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Population risk stratification tools and interventions for chronic disease management in primary care: a systematic literature review

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Abstract

Background Population risk stratification (RS) tools have been proposed to tailor interventions, prioritize resources, and proactively manage high-risk individuals with chronic diseases in primary care settings. This study aims to explore the available evidence on the use of population RS tools in primary care settings, specifically evaluating the impact of targeted interventions based on RS tools on selected chronic patients and healthcare utilization outcomes.

Methods A systematic literature review was conducted across multiple electronic databases to identify relevant articles assessing the impact of targeted interventions based on RS tools in the management of chronic disease patients within primary care settings. We included studies meeting the following inclusion criteria: randomized controlled trials (RCTs), controlled clinical trials (CCTs) or before-after studies (BAs); adults with heart failure, chronic kidney disease, type 2 diabetes mellitus, chronic obstructive pulmonary disease, or dementia; interventions relying on RS tools; comparators with or without RS tools; and outcomes including Emergency Department (ED) visits, outpatient visits, hospitalizations, mortality, and costs.

Results A total of seven studies met the inclusion criteria, comprising one RCT, two CCTs, and four controlled BAs. The findings revealed mixed effects of interventions on patients identified using RS tools. Among the included studies, four reported significant reductions in ED visits. Two studies reported an increase in outpatient visits. Hospitalization rates were reduced in three studies, and two studies reported significant reductions in overall mortality. However, the impact on healthcare costs was inconclusive.

Conclusions The evidence on the effectiveness of RS tools for chronic disease management in primary care settings remains limited. While some studies demonstrated positive outcomes in reducing hospitalizations, ED visits, and mortality, the overall impact on outpatient service use and healthcare costs varied. Further high-quality studies are needed to evaluate the long-term benefits and cost-effectiveness of RS tools in chronic disease management within primary care.

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Keywords Risk stratification tools, Chronic illness, Primary health care, Health services research, Systematic reviews

Background

Worldwide, the prevalence of chronic diseases is growing and represents a significant challenge to healthcare systems. This occurrence mainly affects the primary care settings where most patients receive medical attention and treatments [1–3]. Chronic diseases, such as cardiovascular diseases and respiratory conditions, are the leading causes of mortality and morbidity globally, and effective and sustainable management strategies are needed [3, 4]. The challenges of chronic disease management are exacerbated in primary care with patients requiring continuous care and the coordination of multiple healthcare providers. In this context, timely identifying, managing, and monitoring high-risk patients becomes crucial for improving outcomes and optimizing resource allocation [5, 6].

Population risk stratification (RS) tools have been proposed to address these challenges [7–9]. These tools leverage various data sources, including routinely collected healthcare data, electronic health records (EHRs) and patient-reported outcomes, to categorize patients according to their risk of adverse health events. By doing so, they enable healthcare providers to tailor interventions, prioritize resources, and proactively manage high-risk individuals (Fig. 1). In this context, the intervention cannot be reduced to the mere presence and use of a RS tool. Rather, it involves the modification of subsequent activities resulting from the use of such tools, which are expected to enable more targeted and personalized approaches and, theoretically, lead to better health outcomes.

The adoption of such tools, specifically in primary care settings, holds the promise of transforming chronic disease management by shifting from a reactive to a proactive and personalized approach [10, 11]. However, the integration and yield of population RS tools in primary care vary widely across different healthcare systems and settings. Factors such as the healthcare services organization, the availability and quality of data, and the readiness of healthcare providers to adapt/innovate their strategies following the indications drawn from the adoption of new technologies play a significant role in determining their impact [12, 13]. Due to that, the effectiveness of these tools in improving patient outcomes, reducing healthcare utilization, and enhancing the efficiency of healthcare delivery remains an open empirical issue and a subject of ongoing research. Understanding these dynamics is critical for informing policy, practice, and future research directions in chronic disease management.

Given the key role of primary care in managing chronic diseases and the potential benefits of implementing population RS tools, there is a compelling need to review the current knowledge on their effectiveness and impact on healthcare outcomes. This study aims to explore the available evidence on the use of population RS tools in primary care setting for managing chronic diseases. Specifically, it seeks to evaluate the impact of targeted interventions based on RS tools on selected patients with long term conditions and healthcare utilization outcomes. By doing so, this systematic review intends to provide valuable insights into the potential of RS tools to enhance chronic disease management in primary care.

Methods

Protocol

The review protocol was registered in PROSPERO, the International Prospective Register of Systematic Reviews (CRD42023440604). This systematic review was conducted according to the PRISMA guideline [14].

Search strategy and inclusion criteria

This systematic review conducted a comprehensive search across multiple electronic databases, using keywords specifically designed to identify relevant articles assessing the impact of targeted interventions based on RS tools in the management of chronic disease patients within primary care settings.

We searched MEDLINE, Embase, and Scopus from 1995 to up to December 2023. The search strategy adopted was consistent across the databases and was developed using the following keywords:" stratification", "chronic diseases", "primary care setting", and was as broad as possible, to minimize the risk of missing relevant studies. A literature search was performed using a combinations of free text keywords as well as controlled vocabulary terms. In addition, we screened the reference list of retrieved articles searching for other relevant studies. Language restrictions were applied limiting the search to studies published in English. The full search strategy is detailed in the Table S1 of Supplemental Materials.

