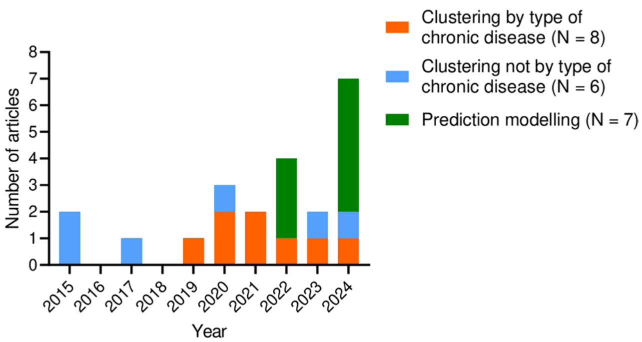

Fig. 2 Temporal distribution of included articles (N=21) by use of machine learning

accurate for predictive modelling, our study found random forests to be more commonly used. These differences highlight the potential value of further exploring neural networks in MCC research, especially given the growing emphasis on predictive modelling in recent years.

Despite advancements in model developments across diverse populations, there is still a significant gap between the development of ML models and their real-world implementation in healthcare. The included articles identified clinical gaps and future research opportunities but did not assess clinical implementation of ML in patients with MCC. Articles that subsequently cited the articles included in this review primarily focused on building upon or validating the findings, rather than exploring clinical implementation. This is also evident in primary care; a scoping review about AI in primary care showed that only 6.9% of research assessed real world AI application (28 of 405 studies), while 66.7% (270 of 405 studies) focused on developing or refining ML models using secondary data [51]. Moreover, hospital settings have shown to face similar challenges, with barriers to AI adoption including concerns over time consumption and perceived unreliability of ML systems [49].