We included studies that met the following inclusion criteria (PICO): (i) Randomized controlled trials (RCTs), Controlled or uncontrolled before-after studies (CBAs and UBAs), or Interrupted Time series studies (ITS); (ii) Enrolled adults (≥ 18 years) with chronic diseases; (iii) Considered at least one of the following *chronic diseases (population)*: heart failure (HF), chronic kidney disease (CKD), type 2 diabetes mellitus (DM2), Chronic obstructive pulmonary disease (COPD), dementia; (iv) described the characteristics of the population RS tools used in primary health settings, and (v) of any targeted *intervention*

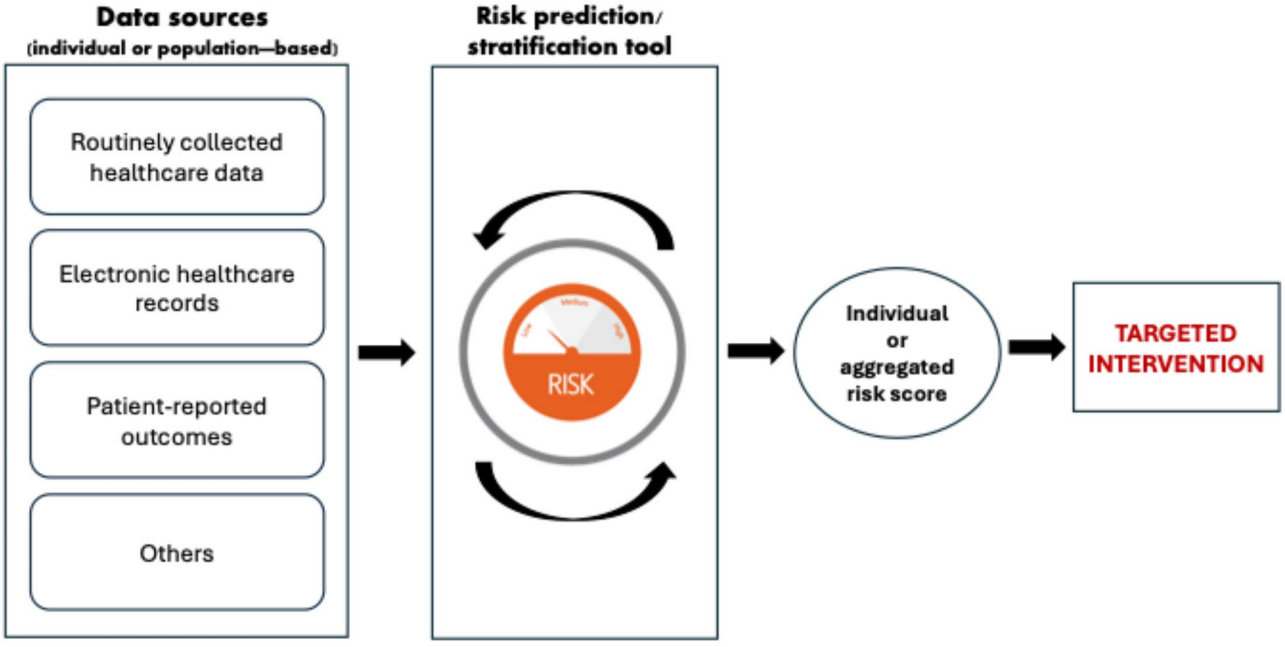

Fig. 1 Targeted interventions based on risk stratification/prediction tools

(intervention) delivered in primary care settings relying on those tools to identify individuals to be targeted by specific actions according to their estimated risk; (vi) The *comparator (control)*, if present depending on the study design (inclusion criteria related to study design was prioritized over the presence of a comparator), was the same intervention without reliance on RS tools or historical/usual care; (vii) reported data about any of the following *outcome (outcome)* of interest: mortality (overall and cause-specific), Emergency Department visits, hospitalizations, re-hospitalizations and costs.

We considered RCTs, nRCTs, CBAs, UBAs, and ITS designs meeting minimum criteria as suggested by the Cochrane Effective Practice and Organization of Care Group (EPOC). We considered ITS studies as eligible if they have a clearly defined point in time when the intervention occurred (i.e., when the RS/population health management (PHM) tool was first used/implemented).

The context of the intervention was defined as primary care settings and practices like family practices, community health centers, and community hospitals. A primary care practice/setting serves as the patient's entry point into the healthcare system and is the continuing coordination point for all needed health care services. Primary care practices provide patients with ready access to their designated physician and multidisciplinary health care team.

We excluded case reports, opinion papers, editorials and letter to editors, as well as studies only evaluating the technical performance of RS tools (i.e., predictive value).

Study selection and data extraction

Seven reviewers (AN, DT, DG, MC, VP, EB, LA) independently screened title and abstracts from the records retrieved. Potentially relevant studies were acquired in full text and assessed for final inclusion independently by three pairs of authors. Disagreements were resolved by discussion. The results of this process were reported using a PRISMA flowchart.

Authors independently extracted the following information from the full texts: general information (Authors, year of publication, title, reference, country, setting); study design; characteristics of participants (disease, number, mean age, gender); characteristics of RS tools; type of intervention; type of outcome and results.

Quality assessment

The methodological quality of the included studies was independently evaluated by seven review authors, and the risk of bias in the RCTs and CCTs was assessed using the criteria developed by the Cochrane Collaboration [15]. The following domains were considered: random sequence generation, allocation concealment, blinding of participants, providers and outcome assessors, incomplete data outcome, and selective outcome reporting. Each domain was classified as "high" or "low" risk of bias. When the information reported in the article was insufficient, the domain was defined as "unclear".

For CBA and ITS the criteria suggested by the EPOC Cochrane Review Group were used [16]. The following domains were considered: independent intervention, shape of intervention, knowledge of the allocated

intervention, incomplete data outcome and selective outcome reporting.

Synthesis of results

Each study was described in detail and the characteristics of those included reported in tables. We summarized the type of risk stratification tool, the type of targeted intervention, and the main outcome, reporting results pre and post intervention for both intervention and control groups. We reported the change from baseline with 95% confidence interval (CI) if present, or the size effect (e.g., mean difference, ratio of means). We also summarized the main policy recommendation, if reported by Authors.