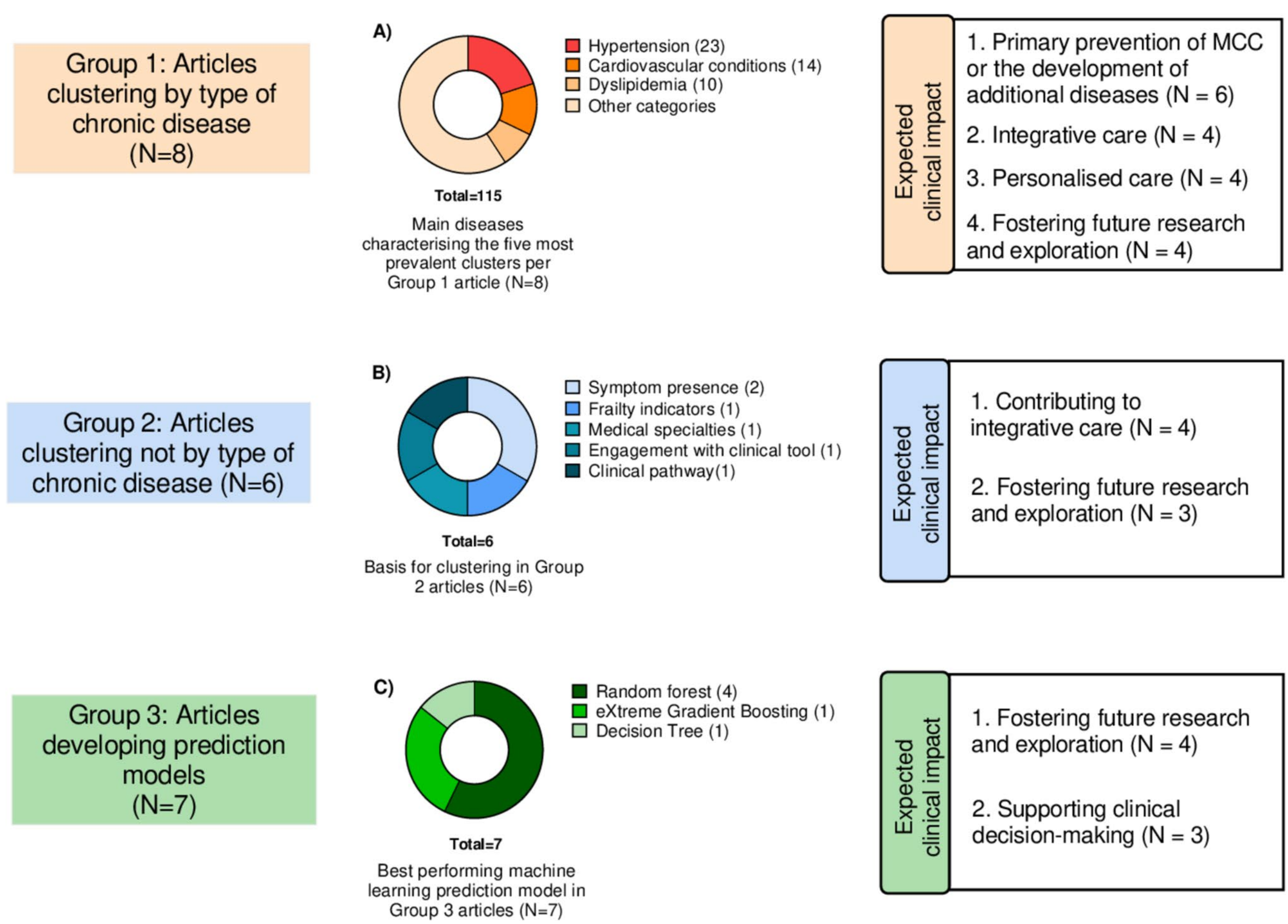

Fig. 3 Overview included articles (N=21) divided by use of machine learning. (**A**) Summary of the three most frequently reported diseases characterising the five most common clusters per article across Group 1 articles. Diseases categories in 'Other categories' is further outlined in Supplementary Table 5 (**B**) Overview of the other bases for clustering than type of chronic disease across Group 2 articles (C) Best performing machine learning prediction methods across Group 3 articles. The main stated and expected clinical impacts of the articles are listed per article group

4.2 Future perspectives: clinical evaluation and implementation are vital to realize the potential of ML applications.

Clinical implementation of ML methods for patients with MCC in specialist care is scarce and is likely to encounter adoption challenges similar to those previously identified in healthcare. To advance the field, the next step is focusing on evaluating clinical impact of research ML techniques. Firstly, researchers should prioritize addressing well-defined clinical challenges where technological advancements are most needed. For instance, based on identified clusters of medical specialists or patient groups, a tailored outpatient integrative care approach could help address the issue of fragmented care within hospitals. Further, predictive modelling could support selecting target groups for integrative care. By aligning innovations with the specific healthcare needs of patients with MCC both locally and nationally, they can deliver standardized, contextually relevant solutions that are ready for implementation.

Furthermore, researchers are encouraged to explore methods such as automatic monitoring, NLP, or large language models (LLMs) for MCC patients as this was not seen in any included study. Given that patients with MCC frequently interact with healthcare systems, their EHRs may contain vast amounts of unstructured data, including clinical notes, investigation reports and social determinants of health. LLMs for example, a form of generative AI trained with NLP techniques forming Generative Pretrained Transformer models, may efficiently summarize large unstructured datasets. This has potential to integrate information from multiple healthcare providers and substantially facilitate the integrative management of MCC patients.

Lastly, a key factor in clinical implementation for researchers could be to explore how healthcare stakeholders, including different specialties and healthcare professionals, and MCC patients engage with ML applications. To help overcome any negative perceptions and demystify the “black box” concept surrounding ML [11], efforts should focus on improving interpretability to healthcare providers through providing education on the clinical meaning of ML outputs, by means of explainable AI [52].

4.3 Strengths and Limitations

One strength of this scoping review is its clinical focus on various types of ML, providing an overview of the current state of ML for this specific population. Additionally, the emphasis on data from medical specialist care is another strength, as this setting typically involves patients with complex and multidimensional health conditions, where data-driven (organizational) advancements are particularly relevant. However, some limitations should be considered. The rapid evolution of AI may have led to missed studies, particularly those published after our search date, though we believe this did not undermine the review's key messages. Additionally, varying terminology for diseases (e.g., heart disease vs. cardiovascular disease) required regrouping, potentially misrepresenting original findings, though we clarified these terms in Supplementary Table 5.

4.4 Conclusion

This scoping review emphasizes the role of ML in specialist care for patients with MCC, where current applications mainly focus on identifying MCC patterns through cluster analysis and are beginning to build predictive models to aid clinical decision-making. Beyond these advancements, ML holds considerable potential to enhance specialist care for MCC patients. The next crucial developments involve clinical validation and evaluation, and exploring the use of NLP and LLMs to extract insights from unstructured EHR data.

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Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Competing interests Each author certifies that he or she has no commercial associations (e.g., consultancies, stock ownership, equity interest, patent/licensing arrangements, etc.) that might pose a conflict of interest in connection with the submitted article.

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