Results

Literature search

The bibliographic search retrieved a total of 4963 records after duplicates were removed. Of these, 4902 were excluded based on title and abstract, and 61 were judged as potentially relevant and acquired in full text. Fifty-four articles were excluded as not meeting the inclusion criteria. Overall, seven studies were considered eligible for inclusion [17–23] (Fig. 2).

Characteristics of included studies

Of the seven included studies, only one was a RCT [17], 2 were CCTs [18, 19], and four were CBA studies [20–23].

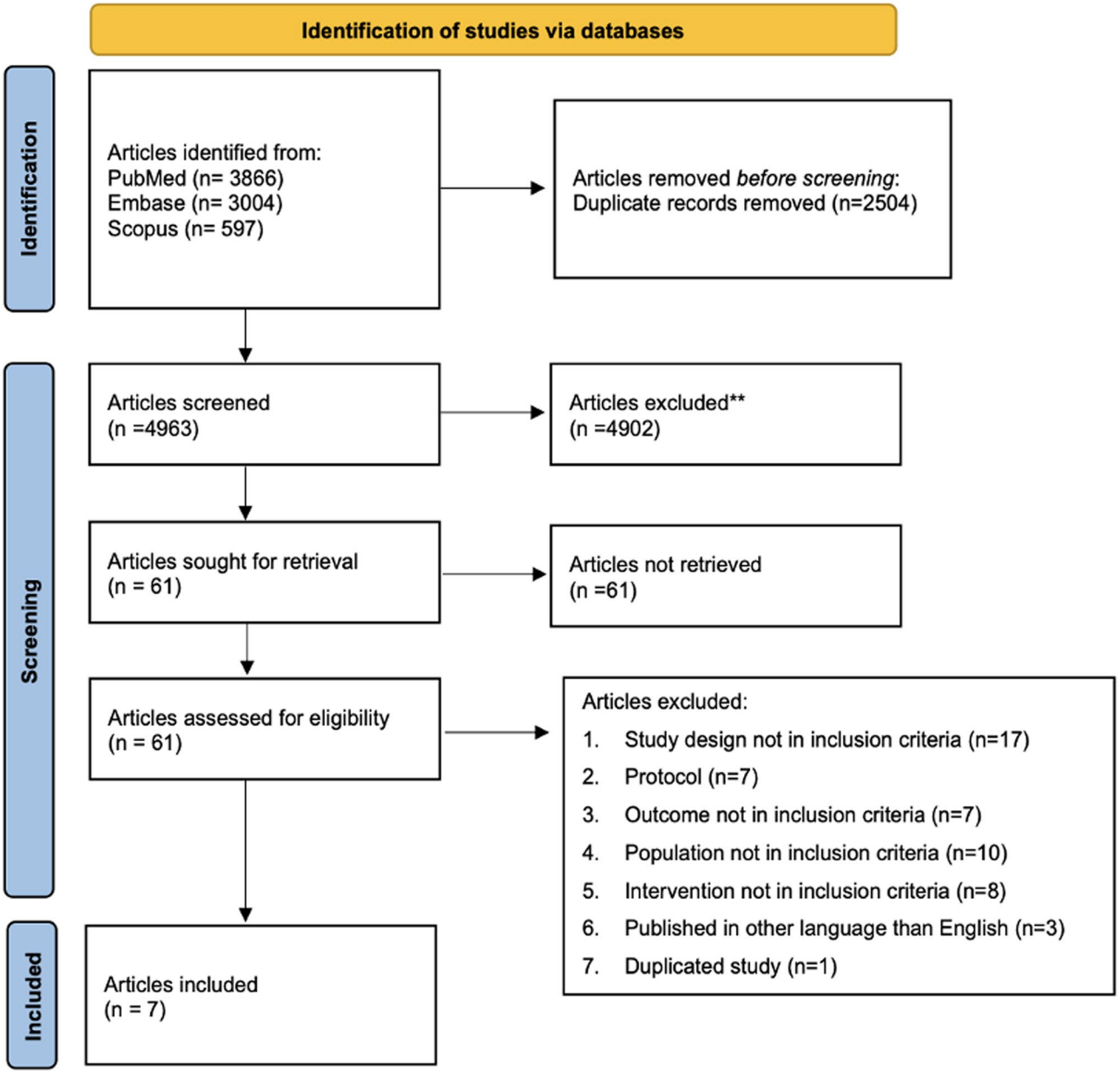

Fig. 2 PRISMA 2020 flowchart for studies' identification

Overall, two studies were conducted in Hong Kong and UK, while the remaining were from Spain, Austria and Germany. All studies provided details about the characteristics of participants. Patients enrolled ranged from ~200 [18] to more than 200,000 [17], with a mean age between 55 and 79 years. The majority of studies (n = 6) included patients with DM2, four studies considered patients with COPD, three studies HF and one study considered hypertension, asthma, CKD, dementia and cancer. Table 1 provides a summary of the main characteristics of the included studies.

Stratification tools

Various RS tools and models aimed at improving chronic disease management in primary care settings were used. These included the Basque population-based algorithm [18], PRISM software [17], HMR CCG Long Term Conditions Test-Bed [20], RAMP-DM [21, 22], Population Health Value (PHV) [23], and the Adapted ACG system [19]. Detailed descriptions of the RS tools are provided in Table 2.

Interventions details

Several targeted interventions were adopted by various providers, relying on the output of the RS tools. For instance, Soto Gordoa et al. [19] described an intervention based on the risk stratification tool that consisted of a chronic-care program with multidisciplinary teams, the introduction of new professional roles like liaison nurse and case manager, an infrastructure of information and communications technologies, and telehealth/empowerment services. Prioritization was based on hospitalization history and risk score using the ACG system. Snooks et al. [17] 's intervention was provided by general practices and consisted of using the PRISM software to calculate risk scores for individual patients, practice-based training on using the PRISM software, clinical support, technical support, and a user-friendly handbook. The duration of the interventions ranged from 12 months to over 5 years. Detailed descriptions of the interventions are provided in Table 2.

Outcomes

Five studies evaluated the impact/effect of the RS tool intervention on emergency department (ED) visits/admissions (4), outpatient visits (5), hospitalizations (4), two on mortality, and three on costs. In Table 3 the results for each study are reported, showing the impact of the interventions on ED visits/admissions, hospitalizations, and mortality, and with mixed results for outpatient visits and healthcare costs.

ED visits/admissions

Mateo Abad et al. [18] reported a significant reduction in ED visits/admissions (0.3 rate per year) compared to the control group (1.3 rate per year, $p < 0.05$). Snooks et al. [17] and Lugo Palacios et al. [20] did not find significant differences between intervention and control groups for ED visits. Wan et al. [22] observed a significant decrease in ED visits/admissions (IRR: 0.588, $p < 0.05$) post-intervention.

Outpatient visits

Mateo Abad et al. [18] and Lugo Palacios et al. [20] did not report significant differences in outpatient visit rates. Wan et al. [22] and Soto Gordoa et al. [19] noted an increase in outpatient visits (IRR: 1.326, $p < 0.05$, and probability: 2.10, $p < 0.05$, respectively), indicating a higher engagement with healthcare services among those in the intervention groups.

Hospitalizations

Mateo Abad et al. [18] reported a significant reduction in hospitalizations (0.5 rate per year) compared to the control group (0.8 rate per year, $p < 0.05$). Gupta et al. [23] found a 2% reduction in monthly hospitalizations for CKD patients (IRR: 0.98, $p < 0.05$). Wan et al. [22] also observed a significant reduction in hospitalizations (IRR: 0.415, $p < 0.05$).

Mortality

Jiao et al. [21] and Wan et al. [22] reported significant reductions in overall mortality rates after the intervention. Jiao et al. noted an adjusted hazard ratio (aHR) of 0.363 ($p < 0.05$), and Wan et al. reported an HR of 0.339 ($p < 0.05$).

Costs

Among the included studies, only three reported cost-related data, and none performed a formal cost-effectiveness analysis. As a result, our ability to evaluate the economic impact of RS-based interventions remains limited. Gupta et al. [23] reported a decrease in healthcare costs for dementia and CKD patients, though not statistically significant. Snooks et al. [17] found no significant difference in per-patient costs between the intervention and control groups.

Size effect and policy recommendations

Size effects of the targeted intervention based on RS tools, and related policy recommendations, if present, are reported in Table 4. For instance, Snooks et al. [17] reported increased ED admission rates (1% increase; 95% CI 0.010 to 0.013), ED attendance rates (3% increase; 95% CI 0.028 to 0.032), outpatient visit rates (5% increase; 95% CI 0.051 to 0.058), and time in hospital (3% increase; 95% CI 0.026 to 0.031). They recommend that policymakers should consider alternative approaches to managing high-risk patients, emphasizing interventions aimed at

Table 1 Main characteristics of the included studies

		Study design					Disease/s	participants intervention/ participants before			participants control/ participants after			Outcome/s analyzed
Study ID	**COUNTRY**	**Study design**	**Inclusion criteria**	**Before period (for CBA/ITS)**	**After period (for CBA/ITS)**	**Length of post-intervention follow-up period**		***N***	**Mean Age (SD)**	**FEMALE%**	***N***	**Mean Age (SD)**	**FEMALE%**	
Mateo Abad 2020 [18]	Spain	*CCT*	*≥ 65 years, 2 + chronic conditions (COPD, CHF, diabetes)*	-	-	*9–12 months*	*COPD, CHF, diabetes*	*101*	*79.6 (6.9)*	*34%*	*99*	*79.2 (6.8)*	*40%*	*ED-visits/admissions; Outpatient visits; Hospitalizations; Others*
Snooks 2018 [17]	England (UK)	*RCT*	*General practices within Abertawe Bro Morgannwg University Health Board*	-	-	*18 months*	*Asthma, COPD, diabetes, hypertension*	*230,099*	*41.2 (23.4)*	*50%*	*230,099*	*41.2 (23.4)*	*50%*	*ED-visits/admissions; Outpatient visits; Costs; Others*
Lugo Palacios 2019 [20]	England (UK)	*CBA (DiD)*	*All patients assisted by 2 Clinical Commissioning Groups*	*Apr 2016-Mar 2017*	*Apr 2017-Mar 2018*	*10–13 months*	*COPD, type II diabetes, heart failure*	*5276 COPD, 1877 HF, 13,741 DM*	*N/A*	*N/A*	*1723*	*N/A*	*N/A*	*ED-visits/admissions; Outpatient visits; Others*
Jiao 2015 [21]	Hong Kong	*CBA (DiD)*	*Age ≥ 18, ICPC- 2 codes T89/T90, at least one primary clinic attendance before baseline*	*1 Aug 2009 - 31 Jul 2010*	*Aug 2010 - 31 Jul 2013*	-	*Type 2 DM*	*9094*	*64.23 (11.05)*	*52%*	*9094*	*64.29 ± 11.96*	*53%*	*Mortality; Others*
Wan 2018 [22]	Hong Kong	*CBA (DiD)*	*Age ≥ 18, type 2 DM, no prior CVD or microvascular complications*	*1 Aug 2009 - 30 Jun 2011*	*Jul 2011-Nov 2015*	-	*Type 2 DM*	*26,718*	*67.76 (11.73)*	*53%*	*26,718*	*67.79 (13.64)*	*53%*	*ED-visits/admissions; Outpatient visits; Mortality; Hospitalizations;*
Gupta 2019 [23]	USA	*CBA*	*Patients in UCLA primary care network*	*CKD before Aug 2016, Dementia and cancer Apr 2017*	*CKD Oct-Dec 2016, Dementia and cancer Jun-Sep 2017*	-	*CKD, Dementia, Cancer*	*Dementia: 4348, CKD: 17,172, Cancer: 27,757*	*Dementia: 85 (9), CKD: 73.5 (15), Cancer: 62.9 (15)*	*Dementia: 34%, CKD: 48%, Cancer: 34%*	*Dementia: 4348, CKD: 17,172, Cancer: 27,757*	*Dementia: 85 (9), CKD: 73.5 (15), Cancer: 62.9 (15)*	*Dementia: 34%, CKD: 48%, Cancer: 35%*	*Costs*
Soto-Gordoa 2019 [19]	Spain	*CCT*	*Individuals with multimorbidity, ≥ 65 years*	*2012*	*2014*	*12 months*	*Multimorbidity (DM, HF, COPD)*	*Not prioritized: 2761, Prioritized: 4225*	*Not prioritized: 77.98 ± 7.42, Prioritized: 80.17 ± 7.06*	*Not prioritized: 36%, Prioritized: 59%*	*Not prioritized: 2704, Prioritized: 3558*	*Not prioritized: 77.61 ± 7.42, Prioritized: 79.2 ± 6.93*	*Not prioritized: 36%, Prioritized: 61%*	*Hospitalizations; Costs; Others;*

RCT Randomized Controlled Trial, *CCT* Controlled Clinical Trial, *CBA* Controlled Before-and-After, *DiD* Difference-in-Difference, *ED* Emergency Department, *COPD* Chronic Obstructive Pulmonary Disease, *HF* Heart Failure, *DM* Diabetes Mellitus, *CVD* Cardiovascular Disease, *CKD* Chronic Kidney Disease, *F* Female, *M* Male, *ICPC- 2* International Classification of Primary Care (ICPC- 2)

Table 2 Stratification tools and interventions

Study ID	Provider Description	Stratification Tool	Intervention Description	Duration
Mateo Abad 2020 [18]	Integrated care organizations (ICO) within the Basque Country health system, Spain.	Basque population-based algorithm	The intervention was the CareWell integrated care model, which included: coordination between health providers, home-based care, patient empowerment, and support from ICT tools. The CareWell model defined a specific care pathway with several phases, focusing on care coordination/communication and patient empowerment/home-based care. The CareWell model for multimorbidity patients includes identification through the Basque population-based risk stratification (Complexity defined as having a predictive risk index higher than 6.28, which means that the probability of using the health services in the following year was at least 6.28 times higher than for an average Basque citizen), baseline assessment, therapeutic plan, follow-up, patient stabilization, integrated care during hospitalization, coordinated discharge. It also included a patient empowerment program called KronikOn, with 4 sessions of 20–30 min provided by nurses.	9–12 months
Snooks 2018 [17]	General practices within Abertawe Bro Morgannwg University Health Board	PRISM software	The intervention consisted of: (1) PRISM software that provided risk scores for individual patients, (2) 2 h of practice-based training on using the PRISM software, (3) clinical support through 2 "GP champions", (4) technical support through a "help desk", and (5) a user-friendly handbook. The intervention was provided to general practitioners, not directly to individual patients. PRISM software estimates emergency admission risk. Practices use risk scores to target services.	1–12 months
Lugo Palacios 2019 [20]	Heywood Middleton and Rochdale Clinical Commissioning Group (HMR CCG)	HMR CCG Long Term Conditions Test Bed	The interventions were: 1. Clinical audit and population management software including risk algorithms (MSDi Optimise). The algorithm provided prediction scores about patients' risk of developing long-term conditions (COPD, heart failure, type 2 diabetes) at 12 and 24 months. 2. Quality improvement program (Evidence into Practice) for COPD and diabetes, delivered over 12 months 3. Remote telehealth monitoring and coaching service (Closer-care) for patients with heart failure or COPD, involving 12 weeks of remote monitoring followed by 6 weeks of weekly 60-minute coaching sessions	12 months
Jiao 2015 [21]	Hong Kong Hospital Authority	RAMP-DM	The intervention is the RAMP-DM program, which involves comprehensive risk factor screening, risk stratification (RAMP-DM provides comprehensive risk screening for diabetes-related complications, with patients stratified into risk groups), and provision of appropriate interventions and education by a multidisciplinary team based on the patient's risk level and HbA1c level. The frequency of the full risk factor screening and assessment varies, with some patients receiving it annually and others every 2–3 years with annual blood tests. Care is managed by trained nurses, including education and lifestyle advice.	Aug 2009 - Jul 2013

Table 2 (continued)

Study ID	Provider Description	Stratification Tool	Intervention Description	Duration
Wan 2018 [22]	Hong Kong Hospital Authority	RAMP-DM	The intervention is the Risk Assessment and Management Programme-Diabetes Mellitus (RAMP-DM), which involves: (1) risk assessment and stratification by nurses, (2) multidisciplinary care coordinated by a nurse manager, (3) individualized care planning based on risk factors, and (4) patient education and lifestyle advice provided by nurses. The RAMP-DM is provided in addition to usual care by the patient's general outpatient clinic doctor.	Aug 2009 - Nov 2015
Gupta 2019 [23]	University of California Los Angeles Health (UCLA Health)	Population Health Value (PHV)	PHV model identifies spending reasons and creates care pathways. Larger lower-risk cohorts receive fewer intensive interventions, smaller higher-risk cohorts receive more intensive interventions, based on data analytics. The interventions included: - For dementia patients: - Dementia education using patient portals and online materials for low-risk patients (tiers 4 and 5) - Referral to the Alzheimer's and Dementia Care (ADC) program, which provided nurse practitioner co-management of dementia care, for middle-risk patients (tiers 2 and 3) - Intensive care management for high-risk patients (tier 1) to coordinate care across primary and specialty teams, reduce utilization, and initiate palliative care - For CKD patients: - Hiring a CKD care coordinator to expedite ambulatory care and increase access to interventional radiology services, who coordinated with extensivist primary care physicians managing high-risk patients (tier 1) - For cancer patients: - Three care pathways defined for five risk tiers, but details not provided	Aug-Sep 2016 & Apr-May 2017
Soto-Gordoa 2019 [19]	Basque Department of Health	Adapted ACG system	The intervention consisted of a chronic-care program with multidisciplinary teams, new roles like liaison nurse and case manager, an infrastructure of information and communications technologies, and telehealth/empowerment services including BetiOn, Active Patient, and Osarean. Prioritization based on hospitalization history and risk score using the ACG system. The aim is to reduce hospital inpatient services by empowering primary care services.	1 year (2014)

Table 3 Outcomes

General information	ED-visits/admissions				Outpatients visit				Overall mortality	
Study ID	**events intervention**	**events control**	***p*-value**	**favorable to intervention?**	**events intervention**	**events control**	***p*-value**	**favorable to intervention?**	**events intervention**	**events control**
Mateo Abad, 2020 [18]	0.3 rate per year	1.3 rate per year	S	Y	2.4 rate per year	3.1 rate per year	NS			
Snooks, 2018 [17]	0.17 rate	0.16 rate	S	N	1.72 rate	1.70 rate	S	N		
Lugo Palacios, 2019 [20]	increase of 79.8%		NS	N	increase of 103.9%		NS	N		
Jiao 2015 [21]									202/9094	552/9094
Wan 2018 [22]	IRR: 0.588		S	Y	IRR: 1.326		S	N	HR: 0.339	
Gupta 2019 [23]										
Soto-Gordoa 2019 [19]					Probability: 2.10	Probability: 1.64	S	N		

Table 3 (continued)

General information	Overall mortality		Hospitalizations				Costs			
Study ID	***p*-value**	**favorable to intervention?**	**events intervention**	**events control**	***p*-value**	**favorable to intervention?**	**events intervention**	**events control**	***p*-value**	**favorable to intervention?**
Mateo Abad, 2020 [18]			0.5 rate per year	0.8 rate per year	S	Y				
Snooks, 2018 [17]							1548 £ per patient per year	1535 £ per patient per year	S	N
Lugo Palacios, 2019 [20]										
Jiao 2015 [21]	S (aHR, 0.363)	Y								
Wan 2018 [22]	S	Y	IRR: 0.415		S	Y				
Gupta 2019 [23]			CKD: 2% reduction in monthly hospitalizations (IRR, 0.98) Dementia: 1% reduction in monthly hospitalizations (IRR, 0.99)		S	Y	CKD = $5,559 Dementia = $1,768		NS	Y
Soto-Gordoa 2019 [19]			Probability: 0.91	Probability: 1.19	S	Y	0.95	1.11	S	Y

S Statistically significant ($p < 0.05$), *NS* Not statistically significant ($p > 0.05$), *HR* Hazard ratio, *IRR* Incidence rate ratio

Table 4 Size effect and policy recommendations

Study ID	Size effect	Policy recommendations
Mateo Abad, 2020 [18]	The paper does not report specific effect sizes with confidence intervals. Still, it does indicate that the CareWell integrated care model was associated with reduced hospitalizations and emergency visits and increased primary care contacts.	The CareWell integrated care model should be considered when caring for complex, multimorbid older patients, as it led to a shift towards more primary care utilization, and fewer emergency and hospital visits.
Snooks, 2018 [17]	- Emergency hospital admission rates: 1% increase (95% CI 0.010 to 0.013) - Emergency department attendance rates: 3% increase (95% CI 0.028 to 0.032) - Outpatients visit rates: 5% increase (95% CI 0.051 to 0.058) - Proportion of days with recorded GP activity: 1% increase (95% CI 0.007 to 0.014) - Time in hospital: 3% increase (95% CI 0.026 to 0.031)	Policymakers should consider alternative approaches to managing high-risk patients, such as focusing on reducing length of hospital stay and preventing readmissions, rather than just identifying high-risk patients. Any interventions using predictive risk stratification tools should have explicit models of how they will work and undergo rigorous evaluation of their clinical and cost-effectiveness before implementation.
Lugo Palacios, 2019 [20]	The size effect for the primary outcome (emergency admissions for COPD, diabetes, and heart failure) was a non-significant increase of 7.6 admissions in the intervention site compared to the comparator (95% CI: − 3.7 to 19.0).	The authors recommend that national orchestrators of the NHS Test Beds scheme should: (1) Reconsider the emphasis on combinatorial innovation, as it may be contributing to implementation challenges. (2) Focus on spreading the individual components of the intervention, rather than the combinatorial approach. Specifically, the Evidence into Practice quality improvement component would be more difficult to spread to a larger area with the same resources.
Jiao 2015 [21]	For all-cause mortality, the hazard ratio was 0.363 (95% CI 0.308–0.428), indicating a 63.7% lower risk in the RAMP-DM group. For total CVD, the hazard ratio was 0.629 (95% CI 0.554–0.715), indicating a 37.1% lower risk in the RAMP-DM group compared to the control group. For CHD, the hazard ratio was 0.570 (95% CI 0.470–0.691), indicating a 43.0% lower risk in the RAMP-DM group.	Not applicable (the authors do not provide any explicit policy recommendations)
Wan 2018 [22]	After adjusting for baseline covariates, the RAMP-DM group had: − 66.1% lower risk of all-cause mortality (HR 0.339, $p < 0.001$)	The authors recommend implementing a multidisciplinary, protocol-driven chronic disease model of care that involves risk stratification and early optimal diabetes control and risk factor management, in order to delay disease progression and prevent complications in patients with diabetes.
Gupta 2019 [23]	For patients with stage 4 or 5 chronic kidney disease (CKD), there was a nearly 2% reduction in monthly hospitalizations, with an IRR of 0.98 and a 95% confidence interval of 0.98–0.99 ($p < 0.0001$). For patients with dementia, there was a 1% monthly reduction in inpatient bed days, with an incident rate ratio (IRR) of 0.99 and a 95% confidence interval of 0.98–1.00 ($p < 0.03$).	Not mentioned (the paper does not contain any explicit policy recommendations)
Soto-Gordoa 2019 [19]	For prioritized patients: - Increase in probability of outpatient visists (OR: 2.10, CI: 1.70–2.39) - Increase in number of primary care contacts (OR: 1.07, CI: 1.05–1.10) - Decrease in probability of hospitalization (OR: 0.91, CI: 0.86–0.96) - Decrease in number of hospitalizations (OR: 0.96, CI: 0.91–1.00) For non-prioritized patients: - Increase in probability of outpatient visits (OR: 1.64, CI: 1.27–2.39) - Decrease in number of primary care contacts (OR: 0.95, CI: 0.92–0.97) - Increase in probability of hospitalization (OR: 1.19, CI: 1.09–1.30)	Based on the study, the key policy recommendations are: 1. Prioritize integrated care interventions on specific populations most likely to benefit, rather than broad populations. 2. Carefully select the target population for integrated care programs to maximize their effectiveness. 3. Utilize observational study designs that capture real-world healthcare contexts, in addition to randomized trials, to evaluate the impact of interventions. 4. Leverage electronic health records and appropriate statistical methods to improve the validity of results when assessing healthcare interventions.

reducing length of hospital stay and preventing readmissions, rather than solely focusing on identifying high-risk patients.

Quality assessment

The only RCT [17] was judged at low risk of bias for selection (random sequence generation and allocation concealment), attrition (incomplete outcome data) and reporting (selective outcome reporting) bias, at high risk for performance bias (blinding of participants and personnel), ad at unclear risk for detection bias (blinding of outcome assessment). Relating to 2 CCTs, the study of Mateo Abad et al. [18] was at low risk of bias for selection (allocation concealment) and attrition (Incomplete outcome data) bias, and Soto Gordoa et al. [19] was judged at high risk of bias for all domains but one (reporting) that was judged at low risk.

Regarding the four CBAs [20–23], all were at low risk for the independent intervention and selective outcome reported, two were at low risk of incomplete outcome data, while in three studies it was unlikely that the intervention affected data collection, in one study the shape of intervention effect was pre-specified and only in one study the allocation of interventions was adequate.

Detailed results of the quality assessment are reported in the supplemental Table S2.

Discussion

This systematic literature review investigated the potential effect of population-based RS tools in managing chronic diseases within primary care settings. While other studies have focused on the validation of the prediction capacity of specific RS tools [11], our research provides meaningful evidence on the impact of these tools on population health outcomes, particularly in chronic disease management carried out by primary care services. Specifically, we aimed to examine the effects of the targeted interventions based on RS tools on selected chronic patients and healthcare utilization outcomes.

We focused our search on the most common chronic conditions—heart failure, diabetes mellitus, chronic obstructive pulmonary disease, and dementia. These conditions are highly prevalent in the population and serve as benchmarks for the extensive and effective application of RS tools. These chronic conditions require complex, continuous management and benefit from RS tools, which help healthcare providers prioritize resources and tailor preventive targeted interventions that can be delivered in out-of-hospital care settings [24, 25]. Our research summarized the latest evidence testing the hypothesis that implementing RS tools in primary care settings for these conditions can lead to better health outcomes, reduced hospitalizations, and improved overall quality of life for patients.

Evaluating population health management tools, such as stratification and risk prediction tools, can be challenging. There is a growing body of evidence on their effectiveness and validation, but real-world implementation and impact studies remain limited and heterogeneous. The latter group of studies vary significantly in their designs, definitions of interventions, population sizes, exposure times, and analyzed outcomes. The still limited and fragmented nature of the related literature makes it difficult to draw broad, generalizable conclusions. However, our analysis attempted to untangle the "web" of scientific evidence and identified key study designs, such as CCTs and CBAs, for future research.

The available literature regarding the effectiveness of RS tool adoption, and related interventions, in enhancing outcomes of interest remains limited both in quality and quantity, with the studies reviewed offering mixed evidence. While some of the findings to date are promising, particularly in terms of reductions in hospitalization and mortality rates, the evidence concerning reductions in ED visits is comparatively weaker. Notably, several studies indicate a simultaneous increase in the utilization of outpatient services, whereas the few analyses examining cost implications reports no significant impact.

The comprehensive review conducted in this study highlighted in the first place the very limited number of evaluations that have assessed the impact of RS tools on improving primary care outcomes. This finding outlines the unexploited potential for policymakers to leverage the sophisticated use of data to enhance primary care interventions. Additionally, we emphasized the importance of adequately defining the intervention based on RS models, when applying such tools to primary care settings for chronic conditions. Interventions can be defined either as the simple use of the stratification tool or, more appropriately, as the comprehensive set of measures, actions, and behaviors (e.g., explicitly through protocols/guidelines) implemented when information about a patient's risk is made available to healthcare professionals (physicians, nurses, or others).

Non-conclusive evidence supports that improving healthcare models relying on RS tools is associated with a reduction in both ED visits and hospital admissions [18, 22]. These outcomes, when considering the management of chronic patients, serve as a proxy for patient mismanagement by primary care services, highlighting their poor capacity to fully address clinical needs, prevent disease recurrence, or clinical decline, leading to overuse of acute care settings [11].

These findings align with other studies indicating that RS can enhance resource allocation and patient management, ultimately improving health outcomes and reducing the strain on healthcare services, in particular reducing hospitalizations [11, 24]. However, as

reported by Snooks et al. [17], any interventions using predictive risk stratification tools should have explicit models of how they will work and undergo rigorous evaluation of their clinical and cost-effectiveness before implementation.

In line with the hypothesis investigated, the implementation of RS tools can be associated with an increase in outpatient visits, as reported by Mateo Abad et al., Wan et al., and Gupta et al. [18, 22, 23]. These findings suggest a better capability of primary care services to treat chronic patients, reducing their risk of needing ED or hospital care, and appropriately moving the setting of care from acute hospital attendances to primary care consultations.

Our systematic review also investigated the impact of complete RS tool implementation on mortality in large healthcare organizations. Although the evidence is still relatively limited, we found two studies reporting lower mortality rates in primary care settings where RS had been implemented, leading to better-informed clinicians and healthcare providers [21, 22]. Two studies [17, 23] also examined the potential impact of RS tools and related interventions on costs but found no significant differences between intervention and control groups. One of the key findings emerging from this review is the limited availability of studies assessing the economic impact of interventions based on risk stratification tools. While our PROSPERO protocol initially emphasized cost-effectiveness as a key aspect of the review, the actual body of evidence identified was insufficient to draw meaningful conclusions in this regard. The lack of structured cost-effectiveness analyses suggests that economic considerations may still be an underexplored aspect in the implementation of RS-based interventions in primary care.

RS tools utilize various data inputs, including electronic health records and patient-reported outcomes, to categorize patients based on their risk of adverse health events [17, 19–21]. This could enable healthcare providers to tailor interventions more precisely, prioritize resources, and engage in proactive management of high-risk individuals. For example, the Adjusted Clinical Groups (ACG) system and the Hierarchical Condition Categories (HCC) model are widely used to predict healthcare utilization and guide clinical decision-making in primary care [11, 26].

Future directions

To maximize the benefits of RS tools, future research should focus on several key areas. Improving the integration of diverse data sources, including social determinants of health, can enhance the predictive accuracy of RS tools. This requires robust health information exchange systems and standardized data collection practices [27, 28]. The effectiveness of RS tools also depends on their validation and adaptability to different healthcare systems, geographical areas, and disease types. Since RS models perform optimally in populations similar to those in which they were originally developed, their widespread application requires local validation and potential recalibration. Also, a systematic description of the interventions that accompanied the adoption of RS tools should be included in future studies. Such an approach can help disclose the mechanisms behind these interventions and identify the factors that contribute most to their success. It is also essential to ensure adequate training and support for healthcare providers to facilitate the effective use of RS tools, including the development of user-friendly interfaces and clear communication of both the benefits and limitations of these tools. In addition, longitudinal studies are needed to assess the long-term impact of RS tools on patient outcomes and healthcare costs, offering valuable insights into their sustainability and overall effectiveness [28–30]. Lastly, developing customizable RS tools that can be tailored to the specific needs of different populations and healthcare settings can improve their relevance and effectiveness, and this should involve collaboration between developers, healthcare providers, and policymakers [31].

Challenges and limitations

Despite their expected benefits, the implementation of RS tools in primary care is not without challenges. One significant issue is the variability in healthcare organization and data quality across different settings, which can affect the accuracy and utility of these tools [9, 24]. Additionally, the readiness of healthcare providers to adopt new technologies and integrate them into existing workflows is crucial for the successful implementation of RS tools [32]. This requires that innovative strategies are endorsed by the entire healthcare system, across all policy and operational levels, to ensure proper transmission of directives and cooperation among the stakeholders involved. Another challenge is ensuring the comprehensiveness of the data used for RS. Many tools primarily rely on biomedical data, potentially overlooking important social determinants of health, such as socioeconomic status and behavioral factors, which can significantly impact patient outcomes [33]. Addressing these gaps requires incorporating broader data sources and enhancing the interoperability of health information systems. Lastly, another limitation emerging from this review is the scarcity of studies assessing the economic impact of interventions based on risk stratification tools. Economic evaluations are crucial for guiding policymakers and healthcare providers in resource allocation and scalability of RS-based interventions. Without a clear

understanding of cost-effectiveness, it remains challenging to determine whether the benefits of risk stratification tools outweigh their implementation and operational costs. Future research should incorporate comprehensive economic evaluations, including cost-effectiveness, cost-utility, and budget impact analyses, to provide a more robust evidence base for decision-making.

Conclusions

Despite the evidence provided by the available scientific literature is limited in quality and quantity, population RS tools represent a promising innovation in the management of chronic diseases within primary care settings. The review found that targeted interventions based on RS tools showed mixed effects on healthcare outcomes, with some studies reporting reductions in hospitalizations, emergency department visits, and mortality, while others showed increased outpatient visits and no significant impact on healthcare costs. By enabling more precise interventions and proactive care, these tools could have the potential to improve patient outcomes and enhance healthcare efficiency. However, addressing the challenges associated with their implementation and ensuring the comprehensiveness of the data used are critical for realizing their full potential. Continued research and development, along with supportive policies and evolving healthcare organizations, are essential to advance the use of RS tools and transform chronic disease management in primary care.

By synthesizing current evidence and identifying key challenges and future directions, this review provides insights into the potential of RS tools to enhance chronic disease management in primary care. Further research and policy efforts are needed to optimize the integration and impact of these tools in diverse healthcare settings.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12913-025-12690-0.

Supplementary Material 1

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Authors' contributions
DG: Writing – review & editing, Writing – original draft, Supervision, Investigation, Data curation, Conceptualization. VP: Writing – review & editing, Project administration, Investigation, Conceptualization. DT: Validation, Methodology, Formal analysis, Data curation. AN: Writing – review & editing, Investigation. EB: Writing – review & editing, Investigation. MDC: Writing – review & editing, Writing – original draft, Investigation. LA: Writing – review & editing, Resources, Investigation. MLB: Writing – review & editing, Validation, Resources, Project administration, Methodology. RG: Writing – review & editing, Supervision, Methodology, Conceptualization. RG: Writing – review & editing, Supervision, Resources, Project administration, Conceptualization.

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Data availability
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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